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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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Abstract

This paper employs a matched firm production/innovation panel data set from Chile to explore the response of firm innovation to the increased competition arising from the China shock. In addition to covering a wider range of innovation inputs and outputs than previously possible, the data allow generating measures of markups and efficiency (physical total factor productivity) that correspond more closely to the concepts of rents and technological leadership envisaged in the Schumpeterian literature. Except for the 10 percent most productive plants, increased competition depresses most measures of innovation. Falling rents exacerbate declines among laggards, while rising rents further increase innovation among leaders.

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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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1 Introduction

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 US, Canada and Europe (e.g. Autor, Dorn, Hanson, Pisano, and Shu, 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, Bloom, Blundell, Griffith, and Howitt (2005), while accepting this view for firms far from the frontier, argue that firms closer to it may calculate post-innovation rents to be higher than pre-innovation 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 UK (see also Hashmi and Van Biesebroeck, 2016), although other evidence has been more ambiguous (Hashmi, 2013; Gorodnichenko, Svejnar, and Terrell, 2010). In contemporaneous work, Aghion, Bergeaud, Lequien, Melitz, and Zuber (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, Blundell, Griffith, Howitt, and Prantl (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 data set 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 et al., 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 we are stripping out possible unobserved correlates with increased competition.

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

[2] This contrasts with canonical Schumpeterian models, where innovation occurs through creative destruction from outsiders, and thus competition unambiguously hurts innovation as it dampens post-innovation 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).

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, Goldberg, Khandelwal, and Pavcnik (2016) that liberalization may increase markups due to greater passthrough 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 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 measure of innovation (see Verhoogen, 2020, 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. 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 increased foreign competition across sectors. 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 non-frontier countries.

On average, we find a depressive effect of increased competition on TFPQ, markups, and innovation inputs and outputs. Both TFPR and TFPQ show non-statistically significant declines except for the top 10 percent, which we define as leaders, where TFPQ falls significantly. On the other hand, leaders show a near equal rise in quality, 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. Where rents decline, innovation among laggards falls more severely; where they rise, leaders show a significant increase in R&D spending and product innovation as well as quality. 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.

2 Empirical Approach

2.1 The China Trade Shock in Chile

Chile is a very open economy and hence sensitive to increases in foreign competition. From 1974-1980, the country reduced tariff rates from over 100 percent to a uniform rate of 10 percent and eliminated non-tariff barriers (NTBs). However, trade with China remained low until the end of the 1990s. 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, import penetration gradually increases, followed by an acceleration phase around the time China joined the WTO in 2001. From 2001-2007, the Chinese import share more than doubled from 6 to 13 percent –roughly the same rise observed in the United States.[4] 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 Appendix). Imports of electrical and non-electrical machinery, and metallic products show especially high increases while areas where China has no particular comparative advantage, such as beverages, show little movement.

2.2 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:

$$y_{ijt} = \alpha_i + \alpha_{jt} + \beta \ln(\text{Imp}_{ij,t-1}) + \gamma X_{ijt} + \varepsilon_{ijt} \quad (1)$$

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

[4]Figure A.1 in the Appendix compares the share of overall manufacturing imports coming from China in Chile and the United States for each year between 1996 and 2007.

where y_{ijt} denotes different innovation outcomes for plant i operating in sector j at time t. $\text{Imp}_{ij,t-1}$ captures the plant's exposure to Chinese import competition.[5] 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 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 follow Autor et al. (2013) and instrument Chinese import penetration in Chile 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. To select the set of countries that best predict Chilean imports from China, we estimate a LASSO regression over the sample of countries with non-zero exports in each 3-digit ISIC sector, penalizing them in terms of their contribution to predicted imports. In the first stage, we predict plant-level imports from China based on the LASSO instrument, sector-year fixed effects, plant fixed effects, and controls:

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

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

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

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.

[5] Our baseline specification (1) departs from that used in papers like Autor et al. (2013) by using the logarithm of imports from China rather than Chinese import penetration – defined as the ratio of sectoral imports over domestic absorption. There are two reasons for this choice. First, computing import penetration measures requires data on initial domestic absorption at the sectoral level. This information is unavailable for most of the countries we use to construct our instrumental variable. Second, Chinese import penetration for Chile shows a strong positive skewness, suggesting that a logarithmic specification provides a better fit to the data.

2.3 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 highlight the importance of using information on physical units of inputs and outputs to estimate physical total factor productivity (TFPQ) and thus avoid relying on biased measures of efficiency to explore the effect of competition on plant performance (see De Loecker and Goldberg, 2014, for a review). At the grossest level, not doing this leaves the price component embedded in the productivity measure, which may reflect rents and hence conflate the two effects. When information on prices at the establishment-level is not available, it is expected that plants that charge higher (lower) prices will sell lower (higher) quantities, which, in turn, implies lower (higher) input quantities. Hence, the correlation between output prices and inputs quantities is likely to be negative, thus leading to a downward output-price bias in the estimated production function elasticities. Similarly, a plant that pays higher input prices will have higher input expenditures that will not lead to higher physical output. Thus, the input price variation will lead to a negative bias of the estimated coefficients (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 Statistical Agency (INE) for each 4-digit ISIC sector.

Once inputs and outputs are deflated with plant-level price indexes, we estimate a translog production function for each 2-digit manufacturing sector, using labor, capital, and materials as production inputs.[7] We follow the methodology by Ackerberg et al. (2015, henceforth ACF), who

[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 investments and outcomes is only available at the plant level, rendering the analysis at the plant-product level unfeasible.

[7] The 2-digit product categories are: Food and beverages, textiles, apparel, wood, paper, chemicals, plastic, non-metallic manufactures, basic and fabricated metals, and machinery and equipment.

extend the framework of Olley and Pakes (1996) and Levinsohn and Petrin (2003, henceforth LP) to control for endogeneity of input choices.[8] Further, we modify the canonical ACF procedure by specifying an endogenous productivity process that accounts for learning-by-exporting and investment effects.[9] All coefficients are identified in the second stage of the ACF's procedure. They are estimated through GMM, using lagged values for labor, capital, materials, and their interactions as instruments. These variables are valid instruments because they are chosen by the plant before it observes productivity. Table A.2 reports the average input elasticities for each 2-digit sector. [10]

We define leaders as the subset of most productive establishments –within 2-digit ISIC sectors– before the entry of China into the WTO in 2001. In doing so, we broadly follow Hansen (2000) and split the sample for each potential sub-samples of leaders and laggards looking for the threshold TFPQ that minimizes the overall RSS of equation (1). Across all variables, we broadly observe a U-shaped pattern when plotting the RSS against the TFPQ cut-off, with the RSS being the largest when defining the TFPQ threshold at the extremes of the TFPQ distribution. This pattern emerges more clearly for the quality, product innovation, and process innovation variables. Overall, the minimum RSS is achieved for cut-offs ranging between the 84th and 96th percentile of the TFPQ distribution. We thus choose the 90th percentile to define leaders. These percent leaders 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 function approach to recover plant-level markups. Under this framework, markups are defined as follows:

$$\text{Markup}_{it} \equiv \frac{P_{it}}{MC_{it}} = \underbrace{\left(\frac{\partial Q_{it}(\cdot)}{\partial V_{it}}\frac{V_{it}}{Q_{it}}\right)}_{\text{Output Elasticity}} \Big/ \underbrace{\left(\frac{P_{it}^{V}\cdot V_{it}}{P_{it}\cdot Q_{it}}\right)}_{\text{Expenditure Share}}, \tag{4}$$

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, Hashemi, Kaplan, and Zoch (2020). Nevertheless, as a robustness check, we

[8]We follow LP in using materials' demand to control for the correlation between input levels and unobserved productivity.

[9]In practice, we include interaction terms between export status and investment as in De Loecker (2013). This avoids overestimating the capital coefficient and thus underestimating productivity.

[10]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 zero.

