# Markups and Misallocation with Evidence from Exchange Rate Shocks

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**Abstract**

In a setting with firms that charge variable markups, this paper finds that firm heterogeneity has welfare implications that result exclusively from the differential markup adjustment to global shocks. Changes in allocative efficiency are summarized by a sufficient statistic that can be directly measured with aggregate data. I use Chilean data between 1995-2007 to show that exchange rate shocks can be an important driver of allocative efficiency, as there are large changes in misallocation over time due to the way firms pass-through these shocks into markups. At the firm-level, there is evidence that importing firms pass-through real exchange rate appreciations into their markups. Over time, due to the compositional effect that ensues, industries that import a larger share of their inputs become more misallocated. In a structural model with productivity gains from importing, where firm market power increases with size, I show how firm reallocation in response to a positive supply shock rationalizes the reduced-form results.

JEL Classification: F12, F14, F43, O47, L11

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# 1 Introduction

The important conclusion of "new-new" trade theory that entry into the global market raises the average productivity of surviving firms was spearheaded by the breakthrough of the Melitz (2003) heterogeneous firm model, which introduced reallocation as an integral component of the gains from trade. In this model, the nature of the market share reallocation is simplified by using Constant Elasticity of Substitution (CES) preferences (Dixit and Stiglitz, 1977), which results in market outcomes identical to the social optimum.[1] Meanwhile, another literature, the one on growth and productivity, has studied within-industry allocative inefficiency, or the possibility to alter the allocation of production such that real income increases. This research finds that misallocation is an important reason for cross-country income differences (Hsieh and Klenow, 2009; Restuccia and Rogerson, 2008).[2] Motivated by this literature, in this paper I incorporate a possible non-optimal market share reallocation to the Melitz model. I use as a starting point the result of Dhingra and Morrow (2019) (DM) that non- constant markups in a monopolistic competition framework imply a sub-optimal allocation across firms. Given this starting point I find a novel measure, or sufficient statistic, for changes in allocative efficiency, which can be directly measured with data. I connect this measure to the experience of Chile, a commodity exporter with a volatile real exchange rate. I show that real exchange rate shocks can be important drivers of allocative efficiency.

The Melitz model is allocatively efficient due to the CES feature of constant market power. However, when the demand side in the Melitz model is generalized to allow for less restrictive preferences, the market equilibrium is not necessarily efficient, as differences in market power allow for firms to over/under- produce relative to the socially optimal case, with a clear mechanism for a more efficient resource allocation. Therefore, I follow the variable elasticity (VES) framework laid out in DM, where preferences are directly additive as in CES (Dixit and Stiglitz, 1977), but the sub-utility function is allowed to be non-homothetic. It allows for variable markups and implies a production allocation that does not equalize relative marginal utilities with relative production costs, as market power allows highly productive firms to only partially pass-through cost advantages. Markup heterogeneity maps onto lower aggregate income relative to the allocatively efficient benchmark and thus creates an aggregate distortion.

In this setting, it is intuitive that a shock to the relative price of domestic versus foreign goods will result in a differential adjustment across firms, and thus a reallocation that

[1] Feenstra and Kee (2008) showed this to be the case in a setting with firm heterogeneity.

[2] Additionally, Basu and Fernald (2002) (BF) expand on Solow productivity gains – akin to shifting out a country's production possibility frontier – to include welfare-improving movements along this frontier that can be measured using real income.

either increases or decreases this aggregate income. Prior to the formal model, I start by showing motivational evidence for Chile. Chile experienced large real exchange rate shocks throughout the period of 1995-2007, as exemplified by a sharp terms of trade increase in the mid-2000's as a result of a commodity boom. During that same period, importers raise their markup relative to non-importers in response to an appreciation, evidence of lower costs passed through to markups. In conjunction, markup heterogeneity increases significantly, and aggregate income growth is slower than would be expected given the growth in production. This is consistent with the findings in Berman et al. (2012) and DeLoecker et al. (2016) which find that cost shocks are passed on to prices at different rates across firms. I then turn to a theoretical model that connects misallocation at the industry level to firm markup adjustments.

