Trade and Innovation: The Role of Scale and Competition Effects*

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Abstract

This paper studies the effects of trade on firm-level innovation in China. Using both econometrics and a calibrated structural model, we disentangle the mechanisms via which trade affects innovation, focusing on scale effects (impact on market size) and competition effects (impact on markups). The structural model also examines heterogeneity of these affects across firms and studies a new mechanism for competition effects: firms can escape the competition by innovating into a market segment where competition is less intense. The econometric estimates and simulations of the calibrated structural model indicate that both scale and competition effects are important for understanding how trade affects innovation in China. In particular, scale effects of trade on innovation are positive in the aggregate, whereas competition effects are negative. However, when firms can innovate to escape the competition, greater competition induced by lower trade barriers can lead firms to increase innovation rather than reduce it.

1 Introduction

This paper studies how trade affects firm-level innovation in China through two channels: scale and competition. On the one hand, an increase in the size of the market available to a firm can raise the returns to successful innovation and hence induce greater investment in innovative activities. At the same time, firms in a larger market face tougher competition, which may either incentivize or disincentivize innovation. We conjecture that these market size and competition effects are precisely what drive innovation in China.

To investigate, we study Chinese firm-level data matched with R&D data, patent data, international trade transactions data, and domestic highway data. We use the data to examine whether

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rising rates of innovation by Chinese firms can be explained by improved access to foreign markets, and whether China's rising productivity and quality can be explained by rising rates of innovation. Econometric evidence strongly suggests that increases in foreign market size have positive effects on firm innovation, while greater competition from other Chinese firms in export markets reduces innovation by Chinese firms in the aggregate.

Motivated by this evidence, we develop a dynamic structural trade model that features both endogenous competition and innovation. In the model, firms choose R&D investments to move up a product grade ladder, where grades differ endogenously in terms of competitiveness and profitability. The incentives for innovation depend on the size of the market and the levels of competition within each grade, which in turn depend on the trade environment. We calibrate the key parameters of the model using the matched Chinese firm-level data, and simulate counterfactuals to study both the aggregate effects of trade on innovation as well the decomposition of these effects into scale and competition effects. Simulations of the calibrated structural model indicate that both scale and competition effects are important for understanding how trade affects innovation in China. In particular, when firms can innovate to escape the competition, greater competition induced by lower trade barriers can lead firms to increase innovation rather than reduce it.

The contributions of this paper to the literature on trade and innovation are thus threefold. First, it extends the body of work that studies the interaction between market size and firm-level innovation to the context of international trade by Chinese firms. In a domestic setting, Acemoglu and Linn (2004) find large effects of potential market size (driven by US demographic changes) on innovation by pharmaceutical firms, while Beerli et al. (2018) find positive effects of domestic market size on innovation by Chinese firms across durable goods sectors. In an international trade setting, Lileeva and Trefler (2010) find positive effects of lower US tariffs on innovation by Canadian plants, while Bustos (2011) finds positive effects of reductions in Brazilian tariffs through the MERCOSUR trade agreement on innovation by Argentinian firms. Similarly, Aw et al. (2011) find that larger export markets for Taiwanese electronics firms leads to greater investments in innovation, while Coelli et al. (2018) find large effects of tariff reductions on firm-level innovation worldwide as measured by patent data. Our results show that these positive scale effects of trade on innovation characterize innovative behavior by Chinese firms as well.

Second, we expand on the area of the literature focusing on the interaction between competition and firm-level innovation. In particular, we study a model with both endogenous competition (variable markups) as well as a motive for firms to innovate in order to move into market segments with less competition. In this sense, we embed the "escape-the-competition" motive for innovation emphasized by Aghion et al. (2001, 2005) into a general equilibrium trade model, and show that this mechanism is important for understanding innovation by Chinese firms. Our study of both scale and competition effects is similar in spirit to work by Aghion et al. (2017) and Impullitti and Licandro (2018), although the key economic mechanisms differ in a meaningful way. In Aghion et al. (2017), there is no "escape-the-competition" motive for innovation, and greater competition unambiguously disincentivizes innovation. In Impullitti and Licandro (2018), competition can induce greater innovation amongst oligopolistic firms due to improvements in static efficiency, although the extensive margin of competition (number of rival producers) is not considered.

By focusing on heterogeneous effects of competition across firms, we also aim to provide some resolution to the question of whether trade-related competition induces or reduces innovation. As yet, the empirical evidence is mixed: for instance, Autor et al. (2017) find that greater competition from Chinese imports led US firms to reduce innovation (as measured by patents), whereas Bloom et al. (2016) find that rising competition from Chinese imports led to an increase in innovative activities within firms most affected by Chinese import competition. Within the Chinese market, Bombardini et al. (2018) find that increased foreign import competition induced by China's accession to the WTO encouraged innovation for only the most productive Chinese firms. These findings are consistent with our model once the combined effects of scale and competition across firms in different market segments are considered. These results also have important policy implications, as Akcigit et al. (2017) show how R&D subsidies in response to foreign competition can be welfare-improving in the long-run, while import tariffs create large dynamic losses.

Finally, we contribute to the literature by studying both scale and competition effects in a general equilibrium setting. In this vein, Atkeson and Burstein (2010) argue that although lower trade barriers can encourage innovation, the resulting welfare gains are small because of offsetting general equilibrium effects that operate via firm entry. Building on this work, Atkeson and Burstein (2018) argue that there is limited scope for innovation subsidies to generate increases in aggregate productivity and output. However, these theoretical analyses are conducted in an environment with constant markups, and hence consider only the scale effects of trade on innovation. Our work aims to extend these general equilibrium results by considering economies with endogenous competition as well.

The outline of the paper is as follows. Section 2 begins by describing the data. Section 3 then discusses econometric evidence for scale and competition effects of trade on innovation. Section 4 then develops the closed economy structural model, while section 5 extends the model to an open economy. Next, section 6 describes calibration of the model's parameters, and section 7 discusses the counterfactual exercises that we employ the model to study. Finally, section 8 concludes.

2 Data

We use the 2000–2006 Chinese Manufacturing Enterprises (CME) database, which includes all state-owned enterprises (SOEs) and large non-SOEs whose annual sales are more than RMB 5 million (approximately $600,000US). We clean the data following Feenstra et al. (2014). Specifically, we eliminate observations with (a) incomplete or internally inconsistent financial variables, (b) fewer than 8 employees, (c) missing firm identification, or (d) invalid entry for year.

We merge theses data with export and import data at the HS8 level from the Chinese General Administration of Customs. We match the CME and customs data following Yu (2015), matching firm name or zip code or telephone number. We are able to match 76,946 firms, which is more than 40% of the firms and 53% of the export value in the customs data.[1] There are two sources of export data because the CME itself reports the total value of a firm's exports (not disaggregated by HS8 or

[1]The 53% is comparable to the match in the Canadian database. The 'lost' export value is due to the fact that many firms export via trade intermediaries.

destination). If a firm is not matched to the customs database but reports zero exports (as opposed to missing exports) then we treat it as a non-exporter.[2] See the online appendix for details of the CME, the customs data and the matching algorithm.

If the CME firm is matched to the customs data then we use the customs data. This is 16% of our sample. If it is not matched then we use CME exports. These exports are sometimes missing and we set them to zero in cases where the firm always reports either zero or missing exports and never positive exports.

Our key variables are exports, quality, markups, and three measures of innovation. We discuss each of these in turn.

2.1 Innovation data

We use three measures of innovation. The first is patents, which we merge in with the CME-customs matched data. Unmatched firms are assumed to have no patents. Because a small number of firms have thousands of patents, we top code patents at 50; however, our results are not sensitive to this. The second innovation measure is R&D intensity, which we define as R&D expenditure as a percentage of firm sales. Since a few firms report inexplicably high values, we top code the data at 20%. The third measure is the share of total sales that are generated by new products. These data are from a new-products question in the CME survey.

We observe that the patent and R&D data are skewed, with very few firms reporting positive amounts of one or the other. We therefore also use the principal component of the three measures. Specifically, we calculate the principal component separately by 2-digit CIC industry.

2.2 Markups (and RTFP)

We estimate markups using De Loecker and Warzynski (2012) and so must first estimate TFP. TFP estimation is described in detail in Orr et al. (forthcoming). We start by dropping firms from the data based on four criteria that are relevant for productivity analysis. First, firms must have complete data on sales, employment, material costs, and capital. Second, they cannot have 'holes' over time: if they appear in years t_0 and t_1 then they must appear in all years between t_0 and t_1. Third, they cannot switch industries or cities over time (city switching is very rare).[3] Fourth, we drop Tobacco (CIC-2 = 16) because it has too few firms. This leaves us with 772,788 firm-years and 298,259 firms in 28 industries.

To prepare the data for estimation, we deflate each firm's sales using an industry-level price deflator. We deflate materials input expenditures at the industry level using input price deflators that have been filtered through the Chinese input-output tables.[4] We estimate the production function by CIC-2 industry for Cobb-Douglas and translog, and for value-added and gross-output production functions. As discussed in Orr et al. (forthcoming), the translog gross-output production function

[2] There are almost no instances in which a matched firm has (non-zero) customs exports and zero CME exports.

[3] Industries are defined at the 2-digit Census Industry Classification level (CIC-2).

[4] We measure labour input using employment and thus do not need a labour deflator. However, capital is simply measured in RMB.

estimates are most sensible as judged by input elasticities, returns to scale, and stability across specifications.[5] In particular, we consider five different variants of the proxy-variable approach:

1. Case 1 (Vanilla): This specification is exactly as in Ackerberg et al. (2015).
2. Case 2 (Exporting): Same as case 1 except we allow the law of motion for firm level productivity to depend on lagged export status. This controls for learning-by-exporting effects as in De Loecker and Warzynski (2012) and De Loecker (2013).
3. Case 3 (Attrition): Same as case 1, except we include the Olley and Pakes (1996) selection correction terms to correct for attrition bias.
4. Case 4 (Over-identification): Same as case 1, except we include lagged capital and lagged capital square as extra instruments.
5. Case 5 (Full Model): The case 2-4 modifications of case 1 are all introduced simultaneously.

Figure 2.1 reports histograms for the elasticity of output with respect to labour, capital and materials. Each panel reports five histograms, one for each specification listed above and, as is apparent from the fact that the five histograms sit on top of each other, the choice of specification makes little difference. As is standard, the labour and capital output elasticities tend to be close to zero (and infrequently negative for some firm-year observations). The returns to scale tend to be strongly concentrated around 1, which is reassuring. Finally, there is little variation across specifications in the distribution of revenue TFP.

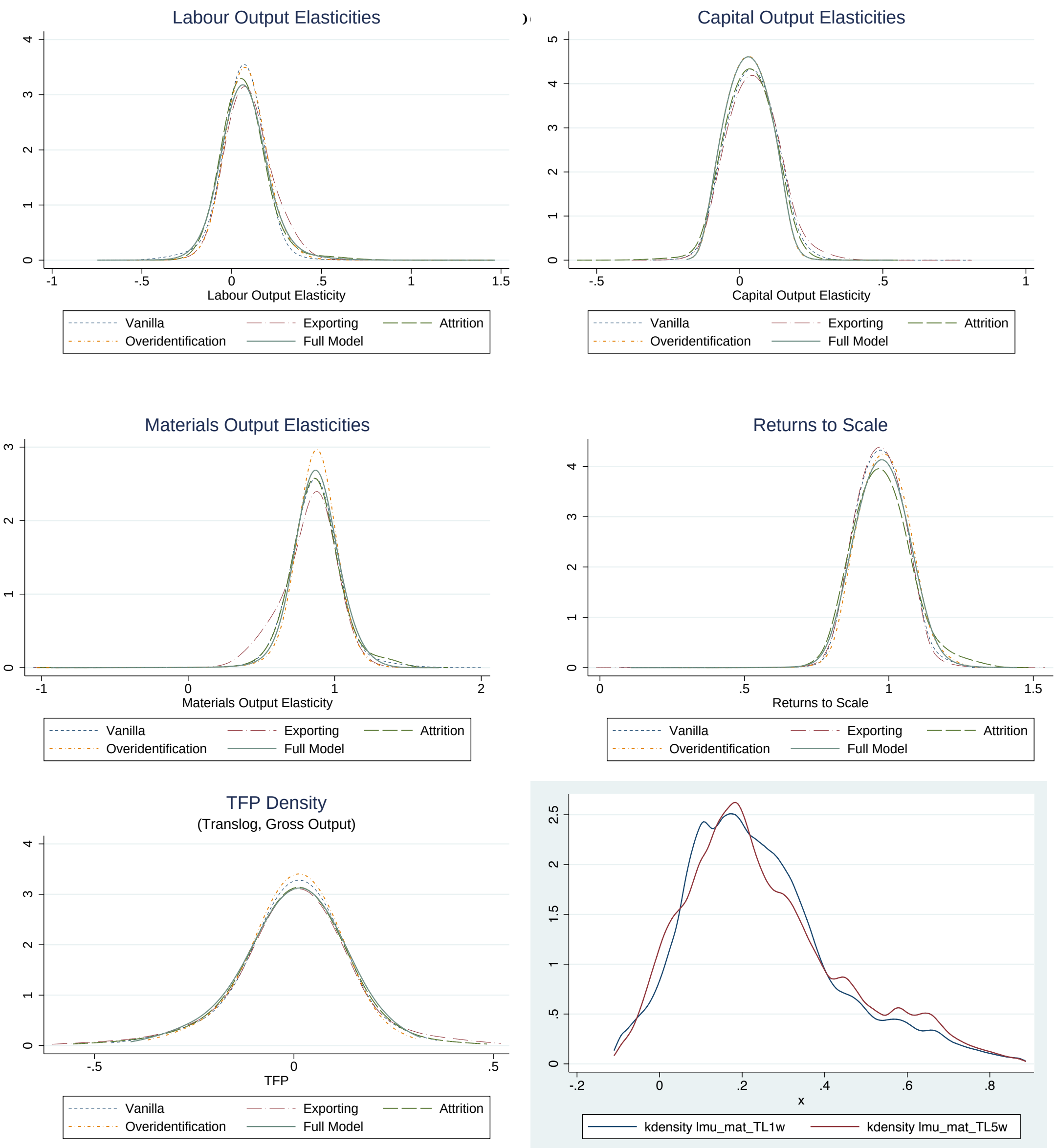
With revenue TFP estimates in hand we estimate markups using the approach in De Loecker and Warzynski (2012). Since labour shares are notoriously low in the CME (see e.g., Brandt et al., 2014), we follow Brandt et al. (2017) in basing markups on material inputs. These appear in the bottom right panel of table 2.1. We only report case 1 and case 5, but the other three cases are very similar. Note that the log markups are relatively close to 0, with most markups being less than 50%. This is much more sensible than the large markups reported in other research.

