AER: Insights 2023, 5(1): 35–54
https://doi.org/10.1257/aeri.20210466

Proximity to the Frontier, Markups, and the Response of Innovation to Foreign Competition: Evidence from Matched Production-Innovation Surveys in Chile[†]

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This paper employs a matched firm production-innovation panel dataset from Chile to explore the response of firm innovation to the increased competition arising from the China shock. The data cover a wider range of innovation inputs and outputs than previously possible and allow generating measures of markups and efficiency (TFPQ) that correspond closely to the concepts of rents and technological leadership envisaged in the Schumpeterian literature. Except for the 10 percent most productive plants that see an increase in quality, increased competition depresses most measures of innovation. These differences are exacerbated when interacted with plant-level movements in rents. (*JEL* D24, L25, L60, O14, O19, O31, O34)

The long theoretical and empirical literature on the relationship between firm innovation and competition remains inconclusive (for reviews, see Cohen 2010; Gilbert 2006) while gaining salience in the debate over the effects of trade openness on growth. Recent evidence from the United States, Canada, and Europe (e.g., Autor et al. 2020; Bloom, Draca, and Van Reenen 2016; Campbell and Mau 2021; Kueng, Li, and Yang 2016) generally find negative or unclear impacts of rising import exposure on innovation that sit somewhat uncomfortably with an extensive literature suggesting that trade liberalization increases productivity.[1] Aghion et al. (2005), while accepting this view for firms far from the frontier, argue that firms closer to it may calculate postinnovation rents to be higher than preinnovation

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[†] Go to https://doi.org/10.1257/aeri.20210466 to visit the article page for additional materials and author disclosure statement(s).

[1] Muendler (2004); Krishna and Mitra (1998); Pavcnik (2002); Amiti and Konings (2007); Eslava et al. (2013); Fernandes (2007); Trefler (2004), for Brazil, India, Chile, Indonesia, Colombia, and Canada, respectively, find that productivity increases in incumbent firms with more trade reforms. See also Blundell, Griffith, and Van Reenen (1999); Schmitz (2005).

rents and invest to escape from competition.[2] They find supportive evidence for an *inverted U-shaped* relationship between industry-level innovation and competition in the United Kingdom (see also Hashmi and Van Biesebroeck 2016), although other evidence has been more ambiguous (Hashmi 2013; Gorodnichenko, Svejnar, and Terrell 2010). In contemporaneous work also exploiting the canonical China shock, Aghion et al. (2021) find a detrimental effect on French firms' sales and patenting for Chinese competition in *output* markets—with the negative impact being concentrated in low-productivity firms—but a weak and positive effect when competition is concentrated in *input* markets. Relatedly, Aghion et al. (2009) find the entry of greenfield foreign firms raises patenting for sectors close to the technology frontier but has a weak or even negative effect in laggard industries.

The present paper advances this literature on several fronts. First, it uses a unique matched production-innovation plant-level panel dataset for Chilean manufacturing that permits studying the effect of foreign competition, not just on patenting as has been the traditional focus, but on a broader range of plant performance and innovation outcomes than has been previously possible. We use the canonical China shock (Autor, Dorn, and Hanson 2013; Bloom, Draca, and Van Reenen 2016; Aghion et al. 2021) to test the reaction of these variables to exogenous competition changes. The ability to control for plant and industry-time fixed effects marks a difference with many similar cross-sectional exercises and ensures that we are stripping out possible unobserved correlates with increased competition.

Second, working at the plant level with comprehensive quantity and price data for both inputs and outputs allows us to go beyond previous studies in exploring the channels through which competition affects innovation. In particular, we follow Ackerberg, Caves, and Frazer (2015) and De Loecker and Warzynski (2012) in calculating TFPQ and markups, which correspond more closely to the innovation drivers of distance from the frontier and rents in models presented by Aghion et al. (2005) than previous measures. The revenue-based total factor productivity (TFPR) measure used to proxy frontier proximity in many studies conflates efficiency and prices and, therefore, markups. Hence, a plant with high TFPR may, in fact, be an inefficient plant far from the technological frontier but with a strong monopoly position. The finding for India of De Loecker et al. (2016) that liberalization may increase markups due to greater pass-through in factor than product markets suggests that previous studies finding a positive correlation between TFPR and trade liberalization may be overstating the true efficiency effect. TFPQ, by abstracting from prices, offers a cleaner technological proxy for productivity and distance from the frontier. Further, markups are a closer measure of rents than measures of competitive pressures such as the Lerner index or the Herfindahl-Hirschman index (HHI), often used (see Holmes and Schmitz 2010) when products are not homogenous.

Third, working at the plant level allows us to link our findings to the emerging micro-level literature on product quality improvements that we also see as a

[2] This contrasts with canonical Schumpeterian models, where innovation occurs through creative destruction from outsiders, and thus competition unambiguously hurts innovation as it dampens postinnovation rents (see Dasgupta and Stiglitz 1980; Macher, Miller, and Osborne 2021, for related evidence). As importantly, while creative destruction has significant welfare effects (Atkeson and Burstein 2019), own-firm improvements—including product and process innovation, as well as quality upgrading—appear to be an order of magnitude more important as a source of aggregate economic growth (Garcia-Macia, Hsieh, and Klenow 2019).

measure of innovation (see Verhoogen (forthcoming), for a review on the determinants of quality upgrading in developing countries). Across countries, product quality rises with development (see Schott 2004; Khandelwal 2010; Krishna, Levchenko, and Maloney 2020; Hallak and Schott 2011, among others). Evidence to date suggests that increased competition facilitates such upgrading (Fan, Li, and Yeaple 2015; Bas and Strauss-Kahn, 2015; Martin and Mejean 2014; Fieler, Eslava, and Xu 2018).