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.[11]

Our main experiment aims to compare the response of innovation outcomes to competition in plants with higher and lower rents induced by the increase in Chinese imports. Since markups are endogenous, we focus on the part of markups that is not under the direct control of the plants, computing for each plant and year the markups predicted by a regression including lagged Chinese imports, plant, and sector-year fixed effects as explanatory variables. We then calculate the change in average markups before and after 2001 and split the sample for plants experiencing increases and decreases in their predicted markups. We found that markups declined in only half of the plants across all sectors after 2001. This reflects the fact that import competition affects markups through two channels. It hurts plants' demand –thus reducing the price they can charge on their products– but it also provides plants access to cheaper inputs, reducing their production cost. Therefore, the overall effect can go either way, depending on whether the demand effect is stronger or weaker than the effect on input cost.

3 Data

3.1 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 (ENIA) and the Technological Innovation Survey (EIT). The former provides standard balance-sheet data for plants with 10 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.[12] Of the roughly 4,800 manufacturing plants tabulated per year, about 20 percent are exporters, and two-thirds are small plants (fewer than 50 workers). Medium-sized plants (50-150 workers) and large plants (more than 150 workers) represent 20 and 12 percent of the universe 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

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

[12] Products in ENIA are defined according to the *Clasificador Unico de Productos* (CUP).

import exposure at the plant-level, using international trade data from the CEPII's BACI dataset for the period 1995-2007.[13] BACI is available at the 6-digit HS level, while production information for Chilean plants is available at the 4-digit ISIC level. We match BACI's 6-digit HS sectors with 4-digit ISIC sectors, using the World Bank's WITS correspondence table. We then aggregate imports at the 3-digit ISIC level to minimize the information loss due to the presence of zeros in the original BACI dataset.[14]

3.2 Innovation Data

We merge the ENIA with the Technological Innovation Survey (EIT hereafter), a nationally representative innovation survey of all manufacturing plants representing 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's 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 1 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 2 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.
- *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.

Table 1 presents summary statistics of the main production and innovation variables, as well as Chilean imports from China. The combined ENIA-EIT dataset gathers information on 4,704 plant-year observations that cover the period before and after the China shock and cover roughly 20 percent of the ENIA for the years where EIT is available. Annex Table A.3 shows that there are

[13] This dataset reconciles inconsistencies in exporters' and importers' declarations found in the UN Statistical Division's trade dataset (COMTRADE)

[14] When using the data at the 4-digit ISIC level, 8.4% of the sector-year observations are zeros. In contrast, only 1.6% of the observations are zeros when aggregating the data at the 3-digit ISIC level.

few systematic differences between the matched and full ENIA data sets. However, as we discuss below, these differences do not seem to correlate with variation in exposure to import competition from China.

4 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 2-digit sector-year fixed effects. We cluster standard errors at the 3-digit sector-year level.

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 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.5 and A.6 in the Appendix).

Columns 1, 2, and 3 show that the increase in average imports from China for the period 2000-2007 (1.64 log points) led to falls in average output (coefficient -.070), markups (-.035) and profits (-.054), significant at the 1 percent level. This is consistent with a contraction of demand caused by increased competition. The fall in markups does not necessarily contradict the findings in De Loecker and Goldberg (2014) that markups increased with trade liberalization when the reductions in marginal costs, gained through access to cheaper intermediate inputs, are not passed through onto prices. Since the main specification controls for industry-year fixed effects, the markup variable captures the effect of competition largely through the downstream channel. The rise in marginal costs (7) (.096) and of output price (4) (.060) 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 (3), TFPQ (5), and TFPR (6) all appear depressed, although the effects are non-significant. Input prices (10) show a positive but not significant movement. Profits (9) display similar results to markups and, thus, we continue with markups as our main measure of rents for the rest of the paper.

As discussed above, the leader/laggard split is determined based on the response of innovation variables. Panel B shows that this division offers intuitively reasonable results for the core performance variables. The fall in output is largely concentrated in laggards (-.08), with a lesser and insignificant impact on leaders. Revenues rise significantly for leaders (.054), and output prices rise twice as much for leaders as for laggards. However, markups and profits fall substantially more for leaders as marginal costs significantly rise more than twice as much for them (.21 vs. .08). TFPR shows no significant change for either type of establishment, while TFPQ falls sharply (-.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 (.085) for leaders, while laggards show a small negative and insignificant effect.[15]

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, Garcia-Marin, and Maloney, 2021), where firms producing more higher quality rugs and wines showed lower TFPQ.[16] 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.

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.7 in the Appendix shows that the response of the core innovation variables to the increase in average imports from China is very similar 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

[15]This is broadly consistent with Verhoogen (2008) who also finds that the initially most productive firms in Mexico upgrade the quality of their goods as a response to an economic shock. However, the nature and impact of the shock on sales in our paper differ from that in Verhoogen's paper. While leaders upgrade the quality of existing products to escape competition (negative shock) in our paper, they do so to take advantage of an exchange rate devaluation (positive shock) and expand the volume of trade in Verhoogen's paper.

[16]Relatedly, Grieco and McDevitt (2016) proposes an approach for estimating productivity when quality is directly observed and applies it to the health care sector to show how the quality-quantity trade-off may affect productivity measurement. Eslava and Haltiwanger (2020) addresses quality differences when estimating the production function using a control-function approach that relies on the presence of CES demand. de Roux, Eslava, Franco, and Verhoogen (2020) expand on this idea proposing a two-stage instrumental variable estimator that does not depend on the particular assumed demand.

stage is very strong (see columns 1–3 in Table A.8 in the 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 (-1.03), process innovation (-.08), and product innovation (-.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.

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, with the exception of the previously found increase in quality. Of course, having industry-time fixed effects strips out any industry level evolution that might be occurring. However, given that average sectoral level evolution is stagnant or negative for all innovation variables (see Figure A.3 in the Appendix), plants further from the frontier are likely to reduce innovation.

Rents and Innovation Effects. To test the pure Schumpeterian hypothesis that falling rents will deter innovation, we calculate the average instrumented 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 2.3 for details). The results in Table 4 offer some support for the Schumpeterian theory. For plants with shrinking 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. These results hold using profits as the measure of rents as well (see Table A.9 in the Appendix).

Table 5 splits the sample in 4 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 sub-sample 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, quality and product innovation increase at the 10 percent level 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, entrepreneurial qualities, for instance– is more important to the incumbent's innovation response to competition than rents.[17]

[17]Table A.10 in the Appendix shows a similar pattern when using profits as a measure of rents.

5 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 data set 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, 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. Rises in rents induce these leaders to invest more in R&D spending, product innovation and product quality. Markup falls exacerbate laggards' contraction and increased markups moderate their decline, however, rising rents never raise the innovation efforts of these plants above the average change for the sector. These findings suggest that improving plant capabilities, managerial practices or intrinsic entrepreneurial quality that drives the leaders, 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.

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% 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.[18] 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 UK by Aghion et al. (2009). This suggests both that in non-frontier 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.

[18] Bergoeing, Kehoe, Kehoe, and Soto (2002) argue that the period of sustained productivity growth across roughly our period was, in fact, due to the removal of financial distortions and reforms of bankruptcy laws.