The first theoretical contribution of this paper is to show that the aggregate distortion is captured by the difference between growth rates of aggregate value added and physical production. These measures coincide in a constant markup environment, so I link a deviation in the two measures to the growth rate of allocative efficiency and show that this distortion is present in the welfare decomposition of a representative consumer. This sufficient statistic, which is new to the literature and can be calculated with widely available data, captures the counterfactual deviation in value added relative to a model that ignores the heterogeneity in market power.

Given that this new measure holds for a commonly used class of models in the literature, a second important contribution is then to identify the mechanisms that underlie it. The sufficient statistic reflects a *compositional* effect, whereby allocative efficiency tracks changes in a weighted-average markup due to reallocation of production from high (low) to low (high) markup firms.[3] I therefore connect allocative efficiency to changes in the price of foreign goods by identifying the heterogeneous effects of aggregate shocks on firm market power. Generally, the shock to the relative price of domestic versus foreign goods has two separate effects. A pro-competitive effect works through firm-level demand elasticities if for example entry rises. Separately, a supply side effect alters marginal costs, for example if domestic firms source cheaper intermediate inputs. The latter effect is the focus of the rest of the paper, in order to explain the observations in the Chilean economy in the mid-2000's.[4]

In order to isolate how the supply shock generates the compositional mechanism, I introduce a structural model that produces the endogenous response of allocative efficiency

[3]This connection between the weighted average of markups and misallocation fits in with recent work (Macedoni and Weinberger, 2019; Peters, 2020; Edmond et al., 2018; Baqaee and Farhi, 2017).

[4]Chile also experiences a depreciation between 1998-2002. My results are consistent with this episode, however the terms of trade shock in the latter period is sharper and provides a more convincing episode in which to investigate cause and effect.

in response to a change in the cost of foreign inputs relative to domestic ones.[5] The main innovation is to combine a specific functional form of VES preferences with importing on the supply side. The sourcing decision of the firm is based on the sufficient statistic result of Blaum et al. (2018), which connects firm size and markups with the share of inputs that are sourced abroad. Furthermore, intrinsic productivity differences generate cross-sectional heterogeneity in import shares. I then investigate the response to exchange rate variation. For example, an appreciation results in lower unit costs which allows firms to charge higher markups due to incomplete pass-through into prices. Heterogeneity in the degree of adjustment generates a reallocation of labor to firms with initially lower markups, and misallocation increases.

In the last section, the connection between markup heterogeneity and global shocks is tied together with two types of empirical exercises. First, I provide reduced-form empirical evidence that changes in aggregate misallocation, measured at the industry level, are due to real effective exchange rate (REER) shocks. I argue for this causality through a differences-in-differences specification that compares treated and non-treated industries based on their exposure to imported inputs. The main empirical result is that, controlling for export shares, industries dominated by firms that rely on imported inputs become more misallocated in response to an appreciation in the REER. A 1 percent increase in the growth rate of the REER leads to about a 1.6 percentage points smaller growth rate in allocative efficiency in a fully treated industry – which I define as the industry with the highest import share – relative to a non-treated industry with an import exposure of zero. This result holds up to a battery of robustness checks and tests of alternative explanations.

Second, I reconcile the reduced form aggregate results with the structural model. Notice that the distortion I measure in the data is at the industry level, but it is the product of aggregating firm-level responses which can be summarized by the sufficient statistic described above. I use simulated method of moments to generate a distribution of firms and then match descriptive statistics of the relationship between importing and market power in the Chilean firm data to discipline the parameters of the model. A counterfactual shock to the price of imported inputs relative to domestic inputs predicts that an industry with an average imported input share as observed in the whole economy would experience a 13% reduction in allocative efficiency in response to a 10% appreciation. On the whole, the model allows me to connect the observed movement in the aggregate measures with the simulated firm reallocation that is transparent in the model.