Finally, Chile offers a clean experiment to explore the effects mentioned above. It is the iconic "textbook" well-run open economy with few micro distortions that, as elsewhere, saw levels of competition shocked by a major increase in import penetration from China—imports rose at an average pace of 27 percent each year from 2001 to 2007, 15 percentage points above the 1996–2001 trend. But, distinct from many trade liberalization episodes, this shock was not accompanied by other sector-specific reforms. Hence, the effects we see are likely to be purely due to differential exposure to the China shock. As importantly, Chile is a middle-income country that is likely to have fewer leading plants than high-income economies. Thus, our findings shed light on the effects of competition in nonfrontier countries.

The post-WTO accession excess rate of growth in imports from China, on average, led to a depressive effect on output (4.0 percent over 2001–2007) and markups (3.1 percent). TFPQ shows nonstatistically significant decline except for the top 10 percent (7.6 percent), which we define as leaders. On the other hand, leaders show a rise in quality (16.5 percent), their only significant increase in innovation, which may explain why they are producing fewer units and hence show falling TFPQ. We find consistently negative impacts of competition across the spectrum of innovation inputs and outputs for the other 90 percent. This finding, jointly with the fact that only a small minority of Chilean plants show increases in innovation, are important to the debate on the impact of trade liberalization because the share of productive units close to the *global* frontier appears lower in developing countries.

Further, markups, whether capturing rents per se or perhaps access to internal financing, appear to exacerbate the leader/laggard differences. Import competition has a negative effect on markups. Yet, other drivers affected the evolution of markups over our sample, too, causing roughly half of plants to show increasing markups overall. We exploit this heterogeneity to study whether firms in markets with increasing rents, from whatever source (import competition or market-level trends), innovated more than those who did not. We find that process and product innovation among laggards with shrinking rents fell 11 percent and 13 percent, respectively. However, for leaders with rising rents, product innovation and product quality rose by 15 percent and 22 percent, respectively. Hence, while we confirm the importance of distance to the frontier on direction of change, we show that rents also play an important role in determining the magnitude of the impact of competition on innovation.

I. Empirical Approach

A. *The China Trade Shock in Chile*

Chile is a very open economy and hence sensitive to increases in foreign competition. From 1974 to 1980, the country reduced tariff rates from over 100 percent to a uniform rate of 10 percent and eliminated nontariff barriers (NTBs). However, trade with China remained low: in 1990, China accounted for only 1 percent of total imports to Chile and had minor participation in most product categories of Chilean imports.[3] Starting in 1995, the share of imports coming from China gradually increased, and from 2001—when China joined the WTO—to 2007, it more than doubled from 6 to 13 percent—roughly the same rise observed in the United States (Figure A.1 in the online Appendix). While much of the economy was affected, there was substantial variation in the path of imports from China across sectors (see Figure A.2 and Table A.1 in the online Appendix). Imports of electrical and nonelectrical machinery and metallic products show especially high increases, while areas where China has no particular comparative advantage, such as beverages, show little movement.

B. *Empirical Strategy*

Our core specification to establish the effect of increasing competition on domestic plant innovation exploits sectoral variation in the exposure to Chinese imports and takes the following form:

$$y_{ijt} = \alpha_i + \alpha_{jt} + \beta \ln\left(Imp_{ij,t-1}\right) + \gamma X_{ijt} + \varepsilon_{ijt}, \tag{1}$$

where y_{ijt} denotes different innovation outcomes for plant i operating in sector j at time t. $Imp_{ij,t-1}$ captures the plant's exposure to Chinese import competition.[4] This measure is a weighted average of Chinese imports in each product category that the plant produces, where the weights are the sales share in total plant sales at the beginning of the sample period. The time dimension of the data allows us to experiment with up to two lags to capture lagged effects, but we find that a second lag adds little. The baseline specification includes plant fixed effects (α_i) to control for time-invariant factors affecting plants' innovative activity and sector-year fixed effects (α_{jt}) to account for sector-specific shocks, domestic absorption, and time trends. Finally, X_{ijt} comprises time-varying plant controls such as plants' size. ε_{ijt} is an error term.

To address the concern that observed imports from China are not supply driven but rather reflect domestic shocks to Chilean industries affecting both import demand and innovative activity, we construct Bartik-like instruments as in Autor, Dorn, and Hanson (2013) using Chinese import penetration for a group of peer countries. This instrument captures the supply component of Chinese imports under the assumption that industry import demand shocks are uncorrelated across countries. As Borusyak, Hull, and Jaravel (2022) discuss, the Autor, Dorn, and Hanson (2013) approach can be understood as leveraging exogenous shock variation, sufficient to achieve identification as long as unobserved shocks do not correlate with the underlying Bartik shocks. Goldsmith-Pinkham, Sorkin, and Swift (2020) are critical of this strategy, arguing that this is likely valid only if the China shock generated

[3] Exceptions include apparel products and a few nonmetallic product categories such as toys, umbrellas, and plastic straws.

[4] Our baseline specification (1) departs from that used in papers like Autor, Dorn, and Hanson (2013) by using the logarithm of imports from China rather than Chinese import penetration for two reasons. First, Chinese import penetration for Chile shows a strong positive skewness. Second, sector-year fixed effects implicitly capture the log of sector-year domestic absorption.

random shocks across the economy. However, they argue that this is more likely to be the case with the inclusion of higher-level industry fixed effects, thereby more plausibly exploiting truly idiosyncratic variation. Hence, we include sector-time fixed effects in all specifications, and the first stage remains strong.[5]