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TABLES

Table 1: Summary Statistics

	Mean	Std. Dev.	P25	P50	P75	Obs.
	(1)	(2)	(3)	(4)	(5)	(6)
Plant-Level Variables						
Output Volume (in logs)	8.879	1.898	7.472	8.560	10.153	29,283
Markups	1.207	0.566	0.859	1.083	1.391	28,839
Revenue (in logs)	13.336	1.823	11.966	12.980	14.510	29,283
Output Price (in logs)	4.456	0.564	4.189	4.478	4.736	29,283
Physical TFP (in logs)	6.587	2.731	5.513	6.660	7.912	29,283
Revenue TFP (in logs)	6.544	2.691	5.687	6.636	7.987	29,283
Marginal Cost (in logs)	4.356	0.694	3.987	4.368	4.745	29,283
Product Quality (in logs)	0.088	1.811	-1.237	-0.237	1.196	24,439
Profit Rate	0.441	0.495	0.170	0.364	0.622	29,283
Input Price (in logs)	4.455	0.508	4.187	4.462	4.729	29,283
Innovation Variables						
log(1+Overall Innovative Spending)	4.280	5.211	0.000	0.000	9.904	4,704
log(1+R&D Spending)	2.802	4.585	0.000	0.000	7.732	4,704
log(1+Patents Stock)	0.727	9.617	0.000	0.000	0.000	4,704
% (Overall Innovative Spending)>0	0.418	0.493	0.000	0.000	1.000	4,704
% (R&D Spending)>0	0.281	0.449	0.000	0.000	1.000	4,704
% (Patents Stock)>0	0.098	0.297	0.000	0.000	0.000	4,704
% (Positive Process Innovation)	0.506	0.500	0.000	1.000	1.000	4,704
% (Positive Product Innovation)	0.432	0.495	0.000	0.000	1.000	4,704
Product Quality	1.441	2.087	-0.150	1.455	3.017	4,345
Chilean Imports of Chinese Products						
Observed Imports (in million US$)	75.98	155.49	3.05	18.17	73.46	364
Predicted LASSO Imports (in million US$)	74.68	154.72	3.10	17.45	71.19	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. 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.

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

	(1) Output	(2) Markup	(3) Revenue	(4) Output Price	(5) TFPQ	(6) TFPR	(7) Marginal Cost	(8) Quality	(9) Profits	(10) Input Price
A. Baseline										
ln(CHN Imports(-1))	-0.0693**	-0.0346***	-0.0083	0.0611***	-0.0377	-0.0158	0.0956***	0.0100	-0.0542***	0.0315
	(0.0299)	(0.0107)	(0.0198)	(0.0226)	(0.0241)	(0.0134)	(0.0262)	(0.0218)	(0.0134)	(0.0240)
First-Stage F-Statistic	74.3	74.3	74.3	74.3	74.3	74.3	74.3	58.2	74.3	74.3
Industry-year FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Plant FE	yes	yes	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	29,283	29,283
B. Interactions with Leaders / Laggards										
ln(CHN Imports(-1))										
× Leaders Indicator	-0.0517	-0.102***	0.0537**	0.105***	-0.0866**	-0.0445	0.207***	0.0851**	-0.0882**	0.0505
	(0.0377)	(0.0220)	(0.0253)	(0.0342)	(0.0403)	(0.0322)	(0.0396)	(0.0358)	(0.0379)	(0.0326)
× Laggards Indicator	-0.0812**	-0.0249**	-0.0248	0.0564**	-0.0397	-0.0165	0.0813***	-0.0060	-0.0505***	0.0286
	(0.0353)	(0.0114)	(0.0224)	(0.0232)	(0.0258)	(0.0140)	(0.0266)	(0.0237)	(0.0142)	(0.0249)
First-Stage F-Statistic	35.5	35.5	35.5	35.5	35.5	35.5	35.5	27.5	35.5	35.5
Industry-year FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Plant FE	yes	yes	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	29283	29,283

Notes: The table regresses different plant outcomes on lagged imports from China (panel A) and its interaction 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 2-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% (15%) maximal IV bias is 16.4 (8.96). Section 3.2 explains the procedure followed to derive the product quality measure. All regressions cluster standard errors at the industry-year level. Key: ** significant at 1%; ** 5%; * 10%.

Table 3: Effect of Chinese Import Competition on Innovation Variables

	(1)	(2)	(3)	(4)	(5)	(6)
	Innovative Spending		Innovation Outputs			
	Overall Spending	R&D Spending	Patents Stock	Process Innovation	Product Innovation	Product Quality
A. Baseline						
ln(CHN Imports(-1))	-1.030**	-0.580	-0.0296	-0.0874***	-0.0741***	0.00356
	(0.437)	(0.495)	(0.0337)	(0.0288)	(0.0283)	(0.0417)
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
B. Interactions with Leaders / Laggards						
ln(CHN Imports(-1))						
× Leaders Indicator	-1.008	0.591	-0.121	-0.0503	0.0445	0.177***
	(0.775)	(0.841)	(0.118)	(0.0662)	(0.0694)	(0.0629)
× Laggards Indicator	-1.210*	-0.913	-0.0303	-0.109***	-0.0907**	-0.0419
	(0.634)	(0.586)	(0.0356)	(0.0367)	(0.0352)	(0.0498)
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 regresses different innovation outcomes on lagged imports from China (panel A) and its interaction 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 2-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% (15%) maximal IV bias is 16.4 (8.96). Innovative spending in columns 1-2 and the patents stock in column 3 are computed as the logarithm of one plus the corresponding spending, to include zeros. Product and process innovation (columns 4-5) are categorical variables taking the value one if the establishment reports successful innovation. Section 3.2 explains the procedure followed to derive the product quality measure. All regressions cluster standard errors at the industry-year level. Key: ** significant at 1%; ** 5%; * 10%.

Table 4: Heterogeneity: Split by Change in Markups

	(1)	(2)	(3)	(4)	(5)	(6)
	Innovative Spending		Innovation Outputs			
	Overall Spending	R&D Spending	Patents Stock	Process Innovation	Product Innovation	Product Quality
ln(CHN Imports(-1))						
× Increasing Markups	-0.448	-0.106	0.0070	-0.106**	-0.0432	0.0141
	(0.643)	(0.611)	(0.0375)	(0.0463)	(0.0349)	(0.0504)
× Shrinking Markups	-1.294**	-0.764	-0.0404	-0.0865**	-0.0970**	-0.00591
	(0.534)	(0.641)	(0.0571)	(0.0387)	(0.0435)	(0.0675)
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 replicates panel A in Table 3 interacting lagged imports from China with an indicator variable for plants increasing/shrinking markups after China entered into 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, and plant fixed-effects. Thus, the indicator variable only considers the fraction of markups that varies due to increased Chinese competition. All regressions are run at the plant-year level, control for the logarithm of employment, and include industry-year (at the 2-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% (15%) maximal IV bias is 16.4 (8.96). Innovative spending in columns 1-2 and the patents stock in column 3 are computed as the logarithm of one plus the corresponding spending, to include zeros. Product and process innovation (columns 4-5) are categorical variables taking the value one if the establishment reports successful innovation. Section 3.2 explains the procedure followed to derive the product quality measure. All regressions cluster standard errors at the industry-year level. Key: ** significant at 1%; ** 5%; * 10%.

Table 5: Change in Markups combined with Leader/Laggard Indicator

	(1)	(2)	(3)	(4)	(5)	(6)
	Innovative Spending		Innovation Outputs			
	Overall Spending	R&D Spending	Patents Stock	Process Innovation	Product Innovation	Product Quality
log(CHN Imports(-1)) × Laggards						
× (Shrinking Markup)	-1.4334*	-1.2614†	-0.0431	-0.127***	-0.1508***	-0.0754
	(0.8616)	(0.7976)	(0.0687)	(0.0475)	(0.0574)	(0.0943)
× (Increasing Markup)	-0.7287	-0.3553	0.0155	-0.1079**	-0.0424	-0.018
	(0.7031)	(0.6541)	(0.0399)	(0.0511)	(0.0398)	(0.0489)
log(CHN Imports(-1)) × Leaders						
× (Shrinking Markup)	-0.8736	0.8556	-0.1183	-0.0794	0.0402	0.1486**
	(0.7621)	(0.7899)	(0.1193)	(0.0713)	(0.0717)	(0.0679)
× (Increasing Markup)	-0.1688	1.7618‡	-0.0596	-0.0604	0.1487*	0.2061*
	(1.2017)	(1.0762)	(0.1451)	(0.0867)	(0.0883)	(0.1129)
First Stage F-Stat	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 replicates panel B in Table 3 interacting lagged imports from China with an indicator variable 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 indicators variables. All regressions are run at the plant-year level, control for the logarithm of employment, and include industry-year (at the 2-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% (15%) maximal IV bias is 16.4 (8.96). Innovative spending in columns 1-2 and the patents stock in column 3 are computed as the logarithm of one plus the corresponding spending, to include zeros. Product and process innovation (columns 4-5) are categorical variables taking the value one if the establishment reports successful innovation. Section 3.2 explains the procedure followed to derive the product quality measure. All regressions cluster standard errors at the industry-year level. Key: ** significant at 1%; ** 5%; * 10%; †: p-value 11.5%; ‡: p-value 10.3%