[5] I emphasize that the model in this paper could also be easily applied to a rise in competition due to trade liberalization. I isolate the other effect by keeping competition constant in the model. I control for a possible rise in foreign trade in the empirical specification.

**Related Literature** The theoretical and empirical contributions should be viewed relative to numerous recent papers. Dhingra and Morrow (2019) characterize qualitative properties of this misallocation and investigate the case where market size increases. Arkolakis et al. (2019) similarly find that this distortion affects the welfare gains from reducing domestic import tariffs. In relation to these two papers, my contribution is to produce a more direct quantitative measure and include shocks to both the input and output markets that motivate time series variation in allocative efficiency. Although my model follows the VES framework of the former, and the directly additive case of the latter paper, I stress that neither paper — nor any other I am aware of — has identified an empirical estimate that maps to the allocative efficiency measure that these papers identify theoretically.

Edmond et al. (2015) also quantify misallocation in the context of a trade model and measure the welfare gains due to trade liberalization. Their framework imposes nested CES preferences so misallocation is due to supply-side frictions and reduces aggregate TFP. In contrast, in Section 3.2 I suggest a measure separate from firm TFP, which is instead based on the change in the covariance of markups and labor input, an interesting statistic that has not been explored in this literature. This feature also differentiates my measure to that in Holmes et al. (2014) which holds only for homothetic preferences.[6] I view my paper as a complement to that study as I also separate allocative efficiency from productive efficiency, albeit in a different setting that translates nicely to available firm balance sheet data. Importantly, I expand on the limited focus of competition on the output side by adding input side effects (the two papers above concentrate on output tariffs only) in order to apply the predictions to a relevant empirical application.

On the empirics side, my findings are consistent with studies on competition, variable markups, and pass-through, but provide aggregate implications that have not been discussed in this context. Liberalization studies find that tougher competition forces firms to lower prices and raises average productivity, and that pass-through of costs to prices is below one (DeLoecker et al. (2016)). Relatedly, Amiti et al. (2014) find that the most productive firms import the most and also have the lowest pass-through. This is consistent with the terms of trade shock in Chile raising total production but also increasing the degree of misallocation due to business stealing of low-markup firms. My empirical results are related to Berman et al. (2012) who show that exchange rate movements tend to affect markups and not export volumes.[7] I focus on how this markup effect relates to reallocation, which clarifies the way

[6]Intuitively, the covariance (and allocative efficiency) increases when production is reallocated towards varieties with a high marginal utility (which is proportional to price), and this is possible up to the point that markups are equalized across firms. I maintain the monopolistic competition environment as in Krugman (1979) and Melitz (2003).

[7]Chatterjee et al. (2013) is another example of an exchange rate shock that affects markup that is

that incomplete pass-through has interesting aggregate welfare implications.[8]

Theoretical trade models have explored variable markups to generalize welfare gains from trade, though earlier papers highlight "pro-competitive" effects as in Krugman (1979). With free entry, competition reduces *average* markups and increases aggregate productivity as each firm increases scale and moves down its average cost curve.[9] The distortion present in this paper is the result of the interaction of non-homothetic demand (with separable preferences) and firm heterogeneity, thus capturing separate welfare implications. Within the directly additive non-homothetic preference framework, Behrens et al. (2014) have investigated the pro-competitive effect of trade liberalization, while Simonovska (2015) and Jung et al. (2019) investigate the effect of price discrimination across destinations. Bertoletti et al. (2018) examine pro-competitive effects when preferences are non-homothetic but not additively separable. Demidova (2017) introduces trade policy to the qualitative statements about gains from trade.[10]

The relation of markups and misallocation has also been a focus outside of the trade literature. Hsieh and Klenow (2009) assume markups are constant due to CES preferences, but distortions imply that firms optimally choose non-equal marginal products even though they face identical factor prices. My paper establishes a new way to observe deviations from allocative efficiency. Consistent with the aggregate productivity growth (APG) literature, a distortion inflicts a wedge between total revenues and output. This literature decomposes APG into growth in average firm productivity and reallocation. In Basu and Fernald (2002), Petrin and Levinsohn (2012) and Baqaee and Farhi (2017), reallocation increases welfare if inputs are reallocated towards the high markup firms.