2.3 Quality

We will need quality to motivate our model. We note that our method only allows us to calculate quality for firms that are matched to the customs data because these are the only firms for which we have quantity and price (unit value) data rather than just revenue data. As a result, we use the quality data to motivate our results, but most of our empirical work will be based on the larger CME sample.

Our starting point is not the demand system of our theory, but the Berry (1994) method. Given the richness of our data, we are also able to improve on the implementation proposed by Khandelwal (2010) and to construct a novel instrument that avoids some of the criticisms of existing instruments (Ackerberg et al., 2007). Consider a Chinese firm f that exports an HS8 good h to destination d in year t. A market is a triplet (h, d, t) and let Ω_{hdt} be the set of firms selling into the market. In what

[5] The Cobb-Douglas elasticities (coefficients on capital, labour and materials) are very similar to those reported in Brandt et al. (2017). See Orr et al. (forthcoming).



Notes: Each panel displays 5 histograms and each histogram corresponds to one of the 5 cases listed in the text. Letting β_{ij} be the coefficient in the translog production function on the interaction between the log of inputs i and j, the panels report labour output elasticities ($\beta_L + 2\beta_{LL} l_{it} + \beta_{LK} k_{it}$), capital output elasticities ($\beta_K + 2\beta_{KK} k_{it} + \beta_{LK} l_{it}$), materials output elasticity ($\beta_M + 2\beta_{MM} m_{it} + \beta_{LM} m_{it} + \beta_{KM} k_{it}$), returns to scale (the sum of the labour, capital and materials elasticities), revenue TFP, and log markups. Since output elasticities, returns to scale and revenue TFP vary across firm-year observations, the histograms are estimated from the 772,788 firm-year observations.

follows, we will repeatedly see this market triplet. How much consumers in d buy will depend not just on prices in the market, but on outside options. For outside options, it will be enough here to model the upper-tier nests. Let $\mathbb{H}$ be an upper-tier nest, which in practice is an HS2 or HS4 category. Firm f's market share is $p_{fhdt}q_{fhdt}/\sum_{f'\in\Omega_{hdt}}(p_{f'hdt}q_{f'hdt})$. This is a core object in demand estimation. Interestingly, our rich data allow us to model the denominator $\sum_{f'\in\Omega_{hdt}}(p_{f'hdt}q_{f'hdt})$ as a fixed effect α_{hdt}. Notice also that Berry's random component of utility will also be subsumed by this fixed effect so that we do not have to estimate this term. Thus, we are left with

$$\ln q_{fhdt} = \alpha_{hdt} + \beta \ln p_{fhdt} + \lambda^*_{fhdt} \tag{2.1}$$

where λ^*_{fhdt} is a measure of the quality of what firm f sells into market (h, d, t).[6]

Aggregating quality from the firm-market level (λ^*_{fhdt}) to the firm level is problematic because quality is never comparable across goods h. To partially address this, we demean quality using the average level of quality in market (h, d, t), i.e., we use $\lambda^*_{fhdt} - \overline{\lambda}^*_{hdt}$. We define a firm's quality in year t as

$$\lambda_{ft} \equiv \sum_{(h,d)} \omega_{fhdt}\left(\lambda^*_{fhdt} - \overline{\lambda}^*_{hdt}\right) \tag{2.2}$$

where ω_{fhdt} is Chinese firm f's exports in year t to market (h, d, t) as a share of its total exports in year t:

$$\omega_{fhdt} \equiv \frac{p_{fhdt}q_{fhdt}}{\sum_{(h',d')} p_{fh'd't}q_{fh'd't}}$$

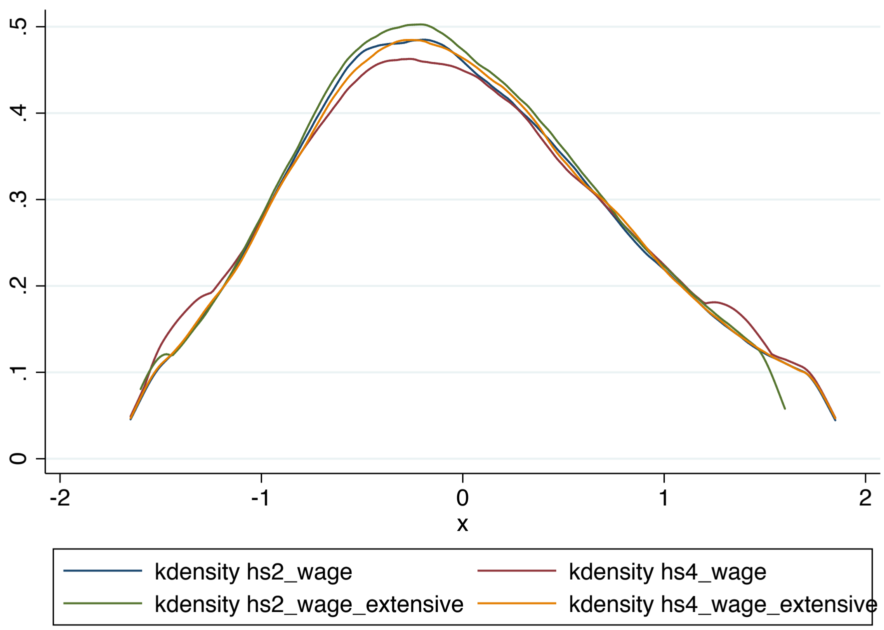
We now turn to instruments. We need a pure supply shock and must avoid demand shocks. One common assumption is that supply shocks are spatially correlated while demand shocks are not. This leads to the Hausman-Nevo instrument which uses the prices of firms in nearby regions as an instrument for the firm's price. We do not think this is a good assumption in our context. Our rich data allow us to take a different approach that has not appeared in the literature. While a firm may be a large employer in its industry within a city, the firm is typically a small employer in its city overall. Consider a firm in a 2-digit CME industry in a city and calculate the average wage paid by firms in that city who are *not* in that industry. This is our instrument.

Finally, we follow Khandelwal (2010) in winsorizing price. We do so by first demeaning price within a market (h, d, t), then winsorizing prices above the 95th percentile and below the 5th percentile. Finally, we add the market mean back in.

The results appear in table 2.1. In our main results below we will define nests at the HS2 level, which has almost 100 products. In order to present the results more, clearly, here we first present results at a more aggregate level of HS sections. The table presents estimates of β in equation (2.1). Consider the first row, which pools all firms exporting chemicals (HS2 codes 28–38). The 'Second Stage' presents the IV estimate of β. 'OLS' presents the OLS estimates of β. 'First Stage' and 'Reduced Form' are the coefficients on the instrument when the dependent variable are price and

[6] We also exploit information about the mode of transportation m, e.g., air or waterborne. This amounts to treating the market not as an (h, d, t) tuplet but as an (m, h, d, t) tuplet. It makes no difference whether we aggregate over mode, but we think that an HS8 product shipped by air may be quite different than one shipped by sea. At any rate, this is a minor point empirically.

Figure 2.2: Distribution of Quality across Four Specifications



Notes: This figure is a kernel density for four different quality measures. Quality is at the firm level (see equation 2.2) and there are 105,093 firm-year observations for each density. Two densities are based on HS2 and two on HS4. Two densities are based on the wage instrument and two are based on both the wage and extensive-margin instruments.

quantity, respectively. Notice that the IV estimates is always negative and more negative than the OLS estimate, as expected. The IV estimate is also almost always less than -1 which means that demand is elastic as required. Notice that there are large numbers of observations, large numbers of firms, and large numbers of markets. We can reject endogeneity ('K-P') and the joint hypothesis of endogeneity and the exclusion restriction ('A-R').

We now turn to the specifications that we use to generate our quality measures. We consider four specifications. We define the nest either at HS2 or HS4 and we either have just one instrument or consider a second instrument. The second instrument is the average number of export destinations per HS2 in a firm's city-year, excluding export destinations exported to by firms in target firm's own 2-digit CME industry. As in Melitz (2003) and Melitz and Ottaviano (2008), the more destinations exported to, the more productive is the region or the lower are the exporting fixed costs of the region, both of which are 'supply shocks.' For the case where we have one instrument and HS2 nests, 70 of 85 HS2 products have negative IV price elasticities. At the 5% significance level, 49 are negative and only 1 is positive.

Figure 2.2 shows the distribution of quality across all four specifications. As is apparent, they are very similar in distributions. Further, in the empirics to come, we get identical results for all four.

Table 2.1: Demand Estimation and Quality

			Second Stage		OLS		First Stage		Reduced Form				No. of		
			DV: quantity		DV: quantity		DV: price		DV: quantity				markets		
Section (HS2)			Log price coeff.		Log price coeff.		Instrument coeff.		Instrument coeff.		Observations	Firms	(h,d,t)	K-P	A-R
6	28-38	Chemicals	-1.08***	(0.18)	-0.86***	(0.024)	0.28***	(0.041)	-0.31***	(0.063)	455,689	5,594	43,818	47.13	0.000
7	39-40	Plastics	-1.75***	(0.22)	-1.02***	(0.028)	0.44***	(0.050)	-0.77***	(0.11)	614,486	12,626	26,832	79.85	0.000
8	41-43	Plastics	-2.11***	(0.53)	-0.70***	(0.024)	0.28***	(0.090)	-0.60***	(0.103)	226,476	4,576	6,160	9.95	0.000
9	44-46	Wood products	-2.89***	(0.63)	-0.57***	(0.044)	0.20***	(0.040)	-0.57***	(0.087)	142,445	2,846	6,696	23.79	0.000
10	47-49	Pulp and paper	-1.09***	(0.41)	-0.60***	(0.043)	0.36***	(0.061)	-0.39**	(0.154)	144,603	6,717	8,238	35.41	0.011
11	50-63	Textiles	-1.58***	(0.09)	-0.78***	(0.018)	0.43***	(0.028)	-0.68***	(0.053)	2,038,845	14,369	80,867	242.20	0.000
12	64-67	Footwear	-1.27***	(0.21)	-0.67***	(0.031)	0.40***	(0.072)	-0.51***	(0.105)	352,585	4,383	10,167	30.63	0.000
13	68-70	Non-ferrous prod.	-1.27***	(0.22)	-0.778***	(0.027)	0.32***	(0.050)	-0.41***	(0.080)	223,144	4,084	14,665	41.09	0.000
15	72-83	Ferrous metal prod.	-2.31***	(0.21)	-1.10***	(0.026)	0.35***	(0.035)	-0.80***	(0.089)	599,325	11,528	41,014	96.74	0.000
16	84-85	Machinery	-1.06***	(0.10)	-0.79***	(0.011)	0.77***	(0.050)	-0.82***	(0.097)	1,792,339	15,096	104,956	240.40	0.000
17	86-89	Transport equip.	-0.80**	(0.31)	-0.74***	(0.045)	0.39***	(0.065)	-0.31***	(0.119)	218,281	3,109	13,142	36.01	0.008
18	90-92	Optical	-0.93***	(0.11)	-0.70***	(0.017)	0.76***	(0.084)	-0.70***	(0.102)	306,112	4,517	23,028	81.00	0.000
20	94-96	Misc manuf.	-1.08***	(0.13)	-0.71***	(0.015)	0.41***	(0.042)	-0.44***	(0.063)	834,724	9,233	31,407	93.02	0.000

Notes: This table presents estimates of β in equation (2.1). Consider the first row, which pools all firms exporting chemicals (HS2 codes 28–38). The 'Second Stage' presents the IV estimate of β. 'OLS' presents the OLS estimates of β. The instrument Z is the average wage of firms in the same city but not in the same 2-digit CME industry. 'First Stage' is the coefficient on the instrument of a regression of price on Z. 'Reduced Form' is a regression of quantity on Z. Standard errors appear in parentheses and these are clustered at the firm level. 'K-P' is the Kleibergen-Paap F statistic for weak instruments. 'A-R' is the Anderson-Rubin p value for the joint null of weak instruments and the exclusion restriction.