Online Appendix

Competition and Innovation

Ana Paula Cusolito   Alvaro Garcia-Marin   William F. Maloney

A Data Appendix

A.1 The Chilean Annual Industrial Survey (ENIA)

Our main dataset is the Encuesta Nacional Industrial Anual (Annual National Industrial Survey – ENIA) for the years 1996-2007. Data for ENIA are collected annually by the Chilean National Institute of Statistics (INE), with direct participation of Chilean manufacturing plants. ENIA covers the universe of manufacturing plants with 10 or more workers, and contains detailed information on plant characteristics, such as sales, spending on inputs, employment, wages, investment, and export status. It also collects rich information at the product-level, for every product produced by each plant, reporting sales, total variable production cost, and the number of units produced and sold, which permits constructing plant-level price indexes and backing out quantities and TFPQ. Products in ENIA are defined according to the *Clasificador Unico de Productos* (CUP). This ENIA-specific product category is comparable to the 7-digit ISIC code.[1] 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, respectively.

We exclude plant-product-year observations that have zero values for total employment, demand for raw materials, sales, or product quantities. Our main analysis exploit within plant variation before and after the entry of China into the WTO in 2001. Consequently, we only consider plants observed in at least one year before and after 2001. Finally, to avoid outliers and/or misreported prices affect our results, we exclude observations where the input or the output price deviate more than five times from the average. Our final sample consists of 29,283 plant-product-year observations.

A.2 Measures of Innovation and Technological Investment in the Chilean Data

The Chilean data offer a unique opportunity to explore the effect of product market competition on innovation investments and then on to efficiency. We merge our baseline data from ENIA with the Chilean Technological Innovation Survey (EIT), which collects detailed data on a wide variety of innovatio-related investments, including (i) overall R&D expenditures, (ii) in-house R&D expenditures, (iii) investments in machinery and equipment, (iv) patents, (v) licenses, and (vi) overall

[1] For example, the wine industry (ISIC 3132) is disaggregated by CUP into 8 different categories, such as "Sparkling wine of fresh grapes", "Cider", "Chicha", and "Mosto".

investments from ENIA. The EIT is a nationally representative survey of Chilean plants, conducted by the Chilean National Statistical Agency every two to three years, and samples about 20% of the establishments in ENIA.[2] Managers retrospectively report data on technological investment for the between survey years, in practice allowing us to generate a time series from 2000-2007, except for 2002.[3]

To test whether there are systematic differences between the plants appearing in the two data sets, we run a simple regression, of each variable of interest against a dummy variable that takes the value one 1 if the plant is included in EIT and zero otherwise, controlling for sector-year fixed effects and clustering standard errors are the industry-year level. The coefficient accompanying the EIT dummy variable is interpreted as the percentage-point difference between plants in EIT and the rest of plants included in ENIA but excluded from EIT. Table A.3 shows that plants in EIT hire 105% more workers than those in ENIA (column 1). But even conditioning for size, plants in EIT show important differences. They have 36% higher sales (column 2), are 6.5% more likely to be exporters (column 3), and have 5.8 higher revenue productivity (column 4). Physical productivity and markups do not appear systematically different across samples (columns 5 and 6). Finally, plants in EIT have about a 5.6% higher profit rate (column 7).

A.3 Productivity Estimation

Productivity – the efficiency with which establishments convert inputs into outputs –, is typically measured as the log-difference between output and the contribution of inputs used in production. Detailed data on physical inputs and outputs is generally unavailable; as a result, researchers traditionally rely on revenues to proxy for establishments' physical output. This measure of productivity is known in the literature as revenue total factor productivity (TFPR), to differentiate it from the real subject of interest, where inputs and outputs are measured in terms of physical units. This last measure of productivity is known as physical total factor productivity (TFPQ).

A recent literature highlights the importance of computing total factor productivity using inputs and outputs in terms of physical units, TFPQ (see De Loecker and Goldberg, 2014, for a review). Deflating sales by industry-level price indexes leads to underestimating the production function coefficients, because more efficient plants tend to charge lower prices. Even if the coefficients were known, the resulting TFPR measure would be an imperfect proxy of TFPQ, because the price component downward biases the response of plant revenues. Similarly, deflating materials' costs by industry-level input indexes also biases the production function coefficients. Plants facing high input prices have higher input expenditure that is not necessarily reflected in higher output (De

[2]However, all entities representing more than 2% of sectoral value-added enter compulsory in the innovation survey.

[3]We do not use earlier waves of the survey because they do not allow us to establish a one-to-one correspondence with the questions from the most recent versions of EIT.

Loecker and Goldberg, 2014). Thus, input price variation may also lead to underestimate the variation in physical total factor productivity.

The presence of multi-product plants introduces an additional challenge in the estimation of TFPQ. The use of inputs is typically not disaggregated for individual products, making the identification of the production function coefficients for each production line within plants challenging. The early literature addressed the problem eliminating multi-product plants from the sample, and focusing only on the subset of single-product plants (see Foster, Haltiwanger, and Syverson, 2008). This approach has pitfalls of its own, as multi-product plants account for a non-trivial fraction of output in the manufacturing sector. A more recent approach relies on the use of single product units, where no assumptions about allocation are needed, to estimate the production function coefficients for each product category (De Loecker et al., 2016). These are then used to infer the allocation of inputs across outputs and generate a measure of plant-level TFPQ using the algorithm developed by De Loecker et al. (2016). A drawback of this approach is that requires assuming that the technology used to produce a given product in single and multi-product units is the same, and in practice, the algorithm may yield corner solutions for inputs use across outputs.

In this paper, we follow a third approach, which consists of deriving plant-level output and input price indexes to deflate plant's revenues and materials expenditure, respectively (see Eslava et al., 2013; Smeets and Warzynski, 2013; Eslava and Haltiwanger, 2020).[4] To derive the price indexes, we perform the following steps. First, we compute for each output and input at the plant-product-year level, the log difference of its price relative to the average industrial price for the same year. Second, we construct a weighted average price deviation index, 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 defined for each 4-digit ISIC sector.

Once inputs and outputs are deflated with plant-level price indexes, we estimate Cobb-Douglas production functions for each 2-digit manufacturing sector (s) using labor (l), capital (k), and materials (m) as production inputs:[5]

$$q_{it} = \beta_l^s l_{it} + \beta_k^s k_{it} + \beta_m^s m_{it} + \omega_{it} + \varepsilon_{it} \tag{A.1}$$

[4] A shortcoming of this more aggregate approach is that plant-level output price indexes may not account for differences in product scope Hottman, Redding, and Weinstein (2016). Though in principle the De Loecker et al.'s (2016) methodology could give us plant-product level TFPQ, our information on productivity-enhancing activities, such as R&D expenditure, is only available at the plant level. In addition, when implementing De Loecker et al.'s (2016) methodology to identify product-specific inputs use and plant-product level TFPQ, we obtained a large number of corner solutions for the use of intermediate input. This complicates the computation of plant-level markups, because markups for products with zero use of the production factors would be indeterminate.

[5] The 2-digit product categories are: Food and Beverages, Textiles, Apparel, Wood, Paper, Chemicals, Plastic, Non-Metallic Manufactures, Basic and Fabricated Metals, and Machinery and Equipment.

where all lowercase variables are expressed in logs; q_{it} stands for output of plant i in year t, l_{it} stands for labor, k_{it} stands for capital, m_{it} stands for material inputs, ω_{it} is the productivity measure, and ε_{it} captures measurement error and output shocks.