The rest of this paper is organized as follows. Section 2 introduces the Chilean data and provides a time series motivation for how the real exchange rate affects markup dispersion. This motivates the theoretical framework in Section 3, which differentiates between growth in real income in the CES and VES cases. I also introduce a model that connects firm imports,

consistent with my empirical findings. Though my firm level results are not new at this point, they provide further evidence for a growing field and do offer a novel connection to the measurement of reallocation.

[8]Pavcnik (2002) and Bartelsman et al. (2013) also attempt to measure productivity growth through reallocation in developing countries, though they focus on different sufficient statistics. In a separate strand of the literature, Amiti and Konings (2007), Kasahara and Lapham (2013) and Goldberg et al. (2010) show how a significant part of the productivity gains are a result of cheaper and more abundant intermediate inputs.

[9](Chamberlin, 1933; Vives, 2001) explore variety and scale trade-offs, but not necessarily misallocation of quantity among existing producers, which requires firm heterogeneity. Feenstra and Weinstein (2017) use a homothetic framework with firm heterogeneity to measure the pro-competitive plus variety effects from increased global competition.

[10]As a note, non-homothetic preferences are not *necessary* for variable markups to introduce distortions with monopolistic competition, as shown in Macedoni and Weinberger (2019) and Behrens et al. (2020).

unit costs, and markups. Section 4 presents empirical evidence for changes in misallocation in response to exchange rate variation, and clarifies the mechanisms with a quantitative analysis of the model with importing. Finally, Section 5 concludes.

# 2 Data and Background

## 2.1 Chile's Open Economy Shocks

The focus of this study is to examine changes in allocative efficiency that reflect micro-level reallocation as a response to a shock in the relative price of domestic versus foreign goods. In this subsection I summarize time series facts about the real exchange rate and output tariffs in Chile, which can be mapped to this type of shock. Chile's trade liberalization continues a trend that starts in the late 1970's, but the real exchange rate provides a larger and more unexpected shock during data range I explore.

Macro and open economy data is taken from a variety of sources. The Central Bank of Chile provides macroeconomic measures that include the open economy. Detailed export and import data at the 4-digit level is provided in the world trade flows database of Feenstra et al. (2005). The real effective exchange rate (REER) is available from IFS (IMF).[11] Terms of trade plus alternative import and export data can be obtained from World Development Indicators (WDI) at the World Bank. The World Integrated Trade Solutions (WITS) database has detailed tariff data that I aggregate to the 4-digit level. [12]

Figure 6 (Appendix) plots manufacturing exports and imports as a ratio of total manufacturing value added.[13] Exports rise steadily throughout this period, with an acceleration after 2003, while imports boom after 2002. Any story explaining Chilean trade must include its large exposure to commodities. This is especially important in the copper industry, which constitutes almost half of its export value in the mid-2000s, after the price of copper *triples* between 2003 and 2007. Therefore, the export surge can be explained as demand driven as Chile gained from the inflation in commodity prices that was due to the increased demand from emerging countries. The large increase in imports post-2002 is driven especially by intermediate inputs.[14] For the manufacturing firms that I consider, importing is as important

[11] A geometric average of relative prices using trade weights. Trade weights from BIS (http://www.bis.org/statistics/eer/) combined with output prices from Penn World Tables (PWT) 8.0 provide a similar result.

[12] Input tariffs are almost identical during this period, as there is a mostly uniform reduction in industry tariffs.

[13] Exports and imports are gross flows (so they can be greater than total manufacturing value added).