To identify the peer set to construct the instrument, we estimate a least absolute shrinkage and selection operator (LASSO) regression over the sample of countries with nonzero imports from China in each three-digit ISIC sector. LASSO minimizes the sum of the least squares' objective function, penalizing model size, through the sum of the absolute values of the coefficients. As Belloni et al. (2012) discuss, LASSO-based procedures produce first-stage predictions that provide good approximations to the optimal instruments set when the first stage is approximately sparse. This ensures that necessary countries are included but irrelevant peers are omitted. In the first stage, we predict plant-level exposure to imports from China based on the LASSO instrument, sector-year fixed effects, plant fixed effects, and controls:

$$\ln\left(Imp_{ij,t-1}\right) = \lambda_i + \lambda_{jt} + \delta \ln\left(Imp_{ij,t-1}^{LASSO}\right) + \theta X_{ijt} + \vartheta_{ijt}. \tag{2}$$

In the second stage, we regress each outcome on predicted lagged imports from China $\left(\widehat{\ln\left(Imp_{ij,t-1}\right)}\right)$ and other controls:

$$y_{ijt} = \alpha_i + \alpha_{jt} + \beta \widehat{\ln\left(Imp_{ij,t-1}\right)} + \gamma X_{ist} + \varepsilon_{ijt}. \tag{3}$$

To ensure that domestic shocks are not correlated across neighboring countries, we explore sensitivity of the estimates to including and excluding them. The second-stage estimates do not change appreciably.

C. *Defining Technological Leaders and Measuring Rents*

The manufacturing database that we employ permits generating measures of distance to the technological frontier and rents that are closer to the Schumpeterian theory than those of previous studies. We discuss next the methodological approach followed in constructing them.

Plant-Level Productivity and Technological Leaders.—The previous literature has largely relied on revenue-based total factor productivity (TFPR) to construct measures of distance to the technological frontier. However, recent studies note potential bias in this measure and employ quantities of inputs and outputs to estimate physical total factor productivity (TFPQ) (see De Loecker and Goldberg 2014, for a review). At the grossest level, TFPR includes the product price, which may reflect rents, thereby conflating the two effects. In addition, when prices are not observed, it is expected that plants that charge higher (lower) prices will sell lower (higher) quantities, which, in turn, implies lower (higher) input quantities. Hence,

[5] Alternatively, Goldsmith-Pinkham, Sorkin, and Swift (2020) argue that identification can be achieved based on the stronger condition of exogeneity of the exposure shares, which can be achieved if the change in Chinese exports does not coincide with other shocks to industries that were highly exposed to Chinese trade.

the correlation between output prices and input quantities is likely to be negative, thus leading to a downward bias in the estimated production function elasticities, with an analogous bias arising from unobserved input prices (De Loecker and Goldberg 2014).

While many approaches have been proposed to address the input and output price biases, we opt for using plant-level price indexes to deflate plant revenues and material expenditures (see Eslava et al. 2013; Smeets and Warzynski 2013; Eslava and Haltiwanger 2020).[6] In doing so, we perform the following steps. First, we log difference each plant-product price observation relative to the average price computed across all plants producing the same product in the respective year. Second, we aggregate the resulting normalized price measures using plant-product revenues and expenditure shares, respectively, as weights. Finally, we compute the plant-level output and input indexes adding the plant-level log deviations derived in the previous step to the average price index calculated by the Chilean National Institute of Statistics (Instituto Nacional de Estatísticas, or INE) for each four-digit ISIC sector.

Once inputs and outputs are deflated with plant-level price indexes, we estimate a translog production function for each two-digit manufacturing sector, using labor, capital, and materials as production inputs.[7] We follow the methodology by Ackerberg, Caves, and Frazer (2015)—henceforth, ACF—who extend the framework of Olley and Pakes (1996) and Levinsohn and Petrin (2003)—henceforth, LP—to control for endogeneity of input choices. Further, we modify the canonical ACF procedure by specifying an endogenous productivity process that accounts for learning-by-exporting and investment effects. All coefficients are identified in the second stage of the ACF procedure. They are estimated through GMM, using lagged values for labor, capital, materials, and their interactions as instruments. Table A.2 in the online Appendix reports the average input elasticities for each two-digit sector.[8]

We define leaders as the subset of most productive establishments—within two-digit ISIC sectors and predating 2001—broadly following Hansen (2000) and iteratively splitting the sample to find the threshold TFPQ that minimizes the overall residual sum of squares (RSS) of equation (1). Across all variables, we find the minimum RSS is achieved for thresholds ranging between the eighty-fourth and ninety-sixth percentiles of the TFPQ distribution. We thus choose the ninetieth percentile to define leaders who account for about 26 percent of manufacturing sales and 28 percent of value added.

Measuring Rents.—We consider plants' markups as our baseline measure of rents, measured following De Loecker and Warzynski (2012), who propose the production

[6] Our data also allow us to implement De Loecker et al.'s (2016) methodology to derive plant-product TFPQ. However, the information on innovation inputs and outcomes is only available at the level of productive units, rendering the analysis at the plant-product level unfeasible.

[7] The two-digit product categories are food and beverages, textiles, apparel, wood, paper, chemicals, plastic, nonmetallic manufactures, basic and fabricated metals, and machinery and equipment.

[8] Consistent with the biases discussed in De Loecker and Goldberg (2014), the production function coefficients and returns to scale are somewhat higher than in other studies estimating revenue production functions for the Chilean manufacturing industry. Overall, we find average returns to scale across all plants equal to 1.11, which are not statistically different from one.

function approach to recover plant-level markups. Under this framework, markups are defined as follows:

$$(4) \qquad Markup_{it} \equiv \frac{P_{it}}{MC_{it}} = \underbrace{\left(\frac{\partial Q_{it}(\cdot)}{\partial V_{it}} \frac{V_{it}}{Q_{it}}\right)}_{\text{Output elasticity}} \Big/ \underbrace{\left(\frac{P_{it}^{V} \cdot V_{it}}{P_{it} \cdot Q_{it}}\right)}_{\text{Expenditure share}},$$

where P (P^V) denotes the price of output Q (input V) and MC stands for the marginal cost of production. Thus, the markup measure is defined as the ratio of the output elasticity of a flexible input, in our case materials (M), to its expenditure share on total sales. Given that we have information on output and inputs in physical units, our measures do not suffer the problems documented by Bond et al. (2020). Nevertheless, as a robustness check, we compute plants' operational profit margin, defined as the ratio of operational profits to revenues. Reassuringly, we find that the correlation coefficient between the two measures is 0.9, suggesting that variations in markups are related to changes in plants' profitability.[9]