To estimate (A.1), we follow the methodology by Ackerberg et al. (2015, henceforth ACF), who extend the framework of Olley and Pakes (1996, henceforth OP) and Levinsohn and Petrin (2003, henceforth LP) to control for potential simultaneity bias that arises because input demand and unobserved productivity are positively correlated.[6] Further, we modify the canonical ACF procedure by specifying an endogenous productivity process that accounts for learning by exporting and investment effects, and we also include interaction terms between export status and investment as in De Loecker (2013) to avoid overestimating the capital coefficient and underestimating productivity. Accordingly, the productivity law of motion is as follows:

$$\omega_{it} \quad = \quad g(\omega_{it-1}, d^x_{it-1}, d^i_{it-1}, d^x_{it-1} \times d^i_{it-1}) + \xi_{it} \tag{A.2}$$

where d^x_{it} is an export dummy, and d^i_{it} is a dummy for periods in which a plant invests in physical capital (following De Loecker, 2013).

A.4 Estimating Plant-Level Markups

We follow De Loecker and Warzynski (2012) in deriving markups from the first order condition (FOC) of a cost minimization problem of the plant. Assuming that (i) at least one input is fully flexible, and (ii) plants minimize costs for each product j permits re-arranging the FOC for the flexible input V and obtaining the following expression for the markup of plant i at time t:

$$\underbrace{\mu_{it}}_{\text{Markup}} \equiv \frac{P_{it}}{MC_{it}} = \underbrace{\left(\frac{\partial Q_{it}(\cdot)}{\partial V_{it}} \frac{V_{it}}{Q_{it}}\right)}_{\text{Output Elasticity}} \Big/ \underbrace{\left(\frac{P^V_{it} \cdot V_{it}}{P_{it} \cdot Q_{it}}\right)}_{\text{Expenditure Share}} \tag{A.3}$$

where P (P^V) denotes the price of output Q (input V), and MC is marginal cost. This implies that the markup can be computed by dividing the output elasticity of product j with respect to the flexible input, in our case materials (M), by its expenditure share (relative to the sales of product j). Under perfect competition, the output elasticity equals the expenditure share, so that the markup is equal to one.

A.5 Inferring Product Quality

The estimation of product quality follows Khandelwal et al. (2013) and Eslava et al. (2013). Specifically, we assume that firm's i product quality in period t, λ_{it}, acts as a demand shifter in consumer

[6] We follow LP in using material inputs to control for the correlation between input levels and unobserved productivity.

preferences. Assuming CES demand, the utility function becomes:

$$U_t = \left(\int (\lambda_{it} q_{it})^{\frac{\sigma-1}{\sigma}} di \right)^{\frac{\sigma}{\sigma-1}} \tag{A.4}$$

implying a demand of the form $q_i = \lambda_i^{\sigma-1} p^{-\sigma} P^{\sigma-1} Y$, where $\sigma > 1$ denotes the elasticity of substitution, P is the aggregate CES price index and Y is aggregate consumption. After taking logs, the quality for the product produced by each firm can be recovered as the residual term from the following linear regression:

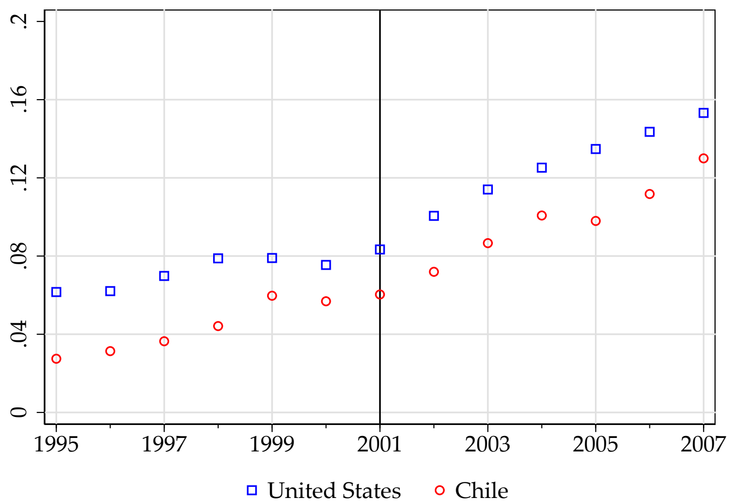
$$\ln q_{it} = -\sigma \ln p_{it} + \alpha_j + \alpha_y + \varepsilon_{it} \tag{A.5}$$

Estimating A.5 through OLS leads to upward bias in the estimated demand elasticity, as the quality shifter is positively correlated to input and output prices. To address this concern, we follow Eslava et al. (2013) and instrument prices using physical total factor productivity (TFPQ). Equation A.5 is estimated separately for each 3-digit manufacturing sector. Once we estimate the demand elasticity, we compute product quality as follows:

$$\widehat{\lambda_{it}} = \widehat{\alpha_j} + \widehat{\alpha_y} + \widehat{\varepsilon_{it}} \tag{A.6}$$

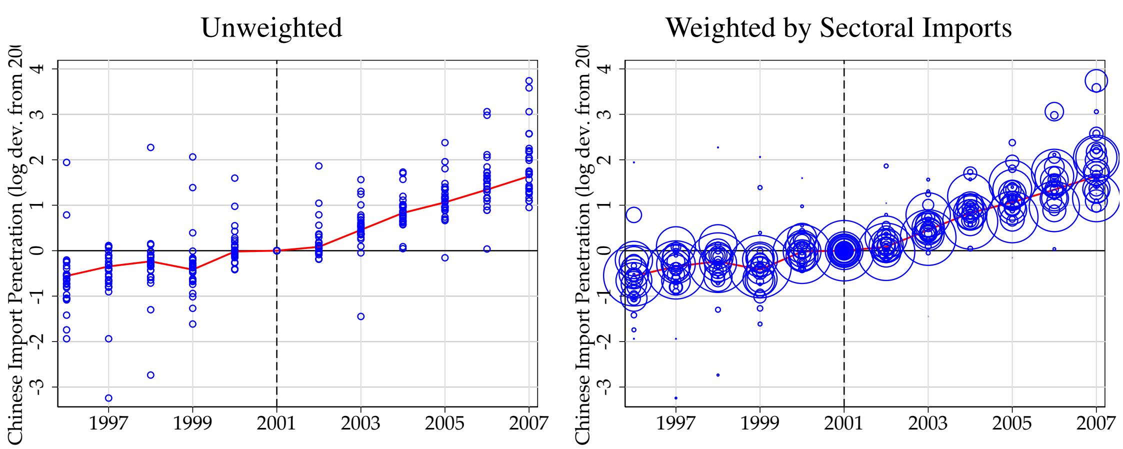
B Additional Figures

Figure A.1: Imports from China as a share of overall manufacturing imports in Chile and the U. S.



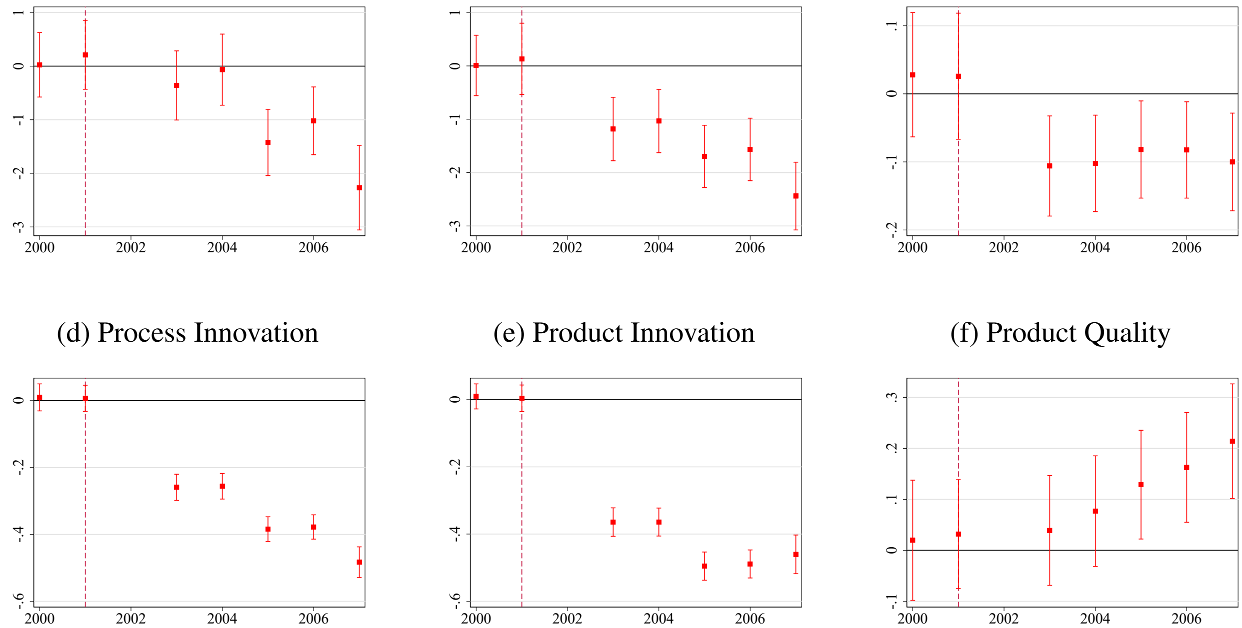
Notes: The figure shows the share of overall manufacturing imports from China in Chile and the United States for each year between 1996 and 2007. The data is from the BACI dataset (Gaulier and Zignago, 2010).