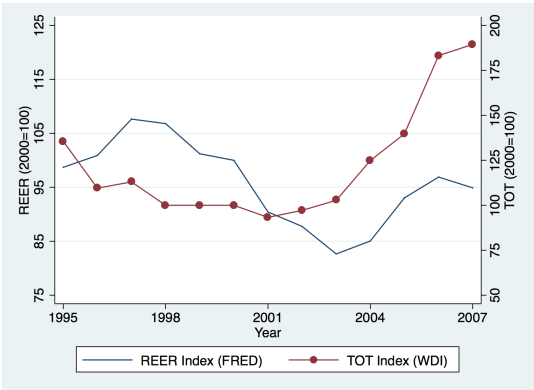
[14] Desormeaux et al. (2010) establishes that firms and households import a significant amount of their

as the export side, as firms rely on imported inputs of machinery and capital goods.[15]

The demand shock for Chile's commodities is reflected in the large terms of trade gain starting in 2003. Figure 1 describes the terms of trade (TOT) along with the REER (both normalized to 100). Chile experienced an appreciation before 1997, a sustained depreciation from 1997-2003, and a sustained appreciation 2003-2006 led by the terms of trade gain. The terms of trade is mostly unaffected by the depreciation, but follows a similar, though magnified, trend in the 2003-2006 period. Although both measures imply a large appreciation post-2002 (with TOT being more extreme), the REER captures more volatility due to the depreciation between 1997-2002.

The shock to the terms of trade, reflected by the real exchange rate appreciation, is likely exogenous to the non-copper industries, as it is driven by the copper boom. In terms of the earlier depreciation, there is no obvious cause, but it occurs in conjunction with a global weakness in developing markets. Still, a shock in any direction affects the cost of imported inputs and/or the output prices relative to foreign competitors. In the empirical analysis I use the REER as the benchmark measure and provide robustness results with the TOT measure. The REER is a better gauge of relative prices, but the appreciation of post-2002 arguably provides a cleaner identification of a shock to non-copper industries.

**Figure 1:** Terms of Trade (2000=100) and Real Effective Exchange Rate (2000=100), 1995-2007




*Sources: WDI Indicators, International Financial Statistics (IMF).* TOT is an index from WDI. REER, taken from IFS data, is calculated using Penn World Tables to calculate Chile's production price index relative to its top trade partners and taking a geometric average using trade shares (from BIS) as weights. I report the indices with the year 2000 as base year.

The open economy is also affected by changes in the trade regime. The time period

intermediary inputs. In Weinberger (2015), customs data is used to report large import growth for Chile in *intermediate inputs* during the same time period. An important component of the growth is in new varieties of inputs being imported (the "sub-extensive" margin in Gopinath and Neiman (2014)).

[15]Berthelon (2011) documents that Chilean export performance from $1990 - 2007$, even taking out copper industries, shows growth in the extensive margin and diversification of products as well as partners.

examined in this paper is subsequent to the big trade reform in Chile that occurred in the late 1970's (and studied in Pavcnik (2002)). Figure 7 (Appendix) shows the average applied tariff rate from the Comtrade database. In the time span of the data, average applied tariffs in the manufacturing sector decrease, however this drop is mostly homogeneous across industries and most likely expected by firms as Chile must gradually lower its output tariffs as a condition to joining the WTO in 1995. Its effect on relative prices of foreign and domestic goods is also likely mitigated by concurrent drop in export tariffs. For these reasons, in this paper I explore only the effect of real exchange rate shocks on allocative efficiency (and firm markups).[16]

## 2.2 Firm and Industry Data

To produce a measure of misallocation and relate it to firm performance requires production data for the universe of Chilean firms. I combine a panel of the Chilean census of firms from 1995-2007 with aggregate statistics from this same period. The firm level data is provided by Encuesta Nacional Industrial Anual (ENIA, National Industrial Survey) and collected by the National Institute of Statistics (INE). It covers a census of manufacturing firms, ISIC (rev. 3) classification 15-37, with more than 10 workers. There are approximately 5,000 firm level observations per year and firms are tracked across time with a unique identification number. Each firm provides detailed economic data such as total sales, number of workers, value of fixed capital, expenditures on intermediate inputs, etc. This data will be used to construct estimates of firm productivity and markups using methods described below. Importantly, firms also report the value of inputs that are imported from abroad and what value of their total sales is exported.