2.4 Scale and its instrument

There are two ways in which a firm might experience an increase in the scale of the demand for its products. The first comes from an increase in the domestic or Chinese demand for its products, the second from foreign demand. Our data record each firm's total sales and exports so that we can compute a firm's domestic sales. However, we do not know this by product. The only product information for domestic sales is the firm's 4-digit CME industry code. Since we will always include fixed effects which are 4-digit industry cross time, this measure of domestic scale is subsumed by the fixed effects.[7]

What is available is foreign demand for a firm's products and this is our measure of scale. Specifically, we measure scale by $Exports_{ft}$ be a firm's exports in year t. This is clearly endogenous and we construct a Bartik instrument as follows. Consider a firm that first exported in year t_0. Let ω_{fht_0} be the share of the firm's export sales in year t_0 that are accounted for by good h. If the firm is matched to the customs data then h is an HS8 product. If not, then h is a 4-digit CME industry code (there are a little more than 400 such codes) and $\omega_{fht_0} = 1$ if the firm is in industry h and equals 0 otherwise. Let M_{ht} be world imports of Chinese good h in year t. This is a measure of the demand shock for h in year t: the larger is M_{ht}, the larger is the potential market for the firm. Taking M_{ht} to the firm level, our instrument for exports (or scale) is:

$$Scale_{ft} \equiv \ln\left(1 + \sum_h \omega_{fht_0} M_{ht}\right) \tag{2.3}$$

2.5 Competition

Most measures of competition are at the industry or industry-year level. Because we include industry-year fixed effects, we cannot use these measures.[8] So once again we turn to measures of competition that can be constructed from trade data.

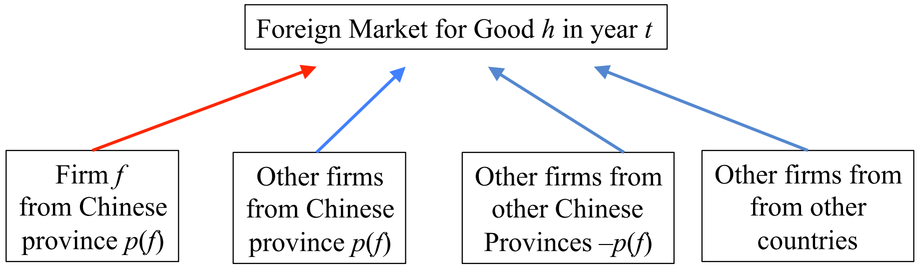
To motivate our approach consider consider a world geography in which there are countries and, within China, there are provinces. We treat countries and Chinese provinces as the geographic units so that Chinese provinces are like countries in the model, meaning, each has its own unique cost structures. This is illustrated in figure 2.3. There is a foreign market for some good h in year t. We are interested in the competition that a target firm f in province $p(f)$ faces when exporting into this foreign market. This competition comes from firms in the same province $p(f)$, from firms in other provinces $-p(f)$, and from firms in other countries. As in our model, the degree of competition comes from underlying cost differences in the various provinces and countries. For firms in other countries, the data are not at the firm level and so are subsumed into the industry-year fixed effects.[9] For firms from the same province, they compete with f but because they also share observed and unobserved

[7] An alternative approach is to find a time- and firm-varying variable. One such variable is the a count of the number of kilometres of arterial highway within 20 kilometres of the firm's address. See Liu et al. (2018). We have explored these data and found some interesting patterns.

[8] In the future we may re-visit these other measures using specifications without industry-year fixed effects.

[9] This is not quite accurate. We typically have 4-digit industry fixed effects, meaning about 400 industries. Using COMTRADE data we could work at the HS6 level and this will give us variation at the 4-digit industry level. In early worked we explored this and found reasonable results.

Figure 2.3: Competition Measure



attributes common to all firms in province $p(f)$, their exports into the foreign market will capture common shocks and not just competition. For firms in other provinces $-r(f)$ their exports into the foreign market will be closer to a pure competition effect. To purify this effect further, we control for the wages paid by firms who are in the same city as f but in a different 2-digit industry.[10]

Operationally, let $X_{-f,ht}$ be the exports of good h in year t summed over all Chinese firms who are *not* in firm f's province. Then:

$$Competition_{ft} \equiv \ln\left(1 + \sum_{h} \omega_{fht_0} X_{-f,ht}\right) \tag{2.4}$$

where ω_{fht_0} is as before.

3 Econometric Results for Scale and Competition

As before, let f index firms and note that each firm is in a 4-digit CME industry i and a city c. We are interested in the impact of scale and competition on outcomes y_{ft} that include quality, markups, and innovation. We consider regressions of the form:

$$y_{ft} = \alpha_f + \alpha_{it} + \alpha_{ct} + \beta Scale_{ft} + \gamma Competition_{ft} + \delta X_{ft} + \varepsilon_{ft} \tag{3.1}$$

where α's are fixed effects and X_{ft} collects time-varying firm characteristics which, in practice, are a binary variable for whether the firm is a state owned enterprise (SOE), a binary variable for whether the firm has foreign investors, and the average wage of firms in the same city c, but not in the firm f's same 2-digit CME industry. The latter controls for cost shocks. Throughout, we cluster standard errors by firm so as to allow for serial correlation. We have also experimented with two-way clustering and our results suggest that this makes no difference.

3.1 Quality

We begin with quality even though it is only available for the restricted sample with matched customs data. Table 3.1 presents estimates of equation (3.1) where the dependent variable is quality.

[10]Think harder about what other things might drive a wedge between the exports of firms in other provinces and the notion of competition.

In columns 1–3 firm exports $\ln(1 + Exports_{ft})$ are included as an endogenous variable, in column 4 the competition variable is included as an exogenous variable, and in columns 5–7 both variables are included with exports being endogenous and competition being exogenous. All specifications have firm fixed effects, city×year fixed effects, and industry ×year fixed effects where industry is defined at the 4-digit CME level. The number of fixed effects appears beneath the observations row. The first stage regression is reported in the bottom panel. Specifically, the panel reports the coefficient on the instrument, the Kleibergen-Paap F statistic for weak instruments, and the Anderson-Rubin p value for the joint null of weak instruments and the exclusion restriction. Standard errors appear in parentheses and are clustered at the firm level.

Several results stand out. First, when we only include exports (not competition) the instrument performs well as judged by the first stage statistics and the coefficients on the instrument $Scale_{ft}$ in both the first stage and the reduced forms. The IV results imply that for those firms induced to export by rising world demand for their products, exporting causally leads to higher quality. Satisfyingly, the IV estimate is smaller than the OLS estimate, though not significantly so.[11]

In column 4 we regress quality on $Competition_{ft}$ and again find that more competition from Chinese firms in other provinces leads to higher quality.

In columns 5–7 we repeat the exercise of columns 1–3, but this time add in $Competition_{ft}$. The reduced form results indicate that both scale and competition matter, though the competition results are only marginally significant. This weakness is mirrored in the deterioration of the first-stage statistics. This deterioration casts doubt on the validity of the IV results. In subsequent tables, we will not have this problem because the instrument works well when the sample is expanded beyond the customs sample to include all firms.

3.2 Markups and Revenue TFP

Table 3.2 has the exact same structure as the previous table, with only the dependent variable changing. It is now log markups. The instrument is valid in both IV specifications and the reduced form coefficients on the instrument come in strongly. We find that for those firms induced to export by rising world demand for their products, exporting causally leads to higher quality. As expected, the IV results are much smaller than the OLS results. $Competition_{ft}$ comes in negatively, suggesting that competition depresses markups, but the results are not statistically strong.

Table 3.3 reports the results when revenue TFP is the dependent variable. Scale-induced exporting is associated with higher revenue TFP and competition with lower relative TFP. (Recall that what we are doing is estimating differential effects, not levels, so that the decline in TFP is relative rather than absolute.) The fact that quality rises and TFP falls suggests that Chinese firms responded by focusing on raising quality rather than cutting costs. This is in line with the findings of Scott Orr (citation needed) for the impact of Chinese competition on Indian machinery manufacturers.

[11] We apologize that, due to time constraints, we are not reporting on coefficient magnitudes.

Table 3.1: Dependent Variable: Quality

	$Scale_{ft}$			$Competition_{ft}$	$Scale_{ft}$ and $Competition_{ft}$		
	IV	OLS	Reduced Form	OLS	IV	OLS	Reduced Form
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$ln(1+Exports)_{ft}$	**0.23653*** **	0.26384***			**0.39966*** **	0.26824***	
	(0.05513)	(0.00356)			(0.15059)	(0.00359)	
$Export\ Competition_{ft}$				**0.03686*** **	**-0.07180* **	-0.03609***	**0.03372*** **
				(0.00559)	(0.04121)	(0.00520)	(0.00575)
$Scale_{ft}$: Instrument			**0.04484*** **				**0.03032** **
for $ln(1+Exports)_{ft}$			(0.01240)				(0.01236)
Controls (f,t)							
SOE Status	0.04519	0.04578	0.04070	0.04401	0.04608	0.04456	0.04173
	(0.04407)	(0.04456)	(0.04513)	(0.04436)	(0.04845)	(0.04460)	(0.04502)
Foreign Invested	0.00098	0.00107	0.00025	-0.00004	0.00096	0.00080	0.00049
	(0.00885)	(0.00881)	(0.00995)	(0.00992)	(0.00892)	(0.00879)	(0.00996)
City Wage	0.17870	0.18408	0.13359	0.17661	0.16415	0.16149	0.15503
	(0.28120)	(0.28054)	(0.30916)	(0.30959)	(0.28804)	(0.28039)	(0.30879)
R^2		0.827	0.787	0.787		0.828	0.788
# observations	84,226	84,226	84,226	84,771	84,226	84,226	84,226
# firm f FEs	27,010	27,010	27,010	27,174	27,010	27,010	27,010
# year-ind4 (i,t) FEs	1,987	1,987	1,987	1,989	1,987	1,987	1,987
# year-city (c,t) FEs	1,348	1,348	1,348	1,354	1,348	1,348	1,348
First Stage							
$Scale_{ft}$: Instrument	**0.18959*** **				**0.07586*** **		
for $ln(1+Exports)_{ft}$	(0.02514)				(0.02346)		
Kleibergen-Paap (F)	57				10		
Anderson-Rubin (p)	0.000				0.014		

Notes: This table presents estimates of equation (3.1) where the dependent variable is quality. In columns 1–3 firm exports $\ln(1 + Exports_{ft})$ are included as an endogenous variable, in column 4 the competition variable is included as an exogenous variable, and in columns 5-7 both variables are included (with exports being endogenous and competition being exogenous). All specifications have firm fixed effects, city cross year fixed effects, and industry cross year fixed effects where industry is defined as 4-digit CIC industry. The number of fixed effects appears beneath the observations row. The first stage regression is reported in the bottom panel. Specifically, the panel reports the coefficient on the instrument, the Kleibergen-Paap F statistic for weak instruments, and the Anderson-Rubin p value for the joint null of weak instruments and the exclusion restriction. Standard errors appear in parentheses and are clustered at the firm level.

Table 3.2: Dependent Variable: Markups

	$Scale_{ft}$			$Competition_{ft}$	$Scale_{ft}$ and $Competition_{ft}$		
	IV	OLS	Reduced Form	OLS	IV	OLS	Reduced Form
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$ln(1+Exports)_{ft}$	**0.00026*** **	0.00061***			**0.00024*** **	0.00061***	
	(0.00007)	(0.00004)			(0.00007)	(0.00005)	
Export Competition$_{ft}$				**-0.00017** **	**-0.00007**	0.00008	**-0.00012**
				(0.00008)	(0.00009)	(0.00008)	(0.00009)
$Scale_{ft}$: Instrument			**0.00019*** **				**0.00018*** **
for $ln(1+Exports)_{ft}$			(0.00005)				(0.00005)
Controls (f,t)							
SOE Status	-0.00640***	-0.00644***	-0.00640***	-0.00627***	-0.00635***	-0.00640***	-0.00634***
	(0.00102)	(0.00102)	(0.00102)	(0.00102)	(0.00102)	(0.00102)	(0.00102)
Foreign Invested	0.00007	-0.00006	0.00004	-0.00028	-0.00032	-0.00048	-0.00034
	(0.00067)	(0.00067)	(0.00067)	(0.00068)	(0.00068)	(0.00068)	(0.00068)
City Wage	-0.03452***	-0.03461***	-0.03444***	-0.03334***	-0.03336***	-0.03345***	-0.03328***
	(0.00598)	(0.00598)	(0.00599)	(0.00601)	(0.00601)	(0.00600)	(0.00601)
R^2		0.962	0.962	0.963		0.963	0.963
# observations	639,549	639,549	639,549	633,811	633,184	633,184	633,184
# firm f FEs	196,898	196,898		195,721	195,599	195,599	195,599
# year-ind4 (i,t) FEs	2,407	2,407		2,409	2,407	2,407	2,407
# year-city (c,t) FEs	2,360	2,360		2,360	2,360	2,360	2,360
First Stage							
$Scale_{ft}$: Instrument	**0.74829*** **				**0.72274*** **		
for $ln(1+Exports)_{ft}$	(0.00306)				(0.00302)		
Kleibergen-Paap (F)	59,713				57,260		
Anderson-Rubin (p)	0.000				0.001		

Notes: This table presents estimates of equation (3.1) where the dependent variable is markups. The table is identical in structure to table 3.1. See that table for details.