Figure A.2: Imports from China in Chile by 3-digit ISIC Sectors, 1996-2007



Notes: The figure shows the imports of Chinese products in Chile (upper panel) and the United States (bottom panel) for each 3-digit ISIC manufacturing industry (revision 2) over the period 1996-2007. The data is from the BACI dataset (Gaulier and Zignago, 2010). For each country and sector, we normalize imports equal to zero in 2001, corresponding to the year when China joined the World Trade Organization. The red line corresponds to the trajectory of aggregate manufacturing imports across all sectors.

Figure A.3: Within-Plant Trajectories for Different Innovation Outcomes



(a) Overall Innovative Spending (b) R&D Spending (c) Patents

(d) Process Innovation (e) Product Innovation (f) Product Quality

Notes: Data are from the third, fourth, fifth and sixth waves of the Chilean Technological Innovation Survey (EIT). The figure shows within-plant trajectories for different innovation outcomes before and after 2001, corresponding to the year when China joined the World Trade Organization. All results are at the plant level; they control for plant fixed effects and 2-digit sector-year fixed effects. Standard errors (clustered at the 3-digit sector-year level) in parentheses. The lines and whiskers represent 90% confidence intervals.

C Additional Tables

Table A.1: Chilean Imports of Chinese Products by 3-digit ISIC industry (1996-2007)

ISIC, Rev. 2	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
311	1.6	2.3	2.7	2.3	2.9	2.6	2.8	4.7	5.8	7.8	8.9	21.2
312	0.3	0.2	0.2	0.6	0.7	0.5	0.9	1.6	2.1	2.5	4.7	8.3
313	0.0	0.0	0.1	0.1	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0
321	56.4	58.8	61.3	58.5	89.3	70.0	79.8	116.6	177.8	224.5	302.2	360.9
322	216.3	245.2	287.7	263.9	347.2	374.9	365.5	499.6	709.1	783.6	986.9	1,193.8
323	16.5	22.9	26.4	22.5	29.6	29.1	32.4	42.0	63.7	73.7	86.5	113.8
324	50.9	62.6	73.2	45.1	73.0	85.0	89.3	121.1	157.4	170.4	207.2	254.6
331	2.1	2.8	3.0	2.6	3.7	4.2	6.8	8.1	10.6	12.3	16.7	20.6
332	3.7	6.4	8.6	6.7	10.6	9.7	11.5	16.5	25.6	30.7	53.8	85.1
341	0.7	1.1	1.2	1.7	3.5	2.5	2.3	3.2	5.0	5.9	8.7	26.6
342	1.3	2.7	2.8	2.4	2.4	2.5	2.3	4.8	4.3	5.9	8.9	11.5
351	20.1	22.8	25.6	27.3	35.4	39.5	43.6	54.6	86.0	133.0	175.6	307.2
352	7.9	7.2	8.8	6.7	10.6	14.2	17.2	28.1	40.4	50.5	62.3	76.2
353	0.0	0.0	0.2	1.1	0.7	0.5	1.8	1.4	0.8	0.9	1.5	1.1
354	0.0	1.2	2.0	2.0	2.1	2.7	2.6	2.6	4.8	16.5	14.9	8.1
355	1.7	2.9	2.1	2.3	4.9	7.3	10.3	20.2	39.6	51.1	56.8	94.4
356	38.0	53.8	62.2	51.7	74.4	79.3	84.0	121.8	167.9	207.5	252.3	291.1
361	14.2	12.4	16.4	14.8	22.1	18.2	16.7	26.1	34.8	35.2	44.1	46.9
362	2.5	4.0	4.9	3.7	6.4	6.9	7.7	12.2	16.5	21.2	26.2	36.5
369	0.6	1.1	1.1	1.3	1.7	2.1	2.9	4.2	8.2	12.2	21.6	39.7
371	17.7	19.2	17.7	16.5	16.5	17.8	18.2	20.0	23.8	38.2	133.5	264.4
372	0.9	0.5	0.6	1.5	3.6	5.6	5.0	6.3	7.6	13.4	29.3	49.6
381	38.4	50.5	56.1	47.6	64.3	57.7	69.1	101.7	148.0	184.2	235.1	306.0
382	42.0	60.0	67.0	71.0	108.6	121.0	135.7	175.2	268.0	447.0	590.1	893.0
383	76.0	108.8	112.9	101.6	145.4	157.8	205.7	325.8	483.5	640.0	821.6	1,111.7
384	10.8	10.9	14.0	17.7	33.2	27.5	38.3	48.8	73.0	99.3	152.1	211.0
385	10.0	12.9	15.1	13.1	28.7	28.6	27.7	41.7	64.9	73.8	108.4	101.3
390	81.6	110.3	116.7	92.5	109.0	100.4	96.9	167.4	219.7	245.0	315.2	389.2
Overall	712.1	883.6	990.8	878.9	1,230.5	1,268.1	1,377.1	1,976.2	2,848.8	3,586.2	4,725.2	6,323.7

Notes: This table shows Chilean imports of Chinese products for each 3-digit ISIC industry (revision 2). All amounts are in million U.S. dollars of 2010.

Table A.2: Input.Output Elasticities, Returns to Scale and Markups by Sector

	Average Elasticities			Returns	Average
	Materials	Capital	Labor	to Scale	Markups
Food and Beverages	0.624	0.135	0.393	1.153	1.241
	(0.036)	(0.059)	(0.071)	(0.035)	(0.554)
Textiles	0.431	0.290	0.313	1.034	1.042
	(0.131)	(0.253)	(0.098)	(0.080)	(0.788)
Apparel and leather	0.589	0.139	0.292	1.019	1.318
	(0.081)	(0.092)	(0.144)	(0.099)	(0.772)
Wood and Furniture	0.567	0.131	0.364	1.062	1.221
	(0.073)	(0.057)	(0.073)	(0.103)	(0.71)
Paper and Printing	0.473	0.234	0.428	1.135	1.310
	(0.058)	(0.025)	(0.15)	(0.091)	(0.741)
Petroleum and Chemical industries	0.565	0.130	0.479	1.174	1.36
	(0.091)	(0.130)	(0.246)	(0.122)	(0.824)
Plastic and rubber	0.532	0.196	0.474	1.202	1.190
	(0.094)	(0.091)	(0.149)	(0.077)	(0.649)
Non-metallic products	0.640	0.119	0.402	1.162	1.603
	(0.124)	(0.104)	(0.135)	(0.132)	(0.834)
Metallic Products	0.418	0.263	0.357	1.038	1.008
	(0.038)	(0.138)	(0.141)	(0.067)	(0.671)
Machinery and Equipment	0.489	0.191	0.443	1.122	1.203
	(0.086)	(0.130)	(0.197)	(0.129)	(0.692)
Average	0.555	0.171	0.389	1.115	1.231
	(0.105)	(0.119)	(0.139)	(0.102)	(0.689)

Notes: The table shows the average elasticities, returns to scale, and markups for each 2-digit sector. Elasticities are computed as the marginal change in physical output as the input use changes. The underlying production function is Translog, and considers physical volume as output measure (deflated with plant-specific input and output price indexes, explained in section A.3). Labor is measured in terms of number of employees, materials considers expenditure deflated with a plant-specific input price index, an capital is constructed using the method of perpetual inventories. To compute markups, we follow De Loecker and Warzynski (2012), considering materials as the relevant flexible input.