Analogous to our exercise with leaders and laggards, and in line with the Schumpeterian view, we examine whether firms in *markets* with increasing rents, from whatever source, innovated more than those that did not. Market-level drivers in markups may arise from increased competition or other technological shocks. To abstract from idiosyncratic shocks that affect measured rents, we compute for each plant and year the predicted markups from a regression on our LASSO exposure measure (instrumented by the corresponding LASSO instrument discussed in section IB), plant fixed effects, and sector-year fixed effects. We then calculate the change in average predicted markups before and after 2001. We find that while, as Table 2 showed, increased Chinese competition decreased markups on average, other drivers external to the plants led to almost half of firms registering positive predicted changes overall, and we split the sample accordingly.

II. Data

A. *Plant-Level Data*

In addition to the country's extraordinary openness and textbook cleanness of its trade regime, what is compelling about Chile's experience is the quality and level of detail of the data collected, both in the Annual National Industrial Survey (Instituto Nacional de Estadísticas, n.d.—hereafter, ENIA) and the Technological Innovation Survey (Ministerio de Economia de Chile, n.d.—hereafter, EIT). The former provides standard balance-sheet data for plants ten employees or above—including detailed information on all outputs produced and inputs used in production, as their respective prices by each plant for the period 1996–2007. Of the roughly 4,800 manufacturing plants tabulated per year, about 20 percent are exporters and two-thirds are small plants (less than 50 workers). Medium-sized plants (50–150 workers) and large plants (more than 150 workers) represent 20 and 12 percent of the universe

[9]This is in line with De Loecker, Eeckhout, and Unger (2020), who show that in their sample of US firms, markups are also highly correlated with different measures of profitability, including accounting profits and stock market performance.

of plants, respectively. We exclude plant-product-year observations that have zero values for total employment, demand for raw materials, sales, or product quantities. We also remove outliers by excluding observations where the input or output price deviates more than five times from the industry-year average. Our final sample consists of 29,283 plant-year observations.

To exploit differences in plants' exposure to Chinese competition, we construct measures of import exposure at the plant level, using international trade data from the CEPII's BACI dataset (CEPII 2022) for the period 1995–2007.[10] BACI is available at the six-digit HS level, while production information for Chilean plants is available at the four-digit ISIC level. We match BACI's six-digit HS sectors with four-digit ISIC sectors, using the World Bank's WITS correspondence table. We then aggregate imports at the three-digit ISIC level to minimize the information loss due to the presence of zeros in the original BACI dataset.[11]

B. *Innovation Data*

We merge the ENIA with the EIT, a national innovation survey that includes a random sample of manufacturing firms and all firms that individually accounts for more than 2 percent of the sectoral value added. EIT collects detailed information on innovation outputs and inputs. Throughout the analysis, we focus on the following innovation outcomes:

- *Patents/intellectual property rights* are the most common innovation measure in the literature. In addition to patents, the EIT counts author's rights and vegetable variety rights but not trademarks.
- *Process or product innovation* are output variables arguably more relevant to a developing country context than patents. They take a value of one if the firm reports introducing a technological improvement to an existing process/product or developed a new (to the firm, country, or international market) technological process/product in the last two years.
- *Product quality* is an additional output measure derived from the ENIA following Khandelwal, Schott, and Wei (2013) where a variety showing higher quantities sold, conditional on price is considered of higher quality. See Appendix A.5 for technical details on the construction of this measure and Peters (2020) for a discussion of how a common industry-level demand elasticity can be consistent with heterogeneity in markups across firms.
- *Research and development* (*R&D*) *spending* is the standard measure of spending on basic, applied, or experimental research.
- *Total innovation spending* is an omnibus measure of the firm's spending capturing inputs in addition to R&D like purchase of licenses and training.

[10] This dataset reconciles inconsistencies in exporters' and importers' declarations found in the UN Statistics Division's trade dataset (Comtrade).

[11] When using the data at the four-digit ISIC level, 8.4 percent of the sector-year observations are zeros. In contrast, only 1.6 percent of the observations are zeros when aggregating the data at the three-digit ISIC level.

Table 1—Summary Statistics

			Percentiles			Sample size	
	Mean (1)	SD (2)	P25 (3)	P50 (4)	P75 (5)	Plant-years (6)	Plants (7)
Plant-level variables							
Output volume (in logs)	8.826	1.886	7.420	8.501	10.091	29,283	3,090
Markups	1.228	0.661	0.854	1.082	1.396	28,839	3,090
Revenue (in logs)	13.283	1.822	11.910	12.929	14.461	29,283	3,090
Output price (in logs)	4.456	0.564	4.189	4.478	4.736	29,283	3,090
Physical TFP (in logs)	6.587	2.731	5.513	6.660	7.912	29,283	3,090
Revenue TFP (in logs)	6.544	2.691	5.687	6.636	7.987	29,283	3,090
Marginal cost (in logs)	4.360	0.730	3.987	4.368	4.746	29,283	3,090
Product quality (in logs)	0.076	1.817	−1.258	−0.250	1.187	24,439	3,088
Profit rate	0.441	0.502	0.170	0.364	0.622	29,283	3,090
Input price (in logs)	4.455	0.508	4.187	4.462	4.729	29,283	3,090
Innovation variables							
Overall innovative spending (IHS)	4.577	5.552	0.000	0.000	10.564	4,704	1,377
R&D spending (IHS)	2.996	4.890	0.000	0.000	8.425	4,704	1,377
Patents stock (IHS)	0.154	0.566	0.000	0.000	0.000	4,704	1,377
Percent (positive process innovation)	0.506	0.500	0.000	1.000	1.000	4,704	1,377
Percent (positive product innovation)	0.432	0.495	0.000	0.000	1.000	4,704	1,377
Product quality	1.469	2.076	−0.118	1.493	3.034	4,345	1,337
Chilean imports of Chinese products							
Observed imports (millions, US)	75.98	155.49	3.05	18.17	73.46	364	364
Predicted LASSO imports (millions, US)	74.68	154.72	3.10	17.45	71.19	364	364