Table 3.3: Dependent Variable: Revenue TFP

	$Scale_{ft}$			$Competition_{ft}$	$Scale_{ft}$ and $Competition_{ft}$		
	IV	OLS	Reduced Form	OLS	IV	OLS	Reduced Form
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$ln(1+Exports)_{ft}$	**0.00017*****	0.00026***			**0.00015****	0.00024***	
	(0.00007)	(0.00004)			(0.00007)	(0.00004)	
$Export\ Competition_{ft}$				**-0.00025*****	**-0.00019****	-0.00015*	**-0.00022*****
				(0.00008)	(0.00008)	(0.00008)	(0.00008)
$Scale_{ft}$: Instrument			**0.00013*****				**0.00010****
for $ln(1+Exports)_{ft}$			(0.00005)				(0.00005)
Controls (f,t)							
SOE Status	0.00253**	0.00252**	0.00253**	0.00244**	0.00245**	0.00244**	0.00246**
	(0.00106)	(0.00106)	(0.00106)	(0.00106)	(0.00106)	(0.00106)	(0.00106)
Foreign Invested	0.00107*	0.00104*	0.00105*	0.00133**	0.00124**	0.00120*	0.00123**
	(0.00061)	(0.00061)	(0.00061)	(0.00062)	(0.00062)	(0.00062)	(0.00062)
City Wage	-0.02195***	-0.02197***	-0.02190***	-0.02187***	-0.02177***	-0.02180***	-0.02172***
	(0.00680)	(0.00680)	(0.00680)	(0.00685)	(0.00685)	(0.00685)	(0.00685)
R^2		0.897	0.897	0.897		0.897	0.897
# observations	639,549	639,549	639,549	633,811	633,184	633,184	633,184
# firm f FEs	196,898	196,898	196,898	195,721	195,599	195,599	195,599
# year-ind4 (i,t) FEs	2,407	2,407	2,407	2,409	2,407	2,407	2,407
# year-city (c,t) FEs	2,360	2,360	2,360	2,360	2,360	2,360	2,360
First Stage							
$Scale_{ft}$: Instrument	**0.74829*****				**0.72274*****		
for $ln(1+Exports)_{ft}$	(0.00306)				(0.00302)		
Kleibergen-Paap (F)	59,713				57,260		
Anderson-Rubin (p)	0.008				0.038		

Notes: This table presents estimates of equation (3.1) where the dependent variable is revenue TFP. The table is identical in structure to table 3.1. See that table for details.

3.3 Innovation

We have three measures of innovation, namely, (1) number of patents, (2) R&D as a share of sales, and (3) the value of new product sales as a share of sales. We begin by computing the principal component of these three measures. (This is done separately for each 2-digit CME industry.) The results of using this principal component appear in table 3.4. The instrument performs well as judged by test statistics and its high significance in the first stages and reduced forms. Also, the IV results are again smaller than the OLS results, as expected. The coefficient signs imply that for those firms induced to export by rising world demand for their products, exporting causally leads to higher innovation. Furthermore, competition in foreign markets from Chinese firms in other provinces reduces innovation.

Tables 3.5, 3.6 and 3.7 repeat the exercise separately for each of the three underlying components. These by and large confirm the insights from using the principal component.

4 Closed Economy Model

Motivated by the econometric results discussed above, we now develop and study a structural model of trade and innovation. This structural approach will offer several additional insights. First, the calibrated model offers a quantification of the effects of trade on innovation and of how the levels of these effects vary across firms. Second, the model serves to formally decompose the effects of trade on innovation into the scale and competition channels highlighted by our econometric results. Finally, it formalizes a theory of how firms might innovate to escape changes in competition induced by trade.

4.1 Model environment

4.1.1 Demand

There are two types of goods in the economy: a homogeneous numeraire good and a differentiated good. The differentiated good is available in multiple *grades* indexed by $g \in \{1, \cdots, G\}$ with $1 < G < \infty$, and each grade of the differentiated good is produced by a continuum of firms of endogenous measure. There is a measure L of households each endowed with one unit of labor, which is supplied inelastically. Time is continuous, and each household has preferences given by:

$$\bar{U}_t = \int_0^\infty e^{-\beta s} U_{t+s} ds \tag{4.1}$$

$$U_t = Q_t^0 + \sum_{g=1}^{G} Q_t^g \tag{4.2}$$

$$Q_t^g = \alpha_0^g \int_{\Omega_t^g} \left(s^g q_{f,t}^g\right) df - \frac{1}{2}\alpha_1^g \int_{\Omega_t^g} \left(s^g q_{f,t}^g\right)^2 df - \frac{1}{2}\alpha_2^g \left[\int_{\Omega_t^g} \left(s^g q_{f,t}^g\right) df\right]^2 \tag{4.3}$$

Table 3.4: Dependent Variable: Principal Component of (1) Patents, (2) R&D over Sales and (3) Value of New Product Sales over Sales

	$Scale_{ft}$			$Competition_{ft}$	$Scale_{ft}$ and $Competition_{ft}$		
	IV	OLS	Reduced Form	OLS	IV	OLS	Reduced Form
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$ln(1+Exports)_{ft}$	**0.00618*****	0.01038***			**0.00417*****	0.01025***	
	(0.00080)	(0.00055)			(0.00101)	(0.00060)	
Export Competition$_{ft}$				**-0.01681*****	**-0.01043*****	-0.00114	**-0.01323*****
				(0.00212)	(0.00268)	(0.00234)	(0.00233)
$Scale_{ft}$: Instrument			**0.00453*****				**0.00266*****
for $ln(1+Exports)_{ft}$			(0.00059)				(0.00064)
Controls (f,t)							
SOE Status	0.04409***	0.04364***	0.04428***	0.04437***	0.04407***	0.04363***	0.04417***
	(0.00854)	(0.00853)	(0.00855)	(0.00855)	(0.00854)	(0.00853)	(0.00854)
Foreign Invested	0.03772***	0.03536***	0.03689***	0.03793***	0.03683***	0.03521***	0.03610***
	(0.00677)	(0.00676)	(0.00678)	(0.00675)	(0.00676)	(0.00676)	(0.00677)
City Wage	0.06867	0.06784	0.07032	0.06903	0.06853	0.06781	0.06947
	(0.04526)	(0.04523)	(0.04529)	(0.04527)	(0.04525)	(0.04522)	(0.04526)
R^2		0.659	0.659	0.659		0.659	0.659
# observations	781,137	781,137	781,137	781,137	781,137	781,137	781,137
# firm f FEs	251,005	251,005	251,005	251,005	251,005	251,005	251,005
# year-ind4 (i,t) FEs	2,964	2,964	2,964	2,964	2,964	2,964	2,964
# year-city (c,t) FEs	2,041	2,041	2,041	2,041	2,041	2,041	2,041
First Stage							
$Scale_{ft}$: Instrument	**0.73255*****				**0.63780*****		
for $ln(1+Exports)_{ft}$	(0.00257)				(0.00282)		
Kleibergen-Paap (F)	81,511				51,044		
Anderson-Rubin (p)	0.000				0.000		

Notes: This table presents estimates of equation (3.1) where the dependent variable is the principal component of (1) patents, (2) R&D over sales and (3) the value of new product sales over total sales. The table is identical in structure to table 3.1. See that table for details.

Table 3.5: Dependent Variable: Number of Patents

	$Scale_{ft}$			$Competition_{ft}$	$Scale_{ft}$ and $Competition_{ft}$		
	IV	OLS	Reduced Form	OLS	IV	OLS	Reduced Form
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ln(1+*Exports*)$_{ft}$	**0.01133*****	0.00955***			**0.00931*****	0.00808***	
	(0.00215)	(0.00118)			(0.00270)	(0.00132)	
Export Competition$_{ft}$				**-0.02469*****	**-0.01046***	-0.01234**	**-0.01671*****
				(0.00450)	(0.00588)	(0.00502)	(0.00491)
$Scale_{ft}$: Instrument			**0.00830*****				**0.00594*****
for *ln*(1+*Exports*)$_{ft}$			(0.00158)				(0.00172)
Controls (f,t)							
SOE Status	-0.01772	-0.01753	-0.01737	-0.01707	-0.01774	-0.01765	-0.01750
	(0.01226)	(0.01225)	(0.01226)	(0.01226)	(0.01226)	(0.01226)	(0.01226)
Foreign Invested	-0.01780	-0.01681	-0.01931	-0.01622	-0.01869	-0.01837	-0.02031
	(0.01290)	(0.01284)	(0.01293)	(0.01286)	(0.01289)	(0.01286)	(0.01293)
City Wage	-0.00395	-0.00360	-0.00092	-0.00298	-0.00408	-0.00394	-0.00200
	(0.07644)	(0.07647)	(0.07647)	(0.07641)	(0.07641)	(0.07642)	(0.07641)
R^2		0.624	0.624	0.624		0.624	0.624
# observations	781,137	781,137	781,137	781,137	781,137	781,137	781,137
# firm f FEs	251,005	251,005	251,005	251,005	251,005	251,005	251,005
# year-ind4 (i,t) FEs	2,964	2,964	2,964	2,964	2,964	2,964	2,964
# year-city (c,t) FEs	2,041	2,041	2,041	2,041	2,041	2,041	2,041
First Stage							
$Scale_{ft}$: Instrument	**0.73255*****				**0.63780*****		
for *ln*(1+*Exports*)$_{ft}$	(0.00257)				(0.00282)		
Kleibergen-Paap (F)	81,511				51,044		
Anderson-Rubin (p)	0.000				0.001		

Notes: This table presents estimates of equation (3.1) where the dependent variable is the number of patents. This ranges from 0 to the top-coded value of 50. The table is identical in structure to table 3.1. See that table for details.

Table 3.6: Dependent Variable: R&D over Sales

	$Scale_{ft}$			$Competition_{ft}$	$Scale_{ft}$ and $Competition_{ft}$		
	IV	OLS	Reduced Form	OLS	IV	OLS	Reduced Form
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$ln(1+Exports)_{ft}$	**0.00544***** (0.00093)	0.00371*** (0.00051)			**0.00412***** (0.00115)	0.00263*** (0.00057)	
$Export\ Competition_{ft}$				**-0.01314***** (0.00242)	**-0.00684**** (0.00301)	-0.00911*** (0.00268)	**-0.00960***** (0.00263)
$Scale_{ft}$: Instrument for $ln(1+Exports)_{ft}$			**0.00398***** (0.00068)				**0.00263***** (0.00073)
Controls (f,t)							
SOE Status	0.08423*** (0.01100)	0.08442*** (0.01100)	0.08440*** (0.01100)	0.08452*** (0.01100)	0.08422*** (0.01099)	0.08433*** (0.01100)	0.08433*** (0.01099)
Foreign Invested	0.05742*** (0.00707)	0.05839*** (0.00704)	0.05670*** (0.00708)	0.05793*** (0.00708)	0.05684*** (0.00708)	0.05723*** (0.00707)	0.05612*** (0.00709)
City Wage	0.03486 (0.04014)	0.03519 (0.04014)	0.03631 (0.04014)	0.03525 (0.04012)	0.03477 (0.04013)	0.03494 (0.04013)	0.03569 (0.04012)
R^2		0.568	0.568	0.568		0.568	0.568
# observations	781,137	781,137	781,137	781,137	781,137	781,137	781,137
# firm f FEs	251,005	251,005	251,005	251,005	251,005	251,005	251,005
# year-ind4 (i,t) FEs	2,964	2,964	2,964	2,964	2,964	2,964	2,964
# year-city (c,t) FEs	2,041	2,041	2,041	2,041	2,041	2,041	2,041
First Stage							
$Scale_{ft}$: Instrument for $ln(1+Exports)_{ft}$	**0.73255***** (0.00257)				**0.63780***** (0.00282)		
Kleibergen-Paap (F)	81,511				51,044		
Anderson-Rubin (p)	0.000				0.000		

Notes: This table presents estimates of equation (3.1) where the dependent variable is R&D expenditures over sales. The table is identical in structure to table 3.1. See that table for details.

Table 3.7: Dependent Variable: Value of New Shipment Sales over Total Sales

	Scale$_{ft}$			*Competition*$_{ft}$	*Scale*$_{ft}$ and *Competition*$_{ft}$		
	IV	OLS	Reduced Form	OLS	IV	OLS	Reduced Form
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ln(1+*Exports*)$_{ft}$	**0.02732****	0.12774***			**0.00254**	0.13688***	
	(0.01114)	(0.00795)			(0.01436)	(0.00892)	
Export Competition$_{ft}$				**-0.13243*****	**-0.12855*****	0.07683**	**-0.13026*****
				(0.03032)	(0.03931)	(0.03409)	(0.03394)
Scale$_{ft}$: Instrument			**0.02002****				**0.00162**
for *ln*(1+*Exports*)$_{ft}$			(0.00816)				(0.00916)
Controls (f,t)							
SOE Status	-0.02490	-0.03560	-0.02406	-0.02495	-0.02513	-0.03486	-0.02507
	(0.12332)	(0.12324)	(0.12335)	(0.12335)	(0.12335)	(0.12323)	(0.12335)
Foreign Invested	-0.00274	-0.05911	-0.00638	-0.01303	-0.01371	-0.04937	-0.01415
	(0.10134)	(0.10132)	(0.10144)	(0.10126)	(0.10132)	(0.10136)	(0.10144)
City Wage	1.14140	1.12171	1.14871	1.14003	1.13972	1.12383	1.14029
	(0.71539)	(0.71472)	(0.71558)	(0.71545)	(0.71544)	(0.71473)	(0.71544)
R^2		0.683	0.682	0.683		0.683	0.683
# observations	781,137	781,137	781,137	781,137	781,137	781,137	781,137
# firm f FEs	251,005	251,005	251,005	251,005	251,005	251,005	251,005
# year-ind4 (i,t) FEs	2,964	2,964	2,964	2,964	2,964	2,964	2,964
# year-city (c,t) FEs	2,041	2,041	2,041	2,041	2,041	2,041	2,041
First Stage							
Scale$_{ft}$: Instrument	**0.73255*****				**0.63780*****		
for *ln*(1+*Exports*)$_{ft}$	(0.00257)				(0.00282)		
Kleibergen-Paap (F)	81,511				51,044		
Anderson-Rubin (p)	0.014				0.860		

Notes: This table presents estimates of equation (3.1) where the dependent variable is the value of new product sales over total sales. The table is identical in structure to table 3.1. See that table for details.