Table A.3: Sample Differences: ENIA vs EIT

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Plant Size		Export Prob.	Productivity		Rents	
Dependent Variable:	ln(workers)	ln(sales)	D(Exp=1)	ln(TFPR)	ln(TFPQ)	ln(markup)	Profit Rate
EIT dummy	1.047***	0.364***	0.0648***	0.0575***	0.0254	-0.0165*	0.0558***
	(0.0692)	(0.0357)	(0.0096)	(0.0130)	(0.0167)	(0.0098)	(0.0138)
Sector-year FE	✓	✓	✓	✓	✓	✓	✓
Observations	29,283	29,283	29,283	29,283	29,283	29,283	29,283

Notes: The Table regresses each column variable on a categorical variable that takes the value one for observations included in the Survey of Technological Innvation (EIT). Thus, the coefficient in each column reports the log-point difference of the dependent variable between plants-years included in EIT compared to plants in the Manufacturing Survey (ENIA). All regressions control for sector-year effects at the 2-digit level and log employment – except for column 1, that only controls for sector-year fixed effects. Standard errors are clustered at the sector-year level. Key: ** significant at 1%; ** 5%; * 10%.

Table A.4: First Stage Regressions, Table 2

Specification	Baseline	Leaders vs. Laggards	
	(1)	(2)	(3)
Dependent Variable:	$\ln(M^{CHN}_{j,t-1})$	$\ln(M^{CHN}_{j,t-1})$ $\times$ Leader	$\ln(M^{CHN}_{j,t-1})$ $\times$ Laggard
$\ln(\hat{M}^{LASSO}_{j,t-1})$	1.251***	—	—
	(0.145)		
$\ln(\hat{M}^{LASSO}_{j,t-1}) \times$ Leader	—	1.319***	—
		(0.119)	
$\ln(\hat{M}^{LASSO}_{j,t-1}) \times$ Laggard	—	—	1.238***
			(0.147)
First Stage F-statistic	74.3	35.5	
Industry-year FE	yes	yes	yes
Plant FE	yes	yes	yes
Observations	29,283	29,283	29,283

Notes: The table show first-stage regressions for the IV specifications in table 2. Column 1 shows the first stage for panel A in table 2, while columns 2 and 3 shows the first stage for panel B, where (lagged) imports from China are interacted with indicator variables for leading and laggard establishments. The regressions instrument Chilean imports from China at the 3-digit level (and their interactions) with the predicted values from a LASSO regression that considers imports from China by all other countries available in the BACI trade dataset (and their interactions). Industry leaders correspond to the top 10 percent of plants with the highest average TFPQ (within industries) before 2001. All regressions are run at the plant-year level, control for the logarithm of employment, and include industry-year (at the 2-digit level) and plant fixed-effects. The (cluster-robust) Kleibergen-Paap rK Wald F-statistic is at the bottom of each column. The corresponding Stock-Yogo value for 10% (15%) maximal IV bias is 16.4 (8.96). All regressions cluster standard errors at the industry-year level. Key: ** significant at 1%; ** 5%; * 10%.

Table A.5: Effect of Chinese Import Competition on Plants' Outcomes, Using Alternative Instrument

	(1) Output	(2) Markup	(3) Revenue	(4) Output Price	(5) TFPQ	(6) TFPR	(7) Marginal Cost	(8) Quality	(9) Profits	(10) Input Price
A. Baseline										
ln(CHN Imports(-1))	-0.0662*	-0.0231	0.0142	0.0804***	-0.0703**	-0.0119	0.103***	0.0370	-0.0357*	-0.00794
	(0.0393)	(0.0170)	(0.0270)	(0.0281)	(0.0313)	(0.0183)	(0.0338)	(0.0292)	(0.0209)	(0.0284)
First-Stage F-Statistic	104.6	104.6	104.6	104.6	104.6	104.6	104.6	82.2	104.6	104.6
Industry-year FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Plant FE	yes	yes	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	29,283	29,283
B. Interactions with Leaders / Laggards										
ln(CHN Imports(-1))										
× Leader Indicator	-0.0691	-0.0706**	0.0347	0.104**	-0.0905*	-0.0506	0.174***	0.0633*	-0.0691	0.0303
	(0.0491)	(0.0298)	(0.0300)	(0.0457)	(0.0523)	(0.0421)	(0.0505)	(0.0383)	(0.0499)	(0.0395)
× Laggard Indicator	-0.0593	-0.0157	0.00822	0.0675**	-0.0598*	-0.00672	0.0832**	0.0316	-0.0288	-0.00964
	(0.0474)	(0.0180)	(0.0312)	(0.0290)	(0.0343)	(0.0195)	(0.0339)	(0.0313)	(0.0217)	(0.0303)
First-Stage F-Statistic	47.9	47.9	47.9	47.9	47.9	47.9	47.9	37.6	47.9	47.9
Industry-year FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Plant FE	yes	yes	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	29283	29,283

Notes: The table regresses different plant outcomes on lagged imports from China (panel A) and its interaction 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 2-digit level) and plant fixed-effects. Each column shows 2SLS coefficients instrumenting Chilean imports from China at the 3-digit level (and their interactions) with the predicted values from a LASSO regression that considers imports from China by all countries from outside South America available in the BACI trade dataset (and their interactions). The (cluster-robust) Kleibergen-Paap rK Wald F-statistic is at the bottom of each column. The corresponding Stock-Yogo value for 10% (15%) maximal IV bias is 16.4 (8.96). Section 3.2 explains the procedure followed to derive the product quality measure. All regressions cluster standard errors at the industry-year level. Key: ** significant at 1%; ** 5%; * 10%.

Table A.6: First Stage Regressions, Table Table: Alternative Instrument - Plants' Outcomes

Specification	Baseline	Leaders vs. Laggards	
	(1)	(2)	(3)
Dependent Variable:	$\ln(M^{CHN}_{j,t-1})$	$\ln(M^{CHN}_{j,t-1})$ $\times$ Leader	$\ln(M^{CHN}_{j,t-1})$ $\times$ Laggard
$\ln(\hat{M}^{LASSO,2}_{j,t-1})$	1.105***	—	—
	(0.108)		
$\ln(\hat{M}^{LASSO,2}_{j,t-1}) \times$ Leader	—	1.224***	—
		(0.0938)	
$\ln(\hat{M}^{LASSO,2}_{j,t-1}) \times$ Laggard	—	—	1.084***
			(0.111)
First Stage F-statistic	104.6	47.9	
Industry-year FE	yes	yes	yes
Plant FE	yes	yes	yes
Observations	29,283	29,283	29,283

Notes: The table show first-stage regressions for the IV specifications in table A.6. Column 1 shows the first stage for panel A in table A.6, while columns 2 and 3 shows the first stage for panel B, where (lagged) imports from China are interacted with indicator variables for leading and laggard establishments. The regressions instrument Chilean imports from China at the 3-digit level (and their interactions) with the predicted values from a LASSO regression that considers imports from China by all countries from outside South America available in the BACI trade dataset (and their interactions). Industry leaders comprise the top 10 percent of plants with the highest average TFPQ (within industries) before 2001. All regressions are run at the plant-year level, control for the logarithm of employment, and include industry-year (at the 2-digit level) and plant fixed-effects. The (cluster-robust) Kleibergen-Paap rK Wald F-statistic is at the bottom of each column. The corresponding Stock-Yogo value for 10% (15%) maximal IV bias is 16.4 (8.96). All regressions cluster standard errors at the industry-year level. Key: ** significant at 1%; ** 5%; * 10%.