Aggregate measures are motivated by theoretical aggregates in Section 3, but also have counterparts in the literature. The goal is to track aggregate real income growth, and compare it to a measure of physical production, as the difference measures the aggregate markup. I make use of industry-level data to construct growth rates of revenue and production of physical quantity. The growth in real revenue is the Aggregate Productivity Growth (APG) measure used by Basu and Fernald (2002) (BF) and Petrin and Levinsohn (2012) (PL) defined by total growth in (deflated) value added within an industry, and corrected for the growth in labor.[17] The aggregate price level is based on the INE's 4-digit ISIC industry

[16]The Appendix provides theoretical effects of greater competition on markup heterogeneity, but I focus on input cost shocks in the main paper in order to have a more unified story.

[17]By the national revenue accounting identity, the sum of value added is equal to the sum of final demand in an industry. See Appendix A.2 for details on the construction of this measure. As in PL, I correct for total industry wage growth since the theory will assume there is no reallocation of labor across sectors.

deflators.[18] Furthermore, I use a real production index provided by the same agency that conducts the annual firm census. This survey tracks only a subset of the census of firms, but gets data on physical production (divorced from prices). This index of production, produced at the 3-digit ISIC level which I aggregate to the 2-digit level, allows me to track annual growth in physical production by incumbent firms.[19] This index follows a subset of firms with bases in 1989 (for the 1995-2002 data) and 2002 (used for the 2003-2007 data).

Next, I use the firm data to provide evidence on the effect of real exchange rate variation on firm markups and data time series evidence of markup heterogeneity. I will return to the industry data above in Section 4.1, which identifies real exchange rate variation as an impetus for changes in allocative efficiency.

## 2.3 Firm Markups in Response to Shocks to Import Prices

The reallocation story that is the mechanism behind changes in misallocation requires heterogeneous markup adjustment across firms. At the firm-level, markups can be estimated using the method from DeLoecker and Warzynski (2012). The first step is to calculate production function coefficients ala Ackerberg et al. (2015) (ACF) – in itself an extension of the seminal contributions of Olley and Pakes (1996) and Levinsohn and Petrin (2003) (OP and LP) – and then to use these coefficients plus cost shares to estimate firm-level markups. The details on production function estimation and translating this to markups is relegated to Appendix A.3 as this method has been used extensively in the trade literature. Table 5 (in the Appendix) shows the production function coefficients and the median markup in all industries. The median markup across the manufacturing sector as a whole is consistent with past estimates, at 25%, while the mean is 22%.

**Firm-Level Summary Statistics** I start with establishing the relationship between firm markups/sales and imports, statistics that I will replicate in the calibration of a structural model in Section 4.2. This is done in a cross-section – across firms – as well as within firm adjustments over time – possibly due to shocks in the relative price of foreign and domestic goods. Table 1 displays the relationship of firm markups and sales with firm import and export shares. The baseline measure of the import share is the ratio of imports to total material expenditure, but the ratio is also computed relative to total sales. With the first

[18] These deflators are computed by the INE, which I take as a reasonable approximation of my aggregate price level. The aggregate in my model is a weighted average of individual prices. The INE constructs a Laspeyres index that is aggregated using 7-digit products.

[19] There are no micro-level quantities to construct an index identical to my model, but this index is a reasonable approximation.

measure, the aggregate import share in Chile averages 0.19 across all years. Across time, the aggregate import share increases from an average of 0.161 before 2003 to 0.237 after the REER appreciates about 10% (although the terms of trade increases more dramatically), which corresponds to a trade elasticity of -3.98.[20]