Notes: The table shows summary statistics for the main variables used in the paper. The analysis considers plant-level data for the universe of Chilean manufacturing establishments employing at least ten employees over the period 1996–2007. The statistics are computed for the subset of plants observed at least one year before and after China's entry into the WTO in 2001. Nominal plant-level variables are in Chilean pesos of 2003. Innovation variables are only available for the subset of plants in ENIA surveyed in the Technological Innovation Survey (EIT). EIT is only available for 1997–1998, 2000–2001, and 2003–2007. Overall innovative spending, R&D spending, and patents stock are transformed using the inverse hyperbolic sine function (IHS, see Bellemare and Wichman 2020) to account for zeros.

Table 1 presents summary statistics of the main production and innovation variables, as well as Chilean imports from China. For patents, R&D spending, and innovative spending, we use the inverse hyperbolic sine transformation (IHS), which provides a good fit for variables with positive skewness and zero-valued observations, while providing a straightforward mapping of coefficients to elasticities (see Bellemare and Wichman 2020, for details).[12] The combined ENIA-EIT dataset gathers information on 4,704 plant-year observations (1,377 unique plants) that cover roughly 20 percent of the ENIA for the years where EIT is available. Online Appendix Table A.3 shows that there are few systematic differences between the matched and full ENIA datasets, and, as we discuss below, these differences appear uncorrelated with variation in exposure to import competition from China.

[12] We present the average elasticities for patents, R&D spending, and innovative spending in all tables.

Table 2—Effect of Chinese Import Competition on Plants' Outcomes

	Output (1)	Markup (2)	Revenue (3)	Output price (4)	TFPQ (5)	TFPR (6)	Marginal cost (7)	Product quality (8)
Panel A. Baseline								
ln(CHN imports(−1))	−0.0441	−0.0346	0.0169	0.0611	−0.0377	−0.0158	0.0973	0.0558
	(0.0216)	(0.0108)	(0.0245)	(0.0226)	(0.0241)	(0.0134)	(0.0261)	(0.0344)
First-stage *F*-statistic	74.3	74.3	74.3	74.3	74.3	74.3	74.3	58.2
Industry-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Plant FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	29,283	29,283	29,283	29,283	29,283	29,283	29,283	24,439
Panel B. Interactions with leaders/laggards								
ln(CHN imports(−1))								
× leaders indicator	0.0105	−0.102	0.116	0.105	−0.0866	−0.0445	0.220	0.167
	(0.0355)	(0.0224)	(0.0350)	(0.0342)	(0.0403)	(0.0322)	(0.0454)	(0.0488)
× laggards indicator	−0.0642	−0.0249	−0.00785	0.0564	−0.0397	−0.0165	0.0826	0.0369
	(0.0289)	(0.0115)	(0.0240)	(0.0232)	(0.0258)	(0.0140)	(0.0261)	(0.0314)
First-stage *F*-statistic	35.5	35.5	35.5	35.5	35.5	35.5	35.5	27.5
Industry-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Plant FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	29,283	29,283	29,283	29,283	29,283	29,283	29,283	24,439

Notes: The table presents the results from estimating equation (3) (panel A) and an extended version that interacts lagged imports from China with an indicator variable for industry leaders and laggards (panel B). Industry leaders correspond to the top 10 percent of plants with the highest average TFPQ before 2001. All regressions are run at the plant-year level, control for the logarithm of employment, and include industry-year (at the two-digit level) and plant fixed effects. Each column shows 2SLS coefficients using (lagged) predicted LASSO imports as an instrument for (lagged) Chinese imports. The (cluster-robust) Kleibergen-Paap rK Wald *F*-statistic is at the bottom of each column. The corresponding Stock-Yogo value for 10 percent (15 percent) maximal IV bias is 16.4 (8.96). Section IIB explains the procedure followed to derive the product quality measure. All regressions cluster standard errors at the industry-year level.

III. Results

Import Competition and Performance Effects.—Panel A of Table 2 shows the impact of instrumented Chinese imports on core plant performance variables for the ENIA sample. All specifications control for the log of plant-level employment as a scale effect, plant fixed effects, and two-digit sector-year fixed effects. We cluster standard errors at the three-digit sector-year level. To calculate the reported effects, we multiply the estimated coefficient by the excess import growth across 2001–2007 relative to the trend over 1996–2001.

Panel A shows that the *F*-statistic corresponding to the instrument (74.3) is significantly above the critical value of 16.4 for 10 percent maximal IV bias. Moreover, the coefficient of log LASSO imports on log imports is positive and statistically significant at the 1 percent level (see Table A.4 in the online Appendix). As an additional robustness check on the exogeneity of our instrument, we run the LASSO but excluding all Latin-American countries. The coefficients change little, suggesting that there is minimal trade-off in consistency with the greater power coming from employing the larger sample (see Tables A.6 and A.7 in the online Appendix).