Here, Q_t^0 denotes consumption of the numeraire good, Q_t^g denotes consumption of a grade g bundle of the differentiated good, $q_{f,t}^g$ for $f \in \Omega_t^g$ denotes consumption of firm f's variety of a grade g good, and Ω_t^g denotes the set of firms producing grade g varieties. Note that preferences are: (i) linear across time (4.1); (ii) linear across the numeraire and grades of the differentiated good (4.2); and (iii) of the Melitz-Ottaviano (2008) type within a grade of the differentiated good (4.3). Furthermore, note that despite the linearity of preferences in equation (4.2), there is love of variety within each grade in equation (4.3), and hence no two varieties of the differentiated good are perfect substitutes.

The weights $\{s^g\}_{g=1}^G$ in (4.3) reflect exogenous quality differences across grades, while the preference parameters $\{\alpha_0^g, \alpha_1^g, \alpha_2^g\}_{g=1}^G$ are also heterogeneous across grades and can be interpreted as follows. First, α_0^g is a demand shifter capturing the extent to which the household prefers grade g varieties of the differentiated good relative to the homogeneous good or other grades of the differentiated product. Second, α_1^g indexes the degree of product differentiation: as $\alpha_1^g \to 0$, all varieties within the grade become perfect substitutes. Third, α_2^g captures the extent of competition effects: as $\alpha_2^g \to 0$, utility is additively separable across varieties within the grade, and hence demand for one variety does not depend on demand for any other variety.

This preference structure implies linear demand functions given by:

$$\bar{q}_{f,t}^g \equiv L s^g q_{f,t}^g = \frac{\alpha_0^g L}{\alpha_1^g + \alpha_2^g N_t^g} + \left(\frac{\alpha_2 N_t^g}{\alpha_1 + \alpha_2 N_t^g}\right)\left(\frac{L}{\alpha_1}\right)\bar{p}_t^g - \left(\frac{L}{\alpha_1}\right)\hat{p}_{f,t}^g \tag{4.4}$$

where $\bar{q}_{f,t}^g$ is aggregate quality-adjusted demand for firm f's output, $\hat{p}_{f,t}^g \equiv p_{f,t}^g / s^g$ is the quality-adjusted price charged by firm f, $\bar{p}_t^g \equiv \frac{1}{N_t^g}\int_{\Omega_t^g} \hat{p}_{f,t}^g df$ is the average quality-adjusted price charged by firms producing grade g varieties, and N_t^g is the measure of firms producing grade g varieties. Note that because of the quasi-linear demand structure (equation (4.2)), the demand for a firm's output depends only on the mass of competitors *within its own grade* as well as the prices charged by these firms. In other words, there is competition within grades but not across grades. This allows us to focus on the effects of competition within the firm's most immediate market, while abstracting from other sources of competition in order to preserve computational tractability of the model.

4.1.2 Production and pricing

The production structure of the model is as follows. The numeraire good is produced one-for-one using labor under perfect competition, which implies a unit wage.[12] For the differentiated sector, all firms producing grade g varieties have access to the same production technology, which enables production of one unit of the good using c^g units of labor.

Each firm $f \in \Omega_t^g$ then takes N_t^g and $\bar{p}_t^g$ as given, and chooses $\hat{p}_{f,t}^g$ to maximize profits subject to the demand function (4.4). Since all firms within the grade have the same marginal cost, each firm chooses the same profit-maximizing price, and we henceforth omit the firm subscript. We also now omit time subscripts for brevity. The solution to the firm profit-maximization problem implies that markups (price over marginal cost), sales, and profits for each firm operating in grade g can be

[12] We assume that the total labor supply L is large enough such that the numeraire is indeed produced and consumed in equilibrium.

expressed as:

$$\mu^g = \frac{\phi^g + \rho^g}{\rho^g} \tag{4.5}$$

$$y^g = L\kappa^g \phi^g \left(\phi^g + \rho^g\right) \tag{4.6}$$

$$\pi^g = L\kappa^g \left(\phi^g\right)^2 \tag{4.7}$$

Here, the role of technology (cost per unit of quality demanded) is captured by the composite parameter:

$$\rho^g \equiv \frac{c^g}{\alpha_0^g s^g}, \tag{4.8}$$

the role of scale is captured by the composite parameter:

$$\kappa^g \equiv \frac{\left(\alpha_0^g\right)^2}{\alpha_1^g}, \tag{4.9}$$

the strength of competition is captured by the composite parameter:

$$\alpha^g \equiv \frac{\alpha_2^g}{\alpha_1^g}, \tag{4.10}$$

and ϕ^g is an endogenous variable that declines with the mass of firms operating within the grade:

$$\phi^g \equiv \frac{1-\rho^g}{2+\alpha^g N^g} \tag{4.11}$$

Note that for these variables, the identifiable parameter set collapses from five parameters $\{\alpha_0^g, \alpha_1^g, \alpha_2^g, s^g, c^g\}$ to three parameters $\{\rho^g, \kappa^g, \alpha^g\}$.

Importantly, observe that the measure of active firms N^g determines the level of competition within the grade, and as N^g increases, markups, sales, and profits all decline. In equilibrium, $\{N_g\}_{g=1}^G$ is determined endogenously by firms' innovation decisions, as described below in section 4.1.4. Furthermore, since the household's marginal utility of consuming any given variety is bounded, there is a maximum price above which the demand specified by (4.4) is equal to zero. We therefore assume that grade qualities and costs vary in such a way that output and profits are positive for any finite N^g.

Assumption 1. *For each grade $g \in \{1, \cdots, G\}$, the cost per unit of quality demanded satisfies $\rho^g < 1$.*

4.1.3 Innovation

In addition to making production decisions, firms also engage in innovative activities. We assume that each firm has access to the production technology for at most one grade at a time, but can move up the grade ladder by investing in R&D.[13] Specifically, a grade g firm that hires $RD^g\left(a^g\right)$

[13] The assumption that firms produce a single product at a time is without loss of generality if firms make innovation decisions at the product level and there are no innovation spillovers across products within a firm. For issues of

units of labor for R&D activities advances to grade $g+1$ according to a Poisson process with rate a^g. Upon a successful innovation, the firm adopts the grade $g+1$ technology and discards the grade g technology; there is hence creative destruction within the firm. The function RD^g captures grade-specific innovation costs, and is assumed to satisfy the following regularity properties.

Assumption 2. *For each grade $g \in \{1, \cdots, G-1\}$, the innovation cost function $RD^g : \mathbb{R}^+ \to \mathbb{R}^+$ satisfies (i) $RD^{g'} > 0$, (ii) $RD^{g''} > 0$, $RD^g(0) = 0$, (iii) $\lim_{a\to 0} RD^{g'}(a) = 0$, and (iv) $\lim_{a\to\infty} RD^{g'}(a) = \infty$.*

In what follows, we will study steady-states of the model in which the value of being a grade g producer, V^g, is constant over time. Given the innovation process, the values $\{V^g\}_{g=1}^{G-1}$ must then satisfy the following Bellman equation:

$$(\beta + \epsilon) V^g = \max_{a^g} \left\{ \pi^g - RD^g(a^g) + a^g \left(V^{g+1} - V^g \right) \right\} \tag{4.12}$$

where ϵ is the rate of exogenous firm exit. Evidently, if $V^{g+1} \le V^g$, a grade g firm will not choose to innovate and therefore will optimally choose $a^g = 0$. On the other hand if $V^{g+1} > V^g$, it is desirable for the firm to move up the grade ladder. The optimal innovation decision for the firm can then be generally characterized by:

$$RD^{g'}(a^g) = \max \left\{ V^{g+1} - V^g, 0 \right\} \tag{4.13}$$

which admits a unique solution for a^g given assumption 2.

The first-order condition (4.13) captures the essence of the theory of innovation in this model. In particular, note that the incentive to innovate depends on the difference between pre- and post-innovation values. The effects of scale on innovation can thus heuristically be interpreted as a proportional change in both V^g and V^{g+1}: if the market for the differentiated product becomes larger overall, firms have greater incentive to innovate. On the other hand, the effects of competition may affect V^g and V^{g+1} differentially. If a firm faces more competitors in its current grade (larger N^g), the value of failing to successfully innovate falls (smaller V^g), and hence innovation is incentivized. Conversely, if competition is tougher in the post-innovation market (larger N^{g+1}), the value of successfully innovating falls (smaller V^{g+1}), and hence innovation is disincentivized.

To complete the description of innovation in the model, it remains to specify what occurs at the boundaries of the grade ladder: how firms at the frontier grade G innovate, and how firms enter the market. First, since the number of grades is assumed to be finite, we model innovation by firms at the frontier by assuming that these firms innovate to reduce the hazard rate of exit. The value of operating as a grade G firm then satisfies:

$$\beta V^G = \max_{a^G} \left\{ \pi^G - RD^G\left(a^G\right) - \epsilon^G\left(a^G\right) V^G \right\} \tag{4.14}$$

where ϵ^G is a function specifying the exit rate at the frontier, and is assumed to satisfy the following regularity properties.[14]

tractability, we abstract from the more general case of multiproduct firms with innovation that spills over across products.

[14] In practice, we use a simple functional form $\epsilon^G(a) = 1/a$.

Assumption 3. *The frontier exit rate function* $\epsilon^G : \mathbb{R}^+ \to \mathbb{R}^+$ *satisfies (i)* $\epsilon^{G'} < 0$*, (ii)* $\epsilon^{G''} > 0$*, and (iii)* $\lim_{a \to 0} \epsilon^{G'}(a) < 0$.

The first-order condition for innovation at the frontier is then:

$$RD^{G'}\left(a^G\right) = -\epsilon^{G'}\left(a^G\right) V^G \tag{4.15}$$

which admits a unique solution for a^G given assumption 3.

Finally, any firm wishing to enter the market for the differentiated good can hire f^E units of labor as an entry cost, following which it obtains the technology for producing a new variety of grade $g = 1$. Free entry then requires:

$$V^1 = f^E \tag{4.16}$$

4.1.4 Mass of firms in steady-state

To determine the measure of firms producing each grade of the differentiated good, we consider the implications of a steady-state equilibrium. First, note that at each point in time, a measure N^E of firms enter and become grade 1 producers, a measureϵN^1 of grade 1 producers exit the economy, and a measure $a^1 N^1$ of grade 1 producers successfully innovate and become grade 2 producers. Therefore in steady-state, the measure of grade 1 producers must satisfy:

$$N^E = \left(\epsilon + a^1\right) N^1 \tag{4.17}$$

Next, consider the inflow and outflow of grade g producers for $g \in \{2, \cdots G - 1\}$. At each point in time, a measure $a^{g-1} N^{g-1}$ of grade $g-1$ producers successfully innovate to become grade g producers. Simultaneously, a measure ϵN^g of grade g producers exit and a measure $a^g N^g$ successfully innovate to become grade $g + 1$ producers. Therefore, in steady-state, the masses of firms must satisfy:

$$a^{g-1} N^{g-1} = (\epsilon + a^g) N^g \tag{4.18}$$

Finally, at the frontier grade G, a measure $a^{G-1} N^{G-1}$ of grade $G-1$ producers successfully innovate to become grade G producers, while a measure $\epsilon^G\left(a^G\right) N^G$ of grade G producers exit. Hence:

$$a^{G-1} N^{G-1} = \epsilon\left(a^G\right) N^G \tag{4.19}$$

4.1.5 Labor market

With the quasi-linear demand structure, labor market clearing simply requires that the numeraire good is indeed produced in equilibrium. Specifically, the total amount of labor employed by firms in the differentiated goods sector for production, innovation, and entry costs must be less than the total labor endowment:

$$\bar{Q}^0 \equiv LQ^0 = L - N^E f^E - \sum_{g=1}^{G} N^g \left[l^g + RD^g\left(a^g\right)\right] > 0 \tag{4.20}$$

where production labor hired by each grade g firm is:

$$l^g = L\kappa^g\rho^g\phi^g \tag{4.21}$$

4.1.6 Welfare

Household utility at each point in time is given by (4.2). Consumption of the numeraire is given by (4.20), while consumption of the grade g bundle can be expressed as:

$$Q^g = \kappa^g N^g \phi^g - \frac{1}{2}\kappa^g N^g \left(\phi^g\right)^2 - \frac{1}{2}\alpha^g\kappa^g \left(N^g\phi^g\right)^2 \tag{4.22}$$

Note again from equations (4.20)-(4.22) that of the set of original model parameters $\{\alpha_0^g, \alpha_1^g, \alpha_2^g, s^g, c^g\}$, only the composites $\{\rho^g, \kappa^g, \alpha^g\}$ matter for welfare.[15]

4.2 Equilibrium definition and solution

4.2.1 Equilibrium definition

A steady-state equilibrium of the model is a mass of entry N^E, a sequence of firm masses $\{N^g\}_{g=1}^G$, a sequence of profits $\{\pi^g\}_{g=1}^G$, a sequence of product innovation rates $\{a^g\}_{g=1}^G$, and a sequence of firm values $\{V^g\}_{g=1}^G$, all of which satisfy the profit equation (4.7), Bellman equations (4.12) and (4.14), R&D optimality conditions (4.13) and (4.15), free-entry condition (4.16), steady-state entry conditions (4.17)-(4.19), and the labor market condition (4.20).