The first two columns of Table 1 include firm and year fixed effects, and are interpreted as the response of markups to changes in the import share *within firms*. Unsurprisingly, markups increase with the import share. Columns (3)-(4) display the results of a pooled cross-section, with sector-year fixed effects. The interpretation is that across firms, those that import more have larger markups. These two specifications are repeated with an outcome of sales relative to the industry mean. Consistent with the trade model introduced in the next section, firms that import more have higher sales in the cross-section (last column).[21] It is also the case (Table 6, Appendix) that export share, capital intensity, employment, TFP, and being a multinational are all positively associated with firm markups. Table 10 shows that this holds in the case that I measure markups using the DeLoecker and Warzynski (2012) method (I label it "Lerner" because I transform them to a Lerner index), and also 2 alternative markups: a profits to sales ratio ("Profit"), and an inverse labor share measure "Lshare". Notice that these imply much larger firm markups, for example the labor share measure has a mean of 63%.[22]

**Firm-Level Response to REER Shocks** In order to establish that firms adjust markups in response to their ability to import, I measure the differential firm markup responses to exchange rate volatility in a difference-in-difference specification in which groups are treated based on their exposure to the real exchange rate shock. When the cost of imported inputs is lower, importers should raise their markup relative to non-importers, reflecting incomplete

[20] A very similar story exists when normalizing imported inputs with sales: the aggregate import share increases from 0.075 to 0.122. The REER appreciates by more than 10% in the most intense period, but I use a consistent definition of the "post" period being 2003-2007.

[21] This scale-free measure can be compared to the model implied sales.

[22] I construct markups three ways. (1)"Markup (Lerner)" $= \mu_{it}$, where $\frac{1}{1-\mu}$ is the price-cost ratio, or ratio of material output elasticity and material cost share ($\frac{\theta^m}{\alpha^m}$) estimated using (DeLoecker and Warzynski, 2012); (2) "Markup (Profit)" $= \frac{Sales_{it} - wages_{it} - capitalcosts_{it} - inputscosts_{it}}{Sales_{it}}$, constructed using sales and input data; (3) "Markup (Lshare)" $= \mu_{it}^{Lshare}$, where $\mu^{Lshare}$ is a Lerner index from the inverse labor share of value added. I drop all firms with a markup that is negative or above 1 in any of the three measures.

**Table 1:** Firm Markups and Characteristics

| | Markup (Lerner) | | | | Relative Sales | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Import Share | 0.095*** | | 0.046*** | | 0.233* | 0.837*** |
| | (0.006) | | (0.006) | | (0.122) | (0.241) |
| Import Share (sales) | | 0.181*** | | 0.066*** | | |
| | | (0.014) | | (0.015) | | |
| Fixed Effects | Firm, Year | Firm, Year | Sector-Year | Sector-Year | Firm, Year | Sector-Year |
| $R^2$ | 0.79 | 0.78 | 0.57 | 0.56 | 0.94 | 0.30 |
| N | 29504 | 29504 | 29462 | 29462 | 29504 | 29462 |

This table measures the relationship of firm outcomes with its characteristics. The benchmark Lerner markups is the outcome in the first four columns. The outcome in the last two columns is relative sales, or firm sales relative to mean sales in the industry in that year. In columns (1), (2), and (5), I take firm and year fixed effects to capture the effect of changes in the outcome with respect to changes in firm characteristics within firms over time. In columns (3), (4), and (6), I add sector-year fixed effects to capture the cross-sectional relationship across firms within sectors. Standard errors (in parenthesis) are clustered at the firm level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

pass-through to a cost shock.[23] I run the following specification:

$$\mu_{it} = \alpha_i + \alpha_t + \chi REER_t * ImportShare_i + REER_t * Z_{it} + e_{it}. \tag{1}$$

Include are both firm ($\alpha_i$) and year ($\alpha_t$) fixed effects, though in the appendix I also show results with industry (4 digit ISIC)-year interacted fixed effects. The outcome measure is the firm markup, and the coefficient of interest is $\chi$, the differential effect across firm exposure to the exchange rate shock. I control for time-varying TFP, as well as time-varying firm characteristics. Due to space limitations, the latter characteristics from the main Tables are omitted (though they are displayed in the Appendix tables). Exposure to the REER shock is captured with the two import measures described above, plus a "Net Exposure" variable constructed as the difference between export share and import share for a firm (described in Ekholm et al. (2012)).[24] The exposure to shocks is fixed over time to not allow for an endogenous change in exposure, however results with varying exposure are reported in Table 9 in the Appendix.