Columns 1 and 2 show that the increase in average imports from China led to falls in average output (coefficient −0.044) and markups (−0.035), significant at the 1 percent level. This is consistent with a contraction of demand caused by increased competition. The rise in marginal costs (0.097) and of output price

(0.061) suggest that, on average, plants move up along the marginal cost curve and, therefore, lose some economies of scale. They also adjust to the demand shock, partly by reducing markups. Revenue, TFPQ, and TFPR all appear depressed, although the effects are nonsignificant. Profits display similar results to markups; thus, we continue with markups as our main measure of rents for the rest of the paper.[13] Panel B shows that our division of leaders and laggards offers intuitively reasonable results for the core performance variables. The fall in output is largely concentrated in laggards (−0.064), with a lesser and insignificant impact on leaders. Revenues rise significantly for leaders (0.116), and output prices rise twice as much for leaders as for laggards. However, markups fall substantially more for leaders as marginal costs significantly rise more than twice as much for them as for laggards (0.220 versus 0.083). TFPR shows no significant change for either type of establishment, while TFPQ falls sharply (−0.087) for leaders, more than twice the (insignificant) fall for laggards. Critical to the interpretation of the observed findings is that quality rises strongly and significantly (0.167) for leaders, while laggards show a small and insignificant effect.

The fall in TFPQ, while TFPR remains unchanged, suggests that many previous studies finding a positive effect of trade liberalization on TFPR may have an upward bias, particularly in light of the findings of De Loecker et al. (2016) of plausible increases in markups with liberalization. That said, rather than interpreting this as increased competition lowering productivity, we postulate that plants are shifting to higher quality products, which implies higher costs per unit (see Katayama, Lu, and Tybout 2009, for a discussion). That this may lead to fewer units being produced and lower apparent productivity (TFPQ) is consistent with evidence from Egyptian rug producers (Atkin, Khandelwal, and Osman 2017) and the Chilean wine sector (Cusolito and Maloney 2018), where firms producing more higher-quality rugs and wines showed lower TFPQ.[14] Such a shift plausibly explains higher output prices, albeit for an upgraded product, and higher marginal costs to make it, although we do not find the increased costs of inputs found by Kugler and Verhoogen (2012). Hence, arguably, competition is contracting the output of low-productivity plants, reducing market power, as revealed by lower markups, and forcing the more productive plants to innovate in quality.[15]

Distance to the Frontier and Innovation Effects.—As we discussed above, the information for innovation outcomes is available for a subset of the plant-years in ENIA. Table A.8 in the online Appendix shows that the response of the core outcome variables to the increase in average imports from China is very similar

[13] Online Appendix Table A.5 shows complete plants' outcomes results, including responses for profits and input prices.

[14] Relatedly, Grieco and McDevitt (2017) propose an approach for estimating productivity when quality is directly observed and apply it to the health care sector to show how the quality-quantity trade-off may affect productivity measurement. Eslava and Haltiwanger (2020) address quality differences when estimating the production function using a control-function approach that relies on the presence of CES demand. De Roux et al. (2020) expand on this idea, proposing a two-stage instrumental variable estimator that does not depend on the particular assumed demand.

[15] This is broadly consistent with Hombert and Matray (2018), who find that the negative impact of Chinese import competition on sales growth and profitability of US companies is substantially smaller for "leaders"—defined as firms with a larger stock of R&D—because R&D allows these firms to increase product differentiation to escape from import competition. Medina (forthcoming) provides similar evidence for the Peruvian apparel industry.

TABLE 3—EFFECT OF CHINESE IMPORT COMPETITION ON INNOVATION VARIABLES

	Innovative spending		Innovation outputs			
	Overall spending (1)	R&D spending (2)	Patents stock (3)	Process innovation (4)	Product innovation (5)	Product quality (6)
Panel A. Baseline						
ln(CHN imports(−1))	−1.132	−0.610	−0.040	−0.087	−0.074	0.079
	(0.464)	(0.524)	(0.043)	(0.029)	(0.028)	(0.059)
Avg. elasticity (IHS variables)	−1.132	−0.610	−0.067	—	—	—
First-stage F-statistic	42.9	42.9	42.9	42.9	42.9	45.75
Industry-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Plant FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,704	4,704	4,704	4,704	4,704	4,345
Panel B. Interactions with leaders/laggards						
ln(CHN imports(−1))						
× leaders indicator	−1.075	0.640	−0.152	−0.050	0.045	0.217
	(0.826)	(0.889)	(0.146)	(0.066)	(0.069)	(0.077)
Avg. elasticity (IHS variables)	−1.075	0.640	−0.159	—	—	—
× laggards indicator	−1.305	−0.965	−0.040	−0.109	−0.091	0.023
	(0.674)	(0.619)	(0.045)	(0.037)	(0.035)	(0.061)
Avg. elasticity (IHS variables)	−1.305	−0.965	−0.093	—	—	—
First-stage F-statistic	14.5	14.5	14.5	14.5	14.5	16.0
Industry-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Plant FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,704	4,704	4,704	4,704	4,704	4,345

Notes: The table presents the results from estimating equation (3) (panel A) and an extended version that interacts lagged imports from China with an indicator variable for industry leaders and laggards (panel B) for different innovation outcomes. Industry leaders correspond to the top 10 percent of plants with the highest average TFPQ before 2001. All regressions are run at the plant-year level, control for the logarithm of employment, and include industry-year (at the two-digit level) and plant fixed effects. Each column shows 2SLS coefficients using (lagged) predicted LASSO imports as an instrument for (lagged) Chinese imports. The (cluster-robust) Kleibergen-Paap rK Wald F-statistic is at the bottom of each column. The corresponding Stock-Yogo value for 10 percent (15 percent) maximal IV bias is 16.4 (8.96). Overall innovative spending (column 1), R&D spending (column 2), and patents stock (column 3) are transformed using the inverse hyperbolic sine function (IHS, see Bellemare and Wichman 2020) to account for zeros. Product and process innovation (columns 4 and 5) are categorical variables taking the value one if the establishment reports successful innovation. Section IIB explains the procedure followed to derive the product quality measure used in column 6. All regressions cluster standard errors at the industry-year level.

when restricting the sample to plant-years in the EIT. This suggests that whatever differences between samples exist, they do not correlate with variation in import competition from China.