4.2.2 Solution algorithm

To solve the model, we iterate backwards on the Bellman equation (4.12) according to the following algorithm, which takes several seconds on a standard personal computer:

1. Guess N^G and compute V^G and a^G from (4.14) and (4.15).
2. For $g \in \{1, \cdots, G-1\}$, given V^{g+1}, N^{g+1}, and a^{g+1}, numerically solve (4.12), (4.13), and (4.18) to obtain V^g, N^g, and a^g.
3. Compute N^E from (4.17).
4. Repeat steps 1-3, adjusting the guess of N^G until the free-entry condition (4.16) is satisfied.
5. Check that the labor market condition (4.20) holds.

5 Open Economy Model

We now extend the model developed above to incorporate multiple (potentially asymmetric) locations and trade costs. Here,we develop the general case with an arbitrary number of countries,

[15] While the size of the labor endowment L does not matter independently from the scale composite parameters $\{\kappa^g\}_{g=1}^G$ for outcomes within the differentiated sector, it does matter for welfare because L determines the size of the differentiated sector relative to the numeraire sector under quasi-linear preferences.

and then focus on a North-South model in the calibration and counterfactual simulations of the model.

5.1 Model environment

There are $J \geq 2$ locations. These locations are potentially asymmetric in terms of labor endowments $\{L_i\}_{i=1}^J$, wages $\{w_i\}_{i=1}^J$, entry costs $\left\{f_i^E\right\}_{i=1}^N$, production technologies $\{s_i^g, c_i^g\}_{i=1}^N$, and R&D costs $\{RD_i^g\}_{i=1}^N$. Given the available data, we assume that households in every location have identical preferences given by (4.1)-(4.3). We also assume that there are iceberg trade costs $\{\tau_{ij}\}_{i,j=1}^J$ between locations, where $\tau_{ij} \geq 1$ denotes the cost of shipping goods from j to i. Finally, we assume that the numeraire good is freely traded and produced using $\frac{1}{w_i}$ units of labor in location i, so that w_i is also the wage in country i.[16] As in the closed economy model, we focus on steady-state equilibria in which the masses of firms producing each grade are time-invariant.

5.1.1 Demand

Consider a firm from location j with access to grade g technology. The demand function faced by this firm in the location i market takes the same form as (4.4), and is given by:

$$\bar{q}_{ij}^g \equiv L_i s_j^g q_{ij}^g = \frac{\alpha_0^g L_i}{\alpha_1^g + \alpha_2^g N_i^g} + \left(\frac{\alpha_2^g N_i^g}{\alpha_1^g + \alpha_2^g N_i^g}\right)\left(\frac{L_i}{\alpha_1^g}\right)\bar{p}_i^g - \left(\frac{L_i}{\alpha_1^g}\right)\hat{p}_{ij}^g \tag{5.1}$$

where $\hat{p}_{ij}^g$ is the quality-adjusted price charged by the firm. Here, $N_i^g = \sum_{j=1}^J N_{ij}^g$ denotes the measure of firms supplying location i with grade g varieties, where N_{ij}^g is the measure of these firms that supply i from j. The average quality-adjusted price charged by firms supplying grade g varieties in location i is given by $\bar{p}_i^g = \frac{1}{N_i^g}\sum_{j=1}^J N_{ij}^g \hat{p}_{ij}^g$.

5.1.2 Production

With positive trade costs, it is possible that some grades will not be traded across locations. In contrast with the closed economy model, we therefore now have to differentiate between the measure of firms that supply location i with grade g varieties, N_i^g, and the measure of firms that have access to the technology for producing grade g varieties in location i, M_i^g .

As shown in the appendix, grade g producers in j will find it profitable to sell in i if and only if their *supply cost* $\rho_{ij}^g \equiv \frac{w_j c_j^g \tau_{ij}}{\alpha_0^g s_j^g}$ is below a certain threshold value $\rho_{i,max}^g$:

$$\rho_{ij}^g \leq \rho_{i,max}^g \equiv \frac{2 + \bar{\rho}_i^g \alpha^g N_i^g}{2 + \alpha^g N_i^g} \tag{5.2}$$

Observe that the right-hand side of (5.2) does not vary with the source country j. This implies that in any equilibrium of the model, grade g varieties are supplied to location i from source countries

[16] As before, we assume that labor endowments in each location are large enough such that the numeraire is produced and consumed in positive amounts in all locations.

with the lowest supply costs. Condition (5.2) can also be written as:

$$\rho_{ij}^g \leq 1 - \frac{1}{2}\alpha^g \tilde{\rho}_{ij}^g \tag{5.3}$$

where $\tilde{\rho}_{ij}^g$ summarizes the state of technology for all suppliers in the grade g market in location i relative to technology for firms from j:

$$\tilde{\rho}_{ij}^g \equiv \sum_{k=1}^{J} N_{ik}^g \left(\rho_{ij}^g - \rho_{ik}^g\right) \tag{5.4}$$

Note that given the supply cost ρ_{ij}^g for firms from j, the term $\tilde{\rho}_{ij}^g$ is greater when there are more firms selling in i with supply costs lower than ρ_{ij}^g, or when there are fewer firms selling in i with supply costs greater than ρ_{ij}^g. Furthermore, observe that $\tilde{\rho}_{ij}^g$ depends only on the measure of suppliers in i from all locations other than j, and in particular does not depend on N_{ij}^g. This implies that in any equilibrium of the model, either all firms from j with access to grade g technology sell in i or none of them do:

$$N_{ij}^g = \begin{cases} M_j^g & , \text{ if } \rho_{ij}^g \leq \rho_{i,max}^g \\ 0 & , \text{ o/w} \end{cases} \tag{5.5}$$

Assuming condition (5.3) holds, the solution for firm prices then implies the following expressions for equilibrium markups, sales, and profits:

$$\mu_{ij}^g = \frac{\phi_{ij}^g + \rho_{ij}^g}{\rho_{ij}^g} \tag{5.6}$$

$$y_{ij}^g = L_i \kappa^g \phi_{ij}^g \left(\phi_{ij}^g + \rho_{ij}^g\right) \tag{5.7}$$

$$\pi_{ij}^g = L_i \kappa^g \left(\phi_{ij}^g\right)^2 \tag{5.8}$$

As in the closed economy, ϕ_{ij}^g is an endogenous variable that summarizes the effect of competition from other firms:

$$\phi_{ij}^g \equiv \frac{1 - \rho_{ij}^g - \frac{1}{2}\alpha^g \tilde{\rho}_{ij}^g}{2 + \alpha^g N_i^g} \tag{5.9}$$

Note that because firms from different locations have potentially different production technologies, what matters for the degree of competition is not only the measure of competitors (N_i^g), but also the supply costs of a firm's competitors relative to its own supply cost ($\tilde{\rho}_{ij}^g$). Observe that if supply costs are identical across all source locations, then $\tilde{\rho}_{ij}^g = 0$ and expressions (5.6), (5.7), and (5.8) reduce to their closed-economy counterparts (4.5), (4.6), and (4.7). In this special case, the market for grade g varieties in i resembles a closed economy.

Finally, to ensure that all locations can be profitably supplied with each grade of the differentiated good by firms from at least one location, we make the following assumption.

Assumption 4. *For each location $i \in \{1, \cdots, J\}$ and each grade $g \in \{1, \cdots, G\}$, the minimum marginal supply cost satisfies* $\min_{j \in \{1,\cdots,J\}} \rho_{ij}^g < 1$.

5.1.3 Innovation

The innovation process in the open economy is the same as in the closed economy. Firms in each location choose investments in R&D and move up the grade ladder stochastically subject to an exit shock that arrives with identical Poisson rate ϵ in all locations. The value of being a producer in location i of a variety of grade $g < G$ then satisfies:

$$(\beta + \epsilon) V_i^g = \max_{a_i^g} \left\{ \pi_i^g - w_i RD_i^g \left(a_i^g\right) + a_i^g \left(V_i^{g+1} - V_i^g \right) \right\} \tag{5.10}$$

As before, the optimal innovation decision is characterized in general by:

$$RD_i^{g'} \left(a_i^g\right) = \max \left\{ V_i^{g+1} - V_i^g, 0 \right\} \tag{5.11}$$

Similarly, at the frontier grade G where innovation reduces the hazard rate of exit, the value of a firm satisfies:

$$\beta V_i^G = \max_{a_i^G} \left\{ \pi_i^G - w_i RD_i^G \left(a_i^G\right) + \epsilon \left(a_i^G\right) V_i^G \right\} \tag{5.12}$$

while the optimal innovation decision is characterized by:

$$w_i RD_i^G \left(a_i^G\right) = -\epsilon' \left(a_i^G\right) V_i^G$$

The key difference here relative to the closed economy is that now total profits in (5.10) and (5.12) are the sum of domestic profits and profits across all potential export destinations:

$$\pi_i^g = \sum_{j=1}^{J} \pi_{ji}^g \tag{5.13}$$

5.1.4 Entry

Firms in location i can enter the economy by paying an entry cost of f_i^E units of labor to obtain technology for producing a grade 1 variety. Free entry in each location therefore imposes:

$$V_i^1 = f_i^E \tag{5.14}$$

5.1.5 Steady-state firm grade distribution

Following the same logic as for the closed-economy, the steady-state mass of producers for each grade in location i satisfies the following:

$$M_i^E = \left(\epsilon + a_i^1\right) M_i^1 \tag{5.15}$$

where M_i^E denotes the mass of entrants. For $g \in \{2, \cdots, G-1\}$, the equilibrium relation is:

$$a_i^{g-1} M_i^{g-1} = \left(\epsilon + a_i^g\right) M_i^g \tag{5.16}$$

while at the frontier grade:

$$a_i^{G-1} M_i^{G-1} = \epsilon \left(a_i^G \right) M_i^G \tag{5.17}$$

5.1.6 Labor market

In order for the numeraire good to be produced in all locations in equilibrium, the total amount of labor employed by firms in the differentiated goods sector for production, innovation, and entry costs must be less than the total labor endowment:

$$L_i - M_i^E f_i^E - \sum_{g=1}^{G} \left[\sum_{j=1}^{J} N_{ji}^g l_{ij}^g + M_i^g w_i RD_i^g \left(a_i^g \right) \right] > 0 \tag{5.18}$$

where total production labor hired by grade g producers in j that sell in i is given by:

$$l_{ij}^g = L_i \kappa^g \rho_{ij}^g \phi_{ij}^g \tag{5.19}$$

5.1.7 Welfare

Household utility in location i at each point in time is given by:

$$U_i = Q_i^0 + \sum_{g=1}^{G} s^g Q_i^g \tag{5.20}$$

Since the numeraire is assumed to be freely traded, production and consumption of the numeraire in each location need not be equal. Each household's consumption of the numeraire in location i is given by its income net of expenditures on differentiated products. Household income is the sum of wages and firm profits (we assume that aggregate profits in each location are disbursed equally to all households in that location). Hence:

$$L_i Q_i^0 = w_i L_i + \Pi_i - \sum_{g=1}^{G} \sum_{j=1}^{J} N_{ij}^g y_{ij}^g \tag{5.21}$$

$$\Pi_i = \sum_{g=1}^{G} \left[\sum_{j=1}^{J} N_{ji}^g \pi_{ji}^g - M_i^g w_i RD_i^g \left(a_i^g \right) \right] - M_i^E f_i^E \tag{5.22}$$

Finally, consumption of the grade g bundle can be expressed as:

$$Q_i^g = \kappa^g \sum_{j=1}^{G} N_{ij}^g \phi_{ij}^g - \frac{1}{2} \kappa^g \sum_{j=1}^{J} N_{ij}^g \left(\phi_{ij}^g \right)^2 - \frac{1}{2} \alpha^g \kappa^g \left(\sum_{j=1}^{J} N_{ij}^g \phi_{ij}^g \right)^2 \tag{5.23}$$

As in the closed economy, note that of the set of original model parameters $\left\{ \alpha_0^g, \alpha_1^g, \alpha_2^g, s_i^g, c_{ij}^g \right\}$, only the composites ρ_{ij}^g, α^g, and κ^g matter for welfare.

5.2 Equilibrium definition and solution

5.2.1 Equilibrium definition

A steady-state equilibrium of the open-economy model is a list of sequences for entry $\left\{M_i^E\right\}_{i=1}^J$, production $\left\{\{M_i^g\}_{g=1}^G\right\}_{i=1}^J$, supply $\left\{\{N_{ij}^g\}_{g=1}^G\right\}_{i,j=1}^J$, profits $\left\{\{\pi_{ij}^g\}_{g=1}^G\right\}_{i,j=1}^J$, innovation probabilities $\left\{\{a_i^g\}_{g=1}^G\right\}_{i=1}^J$, and firm values $\left\{\{V_i^g\}_{g=1}^G\right\}_{i=1}^J$, all of which satisfy the supply conditions (5.5), profit equations (5.8), Bellman equations (5.10) and (5.12), R&D optimality conditions (5.11), free-entry conditions (5.14), steady-state entry conditions (5.15)-(5.17), and the labor market condition (5.18).

5.2.2 Solution algorithm

To solve the model, we employ a computational algorithm similar to that used to solve the closed-economy model (described in section 4.2.2), which as before takes several seconds on a standard personal computer. Again, this involves guessing the measure of firms operating at the frontier grade in each market, iterating backwards on the Bellman equation (5.10), and then checking the free-entry condition (5.14) and labor market condition (5.18). Interested readers are referred to the online appendix for a detailed description of the solution algorithm for the open economy model.