Table A.7: Effect of Chinese Import Competition on Plants' Outcomes - EIT Sample

	(1) Output	(2) Markup	(3) Revenue	(4) Output Price	(5) TFPQ	(6) TFPR	(7) Marginal Cost	(8) Quality	(9) Profits	(10) Input Price
ln(CHN Imports(-1))	-0.115**	-0.0521*	-0.0109	0.104**	-0.0991*	-0.0612	0.153***	0.0036	-0.0962**	-0.0264
	(0.0500)	(0.0301)	(0.0336)	(0.0404)	(0.0564)	(0.0398)	(0.0528)	(0.0417)	(0.0483)	(0.0374)
First-Stage F-Statistic	42.9	42.2	42.9	42.9	42.2	42.9	42.2	45.8	42.9	42.1
Industry-year FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Plant FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Observations	4,704	4,606	4,704	4,704	4,606	4,702	4,606	4,345	4,704	4,525

Notes: The table replicates table 2 for the sample of plant-years available in the Chilean innovation survey (EIT), regressing different plant outcomes on lagged imports from China. All regressions are run at the plant-year level, control for the logarithm of employment, and include industry-year (at the 2-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% (15%) maximal IV bias is 16.4 (8.96). Section 3.2 explains the procedure followed to derive the product quality measure. All regressions cluster standard errors at the industry-year level. Key: ** significant at 1%; ** 5%; * 10%.

Table A.8: First Stage Regressions, Tables 3 and 4

Specification	Baseline	Leaders vs. Laggards		Change in Markups	
	(1)	(2)	(3)	(4)	(5)
Dependent Variable:	$\ln(M^{CHN}_{j,t-1})$	$\ln(M^{CHN}_{j,t-1})$ $\times$ Leader	$\ln(M^{CHN}_{j,t-1})$ $\times$ Laggard	$\ln(M^{CHN}_{j,t-1}) \times \mathbb{I}(\Delta\mu^{after}_{before} > 0)$	$\ln(M^{CHN}_{j,t-1}) \times \mathbb{I}(\Delta\mu^{after}_{before} < 0)$
$\ln(\hat{M}^{LASSO}_{j,t-1})$	1.083***	—	—	—	—
	(0.165)				
$\ln(\hat{M}^{LASSO}_{j,t-1})$ $\times$ Leader	—	1.304***	—	—	—
		(0.116)			
$\ln(\hat{M}^{LASSO}_{j,t-1})$ $\times$ Laggard	—	—	1.027***	—	—
			(0.191)		
$\ln(\hat{M}^{LASSO}_{j,t-1}) \times \mathbb{I}(\Delta\mu^{after}_{before} > 0)$	—	—	—	1.135***	—
				(0.212)	
$\ln(\hat{M}^{LASSO}_{j,t-1}) \times \mathbb{I}(\Delta\mu^{after}_{before} < 0)$	—	—	—	—	1.057***
					(0.154)
First Stage F-statistic	42.9	14.5		23.5	
Industry-year FE	yes	yes	yes	yes	yes
Plant FE	yes	yes	yes	yes	yes
Observations	4,704	4,704	4,704	4,692	4,692

Notes: The table show first-stage regressions for the IV specifications in table 3 and 4. Column 1 shows the first stage for panel A in table 3, while columns 2 and 3 shows the first stage for panel B, where (lagged) imports from China are interacted with indicator variables for leading and laggard establishments. Columns 5 and 6 shows the first stage for table 4, where (lagged) imports from China are interacted with indicator variables for plants with higher/lower markups in 2001-2007 relative to the precedent period 1996-2000. The regressions instrument Chilean imports from China at the 3-digit level (and their interactions) with the predicted values from a LASSO regression that considers imports from China by all other countries available in the BACI trade dataset (and their interactions). Industry leaders correspond to the top 10 percent of plants with the highest average TFPQ (within industries) before 2001. All regressions are run at the plant-year level, control for the logarithm of employment, and include industry-year (at the 2-digit level) and plant fixed-effects. The (cluster-robust) Kleibergen-Paap rK Wald F-statistic is at the bottom of each column. The corresponding Stock-Yogo value for 10% (15%) maximal IV bias is 16.4 (8.96). All regressions cluster standard errors at the industry-year level. Key: ** significant at 1%; ** 5%; * 10%.

Table A.9: Heterogeneity: Split by Change in Profit Rate

	(1)	(2)	(3)	(4)	(5)	(6)
	Innovative Spending		Innovation Outputs			
	Overall Spending	R&D Spending	Patents Stock	Process Innovation	Product Innovation	Product Quality
ln(CHN Imports(-1))						
× Increasing Profit Rate	-0.448	-0.106	0.0070	-0.106**	-0.0432	0.0141
	(0.643)	(0.611)	(0.0375)	(0.0463)	(0.0349)	(0.0504)
× Shrinking Profit Rate	-1.294**	-0.764	-0.0404	-0.0865**	-0.0970**	-0.00591
	(0.534)	(0.641)	(0.0571)	(0.0387)	(0.0435)	(0.0675)
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 replicates Table 4 interacting lagged imports from China with an indicator variable for plants increasing/shrinking profit rate after China joined the WTO in 2001. To split the sample, we run an auxiliary regression of plant-level profit rate against instrumented lagged imports from China, industry-year, and plant fixed-effects. Thus, the indicator variable only considers the fraction of the profit rate that varies due to increased Chinese competition. All regressions are run at the plant-year level, control for the logarithm of employment, and include industry-year (at the 2-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% (15%) maximal IV bias is 16.4 (8.96). Innovative spending in columns 1-2 and the patents stock in column 3 are computed as the logarithm of one plus the corresponding spending, to include zeros. Product and process innovation (columns 4-5) are categorical variables taking the value one if the establishment reports successful innovation. Section 3.2 explains the procedure followed to derive the product quality measure. All regressions cluster standard errors at the industry-year level. Key: ** significant at 1%; ** 5%; * 10%.

Table A.10: Change in Profit Rate combined with Leader/Laggard Indicator

	(1)	(2)	(3)	(4)	(5)	(6)
	Innovative Spending		Innovation Outputs			
	Overall Spending	R&D Spending	Patents Stock	Process Innovation	Product Innovation	Product Quality
log(CHN Imports(-1)) × Laggards						
× (Shrinking Profit Rate)	-1.2070	-0.9300	-0.0444	-0.0660	-0.1160**	-0.0410
	(0.8446)	(0.7386)	(0.0631)	(0.0456)	(0.0497)	(0.0900)
× (Increasing Profit Rate)	-0.7373	-0.6667	0.0376	-0.1279**	-0.0712*	-0.0478
	(0.6564)	(0.6074)	(0.0444)	(0.0525)	(0.0423)	(0.0418)
log(CHN Imports(-1)) × Leaders						
× (Shrinking Profit Rate)	-0.8802	0.8584	-0.0964	-0.0685	0.0441	0.1247*
	(0.7565)	(0.7479)	(0.1220)	(0.0742)	(0.0752)	(0.0711)
× (Increasing Profit Rate)	-0.4105	1.1218	-0.0144	-0.1304	0.0889	0.1179
	(1.1097)	(0.9916)	(0.1386)	(0.0973)	(0.0833)	(0.0925)
First Stage F-Stat	9.3	9.3	9.3	9.3	7.8	14.1
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 replicates Table 5 interacting lagged imports from China with an indicator variable for plants increasing/shrinking profit rate 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 profit rate indicators variables. All regressions are run at the plant-year level, control for the logarithm of employment, and include industry-year (at the 2-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% (15%) maximal IV bias is 16.4 (8.96). Innovative spending in columns 1-2 and the patents stock in column 3 are computed as the logarithm of one plus the corresponding spending, to include zeros. Product and process innovation (columns 4-5) are categorical variables taking the value one if the establishment reports successful innovation. Section 3.2 explains the procedure followed to derive the product quality measure. All regressions cluster standard errors at the industry-year level. Key: ** significant at 1%; ** 5%; * 10%.