Table 3 repeats the previous exercise but for the innovation variables. Two variables capture innovation inputs (overall innovative spending and R&D spending), while four capture innovation outputs (patent stock, product innovation, process innovation, and quality). As before, the first stage is very strong (see columns 1–3 in Table A.9 in the online Appendix for details). In all the cases, with the exception of product quality, the sign of the estimated coefficients is negative as well as statistically significant for overall spending (−1.13), process innovation (−0.09), and product innovation (−0.07). As discussed in the introduction, such a negative finding is not uncommon in the literature and supports the Schumpeterian view that increased competition reduces innovation.[16]

However, disaggregating the results by leaders and laggards in panel B yields a more subtle picture, which is consistent with Aghion et al. (2005). The negative and significant effects are entirely concentrated in the laggards, while leaders show no statistically significant change, except for the previously found increase in quality. The nonresponse of product innovation is surprising given the increase in product quality found in Table 2, although one explanation may lie in the broader concept of product innovation which includes new products and improvements in product quality. Though the industry-time fixed effects implies interpretation of these effects relative to industry-level evolution, the overall stagnation or decline in all innovation variables across the period (see Figure A.3 in the online Appendix) implies that plants further from the frontier are indeed reducing innovation. To check that our results are not driven by spurious correlation, Table A.11 in the online Appendix replicates Table 3 but takes long differences before and after China joined the WTO in 2001. The results are broadly consistent, although while the fall in process innovation and the rise of product quality on leaders are quantitatively similar to the baseline specification, the reduced degrees of freedom now push the coefficients into statistical insignificance.

Rents and Innovation Effects.—To test the pure Schumpeterian hypothesis that falling rents will deter innovation, we calculate the average predicted markup at the plant level for the periods 1996–2000 and 2001–2007 and split the sample into plants that display increasing or shrinking markups (see section IC for details). The results in Table 4 offer some support for the Schumpeterian theory. For plants with declining markups, the coefficient on every category of innovation is negative and for overall spending, process innovation, and product innovation, significantly so. For those with increasing markups, the coefficients are generally less negative or even positive, with only process innovation showing a significant negative coefficient of broadly the same order of magnitude as those with shrinking markups.

Table 5 splits the sample four ways across leadership and markup changes. Despite the resulting reduction in cell size, a more subtle story appears with both leadership and, to a lesser degree, markups playing a role. The coefficients on virtually all variables are negative for laggards, but it is the subsample with decreasing markups that show larger and statistically significant falls. Laggards with increasing markups generally show insignificant effects. Leaders with shrinking markups show a statistically significant impact only on improved quality at the 5 percent level. However, for leaders with increasing markups, product innovation increases at the 10 percent level and quality and R&D at the 11 percent level. It is important to remember that industry-year fixed effects strip out the mean tendency of the sector so that even with increasing markups, the change in every innovation measure for laggards is below the mean change for the sector. This suggests that whatever is causing leaders to be leaders—managerial practices or entrepreneurial qualities, for instance—is more important to the incumbent's innovation response to competition than rents.

[16] Online Appendix Table A.10 shows that the results do not change appreciably excluding the 7 percent of firms that have multiple plants where we imputed the average firm value.

Table 4—Heterogeneity: Split by Change in Markups

	Innovative spending		Innovation outputs			
	Overall spending (1)	R&D spending (2)	Patents stock (3)	Process innovation (4)	Product innovation (5)	Product quality (6)
ln(CHN imports(−1))						
× increasing markups	−0.504	−0.114	0.004	−0.106	−0.043	0.066
	(0.683)	(0.649)	(0.047)	(0.046)	(0.035)	(0.070)
Avg. elasticity (*IHS variables*)	−0.504	−0.114	0.006	—	—	—
× declining markups	−1.416	−0.804	−0.060	−0.087	−0.097	0.087
	(0.567)	(0.680)	(0.072)	(0.039)	(0.044)	(0.080)
Avg. elasticity (*IHS variables*)	−1.416	−0.804	−0.113	—	—	—
First-stage *F*-statistic	23.5	23.5	23.5	23.5	23.5	12.5
Industry-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Plant FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,692	4,692	4,692	4,692	4,692	4,335

Notes: The table presents the results from estimating an extended version of equation (3) that interacts lagged imports from China with an indicator variable for plants increasing/declining markups after China joined the WTO in 2001. To split the sample, we run an auxiliary regression of plant-level markups against instrumented lagged imports from China, industry-year fixed effects, and plant fixed effects to purge idiosyncratic shocks. Thus, the indicator variable only considers the fraction of markups that varies due to increased Chinese competition or market-level drivers to split the sample. All regressions are run at the plant-year level, control for the logarithm of employment, and include industry-year (at the two-digit level) and plant fixed effects. Each column shows 2SLS coefficients using (lagged) predicted LASSO imports as an instrument for (lagged) Chinese imports. The (cluster-robust) Kleibergen-Paap rK Wald *F*-statistic is at the bottom of each column. The corresponding Stock-Yogo value for 10 percent (15 percent) maximal IV bias is 16.4 (8.96). Overall innovative spending (column 1), R&D spending (column 2), and patents stock (column 3) are transformed using the inverse hyperbolic sine function (IHS, see Bellemare and Wichman 2020) to account for zeros. Product and process innovation (columns 4 and 5) are categorical variables taking the value one if the establishment reports successful innovation. Section IIB explains the procedure followed to derive the product quality measure used in column 6. All regressions cluster standard errors at the industry-year level.