6 Model Calibration

To calibrate the model, we focus on an economy with $J = 2$ countries and use data for Chinese firms as described above, as well as data for Canadian firms obtained from Statistics Canada. The latter data are used to represent OECD firms, so as to capture trade between China and developed countries as a whole. As such, we scale the number of Canadian firms by the ratio of OECD to Canadian gross domestic product, and weight the export data by the relevant China-OECD trade shares. The implicit assumption made here is that Canadian firms are representative of OECD firms in terms of firm-level characteristics such as sales, exports, profits, and R&D.

6.1 Model parameters

The only functional form assumptions that need to be imposed before proceeding with the model calibration are for the innovation costs $\left\{\{RD_i^g\}_{g=1}^G\right\}_{i=1}^J$. Here, we assume constant elasticity functions:

$$RD_i^g(a) = b_i^g a^{\eta_i^g} \tag{6.1}$$

where b_i^g measures the level of R&D costs and η_i^g captures the sensitivity of R&D costs to the innovation rate. This parameterization allows us to solve the R&D first-order conditions analytically and speeds up the computation significantly.

The model thus has the following sets of parameters (parameter count in parentheses) - demand parameters ($2G$):

$$\Theta_D \equiv \{\kappa^g, \alpha^g\}_{g=1}^G, \tag{6.2}$$

technology parameters (J^2G):

$$\Theta_P \equiv \left\{ \{\rho_{ij}^g\}_{g=1}^G \right\}_{i,j=1}^J , \tag{6.3}$$

innovation parameters ($J(2G+1)$):

$$\Theta_I \equiv \left\{ f_i^E, \{b_i^g, \eta_i^g\}_{g=1}^G \right\}_{i=1}^J , \tag{6.4}$$

country-level macro parameters ($2J$):

$$\Theta_M = \{w_i, L_i\}_{i=1}^J , \tag{6.5}$$

and a set of parameters $\{\beta, \epsilon, G\}$ that will not be calibrated to data.[17]

6.2 Assignment of grades

To calibrate the model's parameters, we first need to take a stand on what defines a "grade" in the data. In the model, grades are technically defined by segmentation of the differentiated goods sector along various dimensions: demand characteristics, production technologies, and innovation costs. Furthermore, the model's assumptions imply that all firms within a grade are identical in every one of these aspects. Hence, assigning firms in the data to grades is not a straightforward task for two reasons. First, it is not immediately obvious what the most relevant variables for clustering firms should be. For example, should we consider firms that have similar production costs or innovation costs as belonging to the same grade? Second, many of the primitive grade-level characteristics are not directly observable.

To deal with this issue, we explore several avenues. First, the notion of firms operating in segmented markets is in essence a demand-side construct: consumers perceive different grades as having different characteristics that matter for utility. From this perspective, the most natural way to define grades would be by the quality of products that firms produce. As discussed in section 2.3, however, we are able to obtain quality estimates only for Chinese firms that are matched to the customs data. Hence, while assigning grades based on quality would be economically appealing, this would preclude us from studying firms in the full CME sample.

A second option for defining grades would be to focus on the interaction between competition and innovation. From this perspective, the most salient characteristic of a grade is its competitive environment. It is precisely because grades differ along this dimension that the model allows us to study how trade affects innovation through not only the standard scale channel but through competitive effects as well. As such, a potential solution is to group firms based on the markup estimates described in section 2.2. Given the data available to us at the moment, this is a feasible option for Chinese firms, but not for the Canadian firms that we use to calibrate the open economy model, although we are currently working with Statistics Canada to estimate markups for Canadian firms as well, which would relax this data constraint.

[17] We set the discount factor and exit rates to typical values ($e^{-\beta} = .95$, $e^{-\epsilon} = .9$). In the baseline analysis, we set the number of grades at $G = 10$, and explore how different values of G affect our quantitative results.

Finally, the most straightforward option for defining grades is to group firms based on size. In the model calibration and simulation described below, we adopt this approach for the time being due to data availability. Specifically, the assignment of firms to grades in the data is determined by implementing a k-means clustering algorithm on firm sales, which finds the grouping of firms that minimizes the within-group variance of sales. To account for differences across industries and time, the clustering algorithm is implemented separately for each industry-year.

To investigate the robustness of this clustering approach, Figure 6.1 compares the characteristics of grades defined by both sales and markups for Chinese firms in our data. The results are reassuring: clustering on either firm sales or markups yields grades that are generally increasing in sales, exports, profits, R&D expenditures, markups, and quality, and decreasing in the number of operating firms and the level of competition from other Chinese firms (equation (2.4)). In particular, the average estimated markups within each grade are almost identical whether grades are defined by markups or sales. As such, we are confident that the results shown below will be similar to results we hope to eventually obtain based on markup clustering for both Chinese and Canadian firms.

6.3 Calibration algorithm

Having assigned firms in the data to grades, we then calibrate the demand, technology, and innovation parameters $\{\Theta_D, \Theta_P, \Theta_I,\}$ by targeting average sales, exports, profits, and R&D for firms within each grade, as well as the number of firms operating within each grade:

$$y_i^g = \tilde{y}_i^g \tag{6.6}$$
$$y_{xi}^g = \tilde{y}_{xi}^g \tag{6.7}$$
$$\pi_i^g = \tilde{\pi}_i^g \tag{6.8}$$
$$RD_i^g = \tilde{RD}_i^g \tag{6.9}$$
$$N_i^g = \tilde{N}_i^g \tag{6.10}$$

where $\tilde{x}$ denotes the value of a variable x in the data. The calibration algorithm that achieves this proceeds in three steps.

First, suppose that the model exactly matches the number of firms in each grade-market, $\left\{\{N_i^g\}_{g=1}^G\right\}_{i=1}^2$. Then for each grade $g \in \{1, \cdots, G\}$, the two demand parameters $\{\kappa^g, \alpha^g\}$ and four production technology parameters $\left\{\rho_{ij}^g\right\}_{i,j=1}^2$ can be chosen to exactly match the six moment conditions (6.6)-(6.8), where sales, exports, and profits are given by equations (5.7)-(5.8). Intuitively, sales, exports, and profits identify demand, cost, and quality parameters.

Second, suppose that the model exactly matches the number of firms operating at the frontier grade in each market, $\left\{N_i^G\right\}_{i=1}^2$. Then for grade G, the four innovation parameters $\left\{b_i^G, \eta_i^G\right\}_{i=1}^2$ can be chosen to exactly match the two moment conditions (6.9) and the targeted exit rates in each location, $\epsilon^G\left(a_i^G\right) = \epsilon$. Similarly, for each grade $g \in \{1, \cdots, G-1\}$, the four innovation parameters $\left\{b_i^G, \eta_i^G\right\}_{i=1}^2$ can be chosen to exactly match the four moment conditions (6.9)-(6.10). Intuitively,

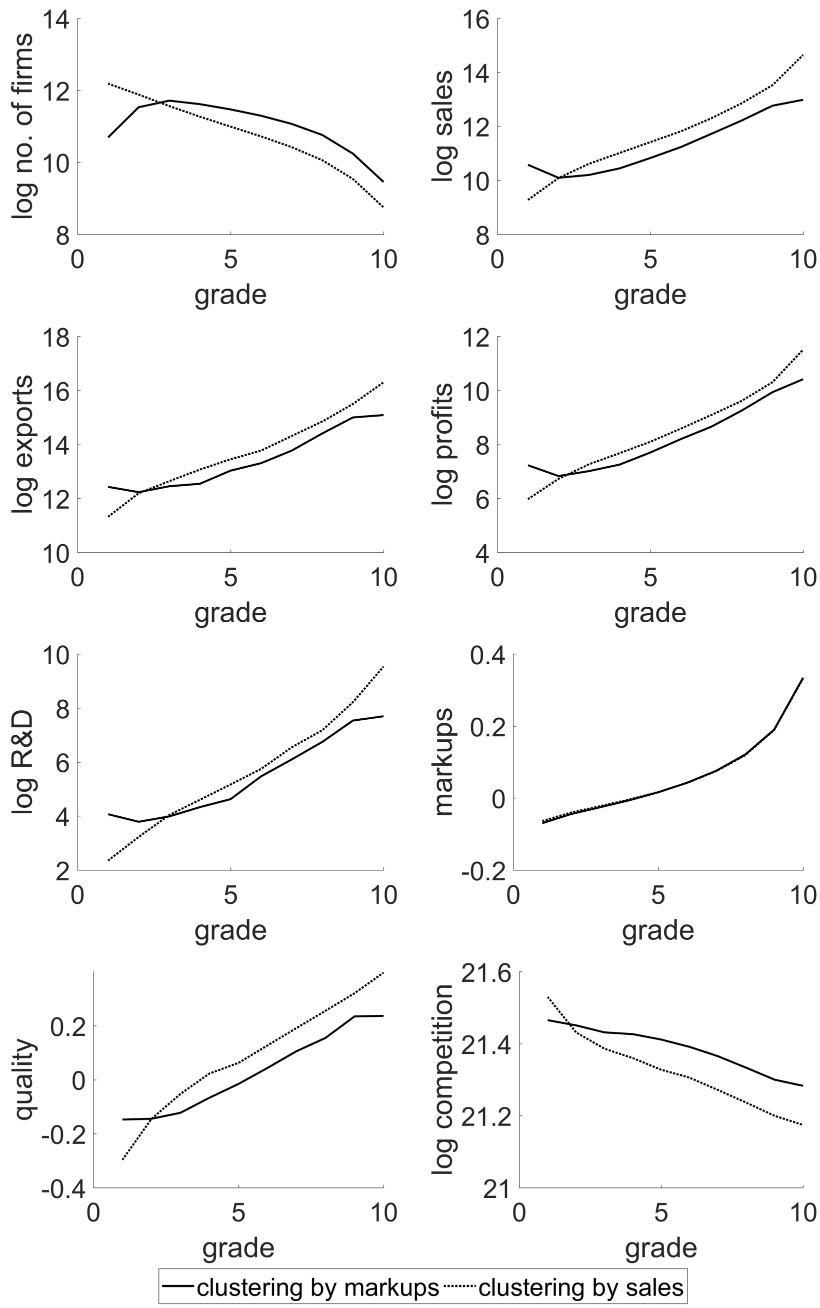


Figure 6.1: Clustering of Chinese firms by sales and markups

R&D expenses and the relative distribution of firms across grades identify the innovation parameters.

Third, to ensure that the model does in fact match moment condition (6.10) for the frontier grade G, a simple two-dimensional search over the space of values for the entry costs $\left\{f_i^E\right\}_{i=1}^2$ is implemented. Intuitively, the overall level of entry identifies the entry costs. This last step of the calibration algorithm ensures that the first two steps yield parameter values that allow the model to match all targeted moments exactly.

Finally, the country-level macro parameters Θ_M are calibrated as follows. First, we interpret the differentiated goods sector as representing manufacturing, and choose the labor endowments $\{L_i\}_{i=1}^G$ to match manufacturing shares of 40% and 20% in China and the OECD respectively. Second, the wage in China is chosen as the numeraire, and the OECD wage is chosen to match relative hourly compensation costs based on data from the Bureau of Labor Statistics' International Labor Comparisons dataset.

6.4 Calibration results

6.4.1 Model fit

The fit of the model to the targeted moments is shown in Figure 6.2. The model is exactly identified by construction, and hence the model matches the targeted moments exactly. Note that the k-means clustering algorithm on sales within industry-year generates groupings of firms such that higher grades generally have larger average firm sales, exports, profits, and R&D, as well as fewer operating firms.

6.4.2 Equilibrium innovation rates

The equilibrium innovation rates implied by the model for Chinese and OECD firms are shown in Figure 6.3. Note that for both locations, the innovation rates exhibit an inverted-U pattern: firms that are either very far from the frontier grade or very close to it choose lower innovation rates than firms in the middle of the grade ladder. We interpret this result as being consistent with the "escape-the-competition" motive for innovation, as firms in the middle of the grade ladder face the greatest incentive to invest in R&D, so as to escape from tougher competition at lower grades and to move towards the frontier grade where competition is less intense and profits are higher.

7 Counterfactual Exercises

To study the effects of trade on innovation, we employ the model developed above to simulate two counterfactual exercises: a 5% reduction in the cost of exporting (for all grades) from China to the OECD, and a 5% reduction in the cost of exporting (for all grades) from the OECD to China. In each case, we examine the responses of six variables: (i) firm sales, (ii) exports, (iii) profits, (iv) R&D, (v) equilibrium innovation rates, and (vi) the measure of firms operating in each grade.

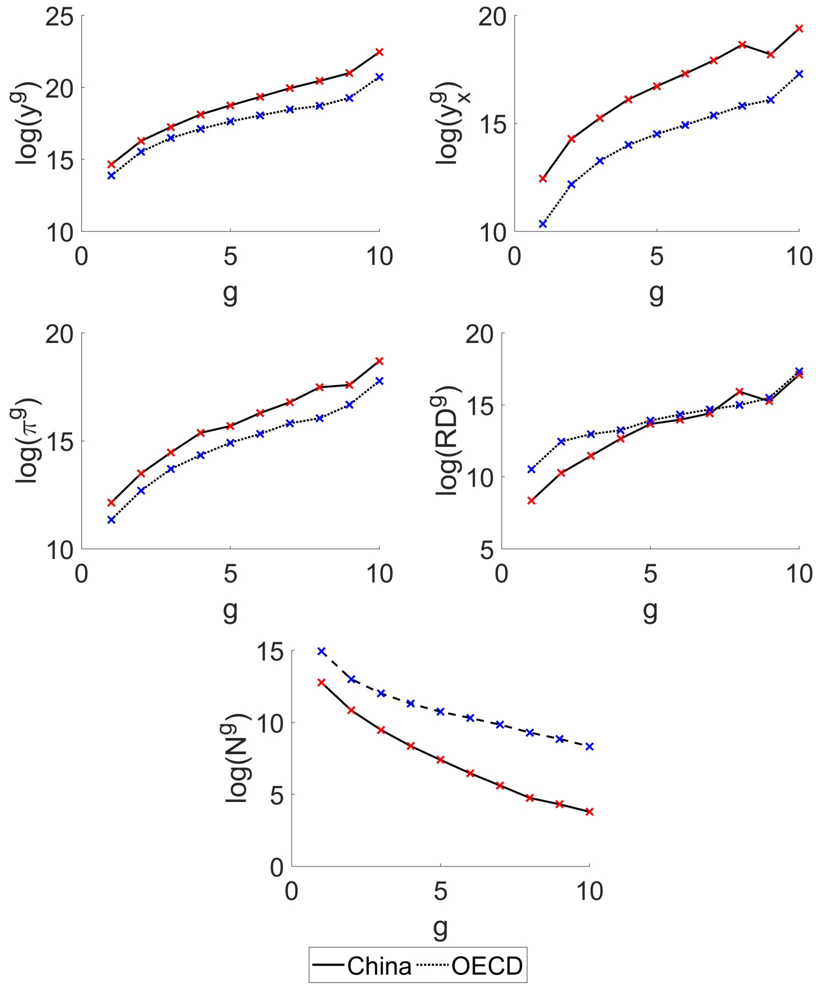


Figure 6.2: Model fit

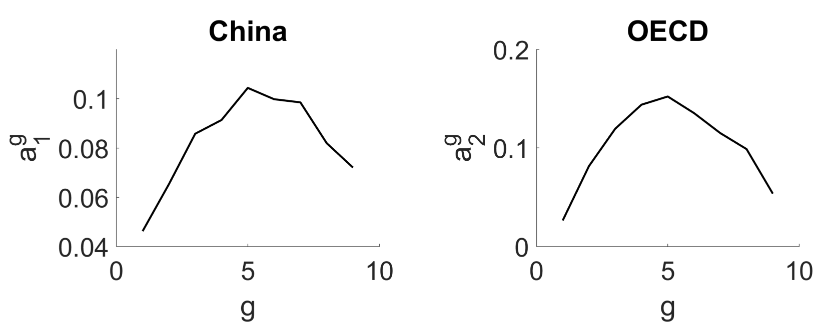


Figure 6.3: Equilibrium innovation rates

7.1 Lower export costs for Chinese firms

First, consider the effects of lower export costs from China to the OECD. The results of this counterfactual simulation are summarized in Figure 7.1. Here, we see that sales, exports, profits, R&D, equilibrium innovation rates, and the measure of firms in each grade increase for Chinese firms in all grades. This is intuitive: lower export costs lead to greater firm size and profitability, which raises the incentives for R&D, leading to higher innovation rates. Since firm values increase, more Chinese firms enter the market. For OECD firms, on the other hand, firm size and exports fall, and the measure of operating firms decreases in all grades. Again, this is intuitive: more competition from Chinese firms reduces OECD firm size and leads some firms to exit the market.

One might conclude from these results that lower Chinese export costs must therefore reduce R&D and innovation by OECD firms. Note from Figure 7.1, however, that the converse is true: R&D and equilibrium innovation rates *increase* for OECD firms in almost all grades. The reason for this is that the reduction in Chinese export costs affects OECD firms operating in different grades differentially. In particular, it reduces profits for firms operating in the lowest grades, but *increases* profits for firms operating in the highest grades. This latter effect is possible only because the reduction in Chinese export costs induces *exit* by some OECD firms, which reduces domestic OECD competition. Hence, the reduction in Chinese export costs raises the value of operating in high grades versus low grades for OECD firms, which from the R&D first-order condition (5.11) leads to an increase in innovation.

The result that lower Chinese export costs can induce an increase in innovation by OECD firms stems from the differential effects of the scale and competition channels embedded in the model. In particular, these simulations suggest the importance of accounting for both mechanisms when evaluating the effect of trade on firm-level innovation.

7.2 Lower export costs for OECD firms

Next, consider the effects of lower export costs from the OECD to China. The results of this counterfactual simulation are summarized in Figure 7.2, and are in essence the immediate opposite of those observed in the first simulation discussed above. In particular, sales, exports, profits, and the measure of firms in each grade increase for OECD firms and fall for Chinese firms in all grades. These responses are again intuitive for the reasons discussed above.

However, in response to lower OECD export costs, R&D and equilibrium innovation rates fall for *both* Chinese and OECD firms. For Chinese firms, the increase in competition from OECD firms reduces the incentive to innovate, hence leading to lower R&D in equilibrium. For OECD firms, the fall in export costs induces more OECD firms to enter the market. Hence, although profits increase because of the reduction in trade costs, the increase in entry causes profits for firms operating in the highest grades to fall relative to profits for firms in the lowest grades, which also reduces the incentives for innovation by OECD firms.

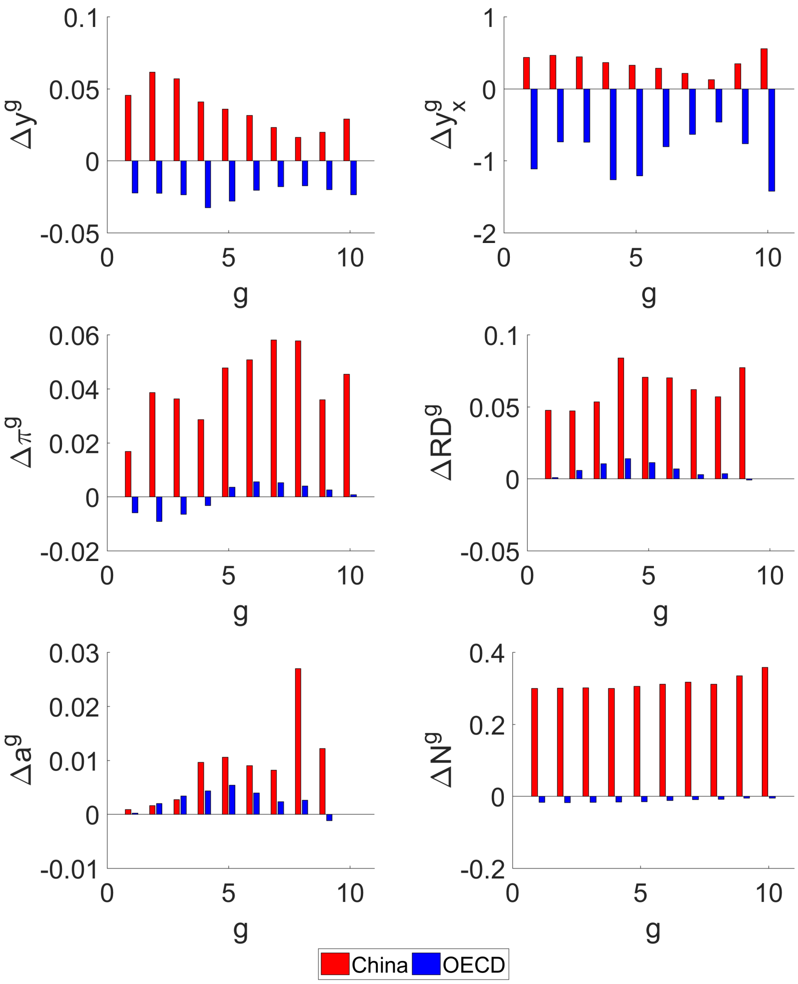


Figure 7.1: Counterfactual: 5% reduction in export costs from China to OECD

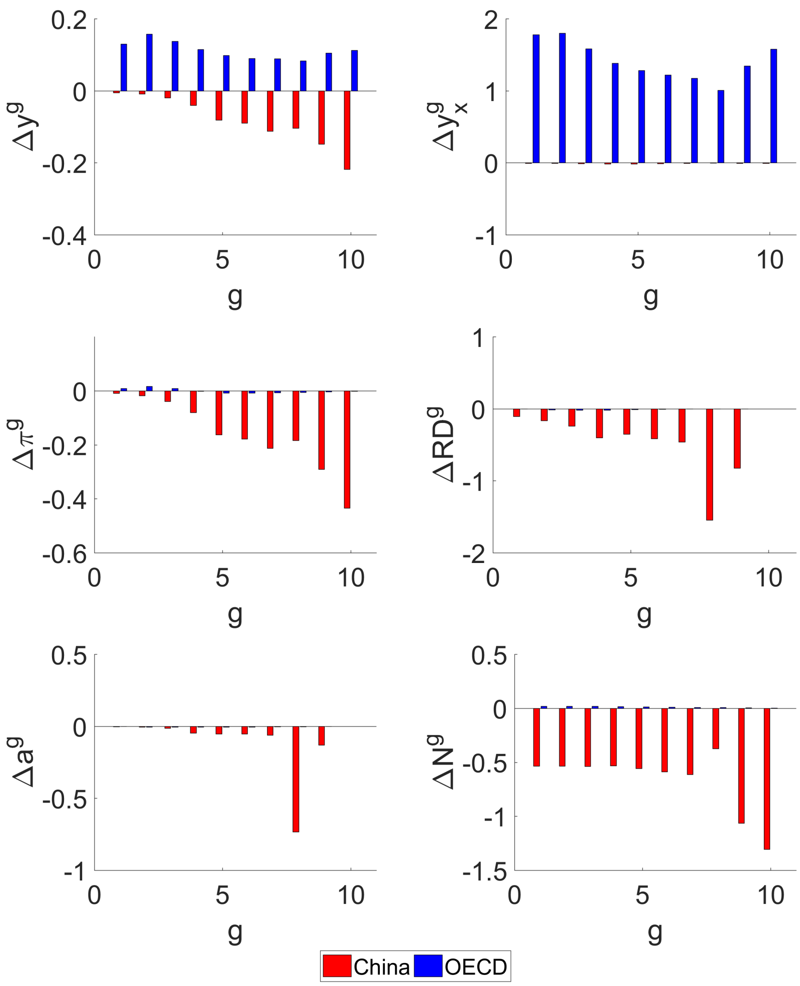


Figure 7.2: Counterfactual: 5% reduction in export costs from OECD to China

8 Conclusion

In this paper, we have established empirically that increased market size promotes innovation as measured by innovation inputs (R&D and patents). Further, increased innovation leads to increased TFP, higher markups, a larger number of exported products (increased variety), and an increase in the share of revenues generated by new products. We also found that increased competition within China has important effects on firm-level innovation, reducing innovation in the aggregate. The calibrated structural model formalizes these economic mechanisms, and simulations of the model indicate that accounting for the heterogeneous effects of trade on innovation by different firms through both the scale and competition channels is essential for understanding firm-level innovation in China. In particular, when firms can innovate to escape the competition, greater competition induced by lower trade barriers can lead firms to increase innovation rather than reduce it.

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A Pricing in the Open Economy

Assuming that it is profitable for grade g producers in j to sell in i, the demand function (5.1) implies the following optimal quality-adjusted price:

$$\hat{p}_{ij}^{g} = \frac{1}{2}\left(\hat{p}_{i,max}^{g} + \alpha_{0}^{g}\rho_{ij}^{g}\right) \tag{A.1}$$

where $\rho_{ij}^{g} \equiv \frac{w_j c_j^g \tau_{ij}}{\alpha_0^g s_j^g}$ is the marginal cost of supplying a unit of quality demanded in location i from location j for a grade g variety (henceforth, the "supply cost"), and $\hat{p}_{i,max}^{g}$ is the maximum quality-adjusted price for grade g varieties in i at which demand is non-negative :

$$\hat{p}_{i,max}^{g} = \frac{\alpha_0^g \alpha_1^g + \alpha_2^g N_i^g \bar{p}_i^g}{\alpha_1^g + \alpha_2^g N_i^g} \tag{A.2}$$

The average quality-adjusted price in i can then be written as:

$$\bar{p}_{i}^{g} = \frac{1}{2}\left(p_{i,max}^{g} + \alpha_{0}^{g}\bar{\rho}_{i}^{g}\right) \tag{A.3}$$

where $\bar{\rho}_i^g$ is the average supply cost across producers from all locations supplying grade g varieties in i:

$$\bar{\rho}_{i}^{g} \equiv \frac{1}{N_i^g}\sum_{j=1}^{J} N_{ij}^{g}\rho_{ij}^{g} \tag{A.4}$$

Solving equations (A.1)-(A.3), we obtain the following expressions for the optimal, maximum, and average prices as functions of the masses of suppliers in i, $\left\{N_{ij}^g\right\}_{j=1}^{J}$:

$$\hat{p}_{ij}^{g} = \alpha_0^g\left(\phi_{ij}^g + \rho_{ij}^g\right) \tag{A.5}$$

$$\hat{p}_{i,max}^{g} = \alpha_0^g\left(\frac{2 + \alpha^g \bar{\rho}_i^g N_i^g}{2 + \alpha^g N_i^g}\right) \tag{A.6}$$

$$\bar{p}_{i}^{g} = \alpha_0^g\left(\frac{1 + \bar{\rho}_i^g + \bar{\rho}_i^g \alpha^g N_i^g}{2 + \alpha^g N_i^g}\right) \tag{A.7}$$

Note that grade g producers in j will find it profitable to sell in i if and only if $\hat{p}_{ij}^g \leq \hat{p}_{i,max}^g$. From (A.5) and (A.6), this is equivalent to the following condition:

$$\rho_{ij}^{g} \leq \frac{2 + \bar{\rho}_i^g \alpha^g N_i^g}{2 + \alpha^g N_i^g} \equiv \rho_{i,max}^{g} \tag{A.8}$$