IV. Concluding Remarks

This paper uses detailed plant-level data on production and innovation inputs and outputs to explore the relationship between competition and innovation. The dataset is uniquely suited to the exercise, as it contains information on prices at the product and input level, allowing the estimation of unbiased TFPQ measures and the calculation of markups, the two variables that best correspond to the distance to the frontier and rents discussed in the literature.

The overall effect of competition on innovation is negative. This is consistent with much of the recent literature. However, exploring the heterogeneity across establishments, we find that the 10 percent of plants closer to the technological frontier, accounting for roughly a quarter of industrial value added, upgrade the quality of their goods (16.5 percent), consistent with the view by Aghion et al. (2005) to escape competition. We also find evidence for the Schumpeterian view of the role of rents. While increased Chinese competition decreased markups on average (3.1 percent), other drivers external to the plants led to almost half of firms registering positive predicted changes overall. We find that rises in rents induce leaders to invest more in R&D spending, product innovation, and product quality. Markup falls exacerbate laggards' contraction of product and process innovation, while increased markups moderate their decline. These findings suggest that improving plant capabilities, managerial practices, or intrinsic entrepreneurial quality that drives the leaders,

Table 5—Change in Markups Combined with Leader/Laggard Indicator

	Innovative spending		Innovation outputs			
	Overall spending (1)	R&D spending (2)	Patents stock (3)	Process innovation (4)	Product innovation (5)	Product quality (6)
log(CHN imports(−1)) × laggards						
× (declining markup)	−1.533	−1.333	−0.060	−0.127	−0.151	0.009
	(0.911)	(0.844)	(0.086)	(0.048)	(0.057)	(0.100)
Avg. elasticity (*IHS variables*)	−1.533	−1.333	−0.095	—	—	—
× (increasing markup)	−0.799	−0.376	0.021	−0.108	−0.042	0.031
	(0.747)	(0.694)	(0.050)	(0.051)	(0.040)	(0.070)
Avg. elasticity (*IHS variables*)	−0.799	−0.376	0.046	—	—	—
log(CHN imports(−1)) × leaders						
× (declining markup)	−0.951	0.916	−0.153	−0.079	0.040	0.196
	(0.817)	(0.836)	(0.150)	(0.071)	(0.072)	(0.083)
Avg. elasticity (*IHS variables*)	−0.951	0.916	−0.208	—	—	—
× (increasing markup)	−0.217	1.873	−0.071	−0.060	0.149	0.218
	(1.275)	(1.143)	(0.179)	(0.087)	(0.088)	(0.135)
Avg. elasticity (*IHS variables*)	−0.217	1.873	−0.072	—	—	—
First-stage *F*-statistic	7.8	7.8	7.8	7.8	7.8	10.6
Industry-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Plant FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,692	4,692	4,692	4,692	4,692	4,335

Notes: The table presents the results from estimating an extended version of equation (3) that interacts lagged imports from China four-way with indicator variables for leaders/laggards and for plants increasing/shrinking markups after China joined the WTO in 2001. See the notes to Tables 3 and 4 for details on the construction of the leaders/laggards and increasing/shrinking markups indicator variables. All regressions are run at the plant-year level, control for the logarithm of employment, and include industry-year (at the two-digit level) and plant fixed effects. Each column shows 2SLS coefficients using (lagged) predicted LASSO imports as an instrument for (lagged) Chinese imports. The (cluster-robust) Kleibergen-Paap rK Wald *F*-statistic is at the bottom of each column. The corresponding Stock-Yogo value for 10 percent (15 percent) maximal IV bias is 16.4 (8.96). Overall innovative spending (column 1), R&D spending (column 2), and patents stock (column 3) are transformed using the inverse hyperbolic sine function (IHS, see Bellemare and Wichman 2020) to account for zeros. Product and process innovation (columns 4 and 5) are categorical variables taking the value one if the establishment reports successful innovation. Section IIB explains the procedure followed to derive the product quality measure used in column 6. All regressions cluster standard errors at the industry-year level.

rather than maintaining high rents, is an important innovation policy and arguably a vital complement to policies intended to increase competition.

There may be at least two reasons why plant productivity often appears to increase with trade liberalization, even in developing countries, but innovation does not. The first may have to do with the fact that the TFPR measure commonly used in the literature combines efficiency, quality, and rents. Thus, if greater trade exposure actually leads to higher margins, as shown by De Loecker and Goldberg (2014), then this will show up as increased "productivity." Second, it is possible that increased competition leads to one-off adjustments—shedding excess workers, for example—but does not lead to dynamic increases arising from innovation.

Though Chile provides a case of increased competition without other confounding reforms, it is important to acknowledge that the China shock may have had other ancillary effects—for instance, through increased demand for Chilean goods. This should largely be captured by the sector-time fixed effects included in the regressions. Yet, to the degree that impacts of these economy-wide effects have heterogeneous effects within sectors, our estimates may be understating the true decline in innovation due to competition.

A finding of limited incumbent rise in innovation and perhaps lesser confidence in previous findings of increased productivity with trade liberalization does not, of course, dictate reducing competition. Competition works through other margins, such as the reallocation of resources from low-productivity plants to high-productivity plants and through the entry of more productive plants and the exit of less productive ones. For the same period covered in the present study, Cusolito and Maloney (2018) show that over 60 percent of the gains in TFPQ in Chile arose precisely from entry and exit. Liu (1993) finds that in the early phases of the Chilean reforms, much productivity growth occurred along the extensive margin, which rings true given the extraordinary levels of protection and distortions being unwound at the time. Moreover, although the share of value added of innovation-increasing incumbent plants at 25 percent is not negligible, the number of leader plants is small in Chile compared to, for instance, the 50 percent found in the United Kingdom by Aghion et al. (2009). This suggests both that in nonfrontier countries, expectations of the positive impact through incumbent plants should probably be moderated and that increased competition might be accompanied by the building of leader establishment skills—for instance, through managerial consulting support.

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