[23]The differential adjustment *within importers* will be present in the *aggregate* measures as it implies a compositional change in the allocation of production. In this section I merely confirm that importers adjust their markups in response to the shock.

[24]They model firm revenues and costs in order to compute the elasticity of each with respect to the real exchange rate the firm faces. In this partial equilibrium approach, the firms' export share is equal the elasticity of revenues with respect to the real exchange rate and the share of imports in total costs is the elasticity of costs with respect to the real exchange rate. Then the net exposure, the difference between the export share and share of imported inputs, directly affects the elasticity of profits (and therefore markups) with respect to the real exchange rate.

**Regression Results** The firm level regressions affirm the predicted markup responses. Table 2 uses import shares, as well as the net exposure, to measure the degree to which firms are exposed to exchange rate variations. The first two columns include the two separate measures of the import share respectively. A positive REER shock induces firms with a higher import share to raise their markups more. With imports as a share of total input costs (column (1)), a firm that imports *all* of its inputs raises its markup by 20.1 percentage points more than a firm with no imported inputs in response to a 1% appreciation (note again that the share if fixed over time). The negative coefficient on the interaction between the real exchange rate and net exposure in the third column means that a real effective exchange rate (REER) increases markups for firms that have negative exposure (input importers) relative to firms with no (or exporting) exposure. A firm that imports all of its inputs and does not export raises its price-cost margin by 11.1 percentage points more than a firm that neither exports nor imports in response to a 1% appreciation. In column (4) I check that this is not driven by how the import share interacts with changes in tariffs. The Appendix includes results with industry-year interacted, as well as region-year interacted, fixed effects. I also run separate analysis for 1995-2001 and 2002-2007, and the response to the REER holds in both periods.

Finally, the last two columns repeat the specification in the first and third columns, but I replace the main markup measure with the ($Profit$) measure. The advantage is that it doesn't require an estimation of the production function, which assumes firms face the same material prices.[25] However, measures such as this one and the labor share one are afflicted with various problems that have been documented in the production function literature. The relationship still holds as in the baseline specification, although the results are less robust.

**Markup Dispersion** The majority of the literature on variable markups has focused on average markups due to a "pro-competitive" effect (Feenstra and Weinstein, 2017). That focus does not include possible allocative inefficiencies, which requires that markups vary across firms (Basu and Fernald, 2002; Petrin and Levinsohn, 2012). In a setting that is similar to this paper, Berman et al. (2012) show that French exporters react to real exchange rate shocks differentially depending on their productivity. Next, I show the time series of the dispersion of markups, to motivate the heterogeneity present in the way firms adjust their markups in Chile. Unlike Berman et al. (2012), I will investigate the *compositional* effects of the markup adjustment by measuring aggregate misallocation in response to the

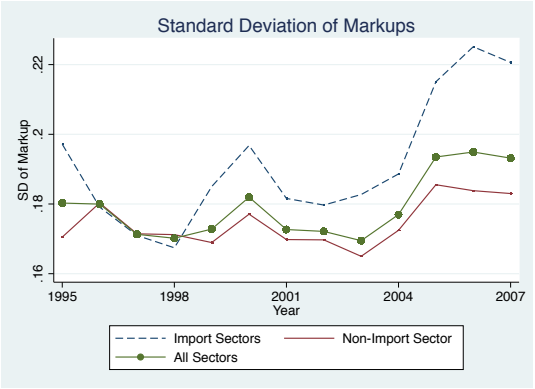
[25] In running the DeLoecker and Warzynski (2012) procedure, I control for import status (Kasahara and Rodrigue, 2008). I also add TFP as a control in the Columns (1)-(3), since it is estimated jointly in the procedure.

**Table 2:** Firm Level Differential Effect on Markup Adjustment

| | Markup (Lerner) | | | | Markup (Profit) | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| REER*ImportShare | 0.209*** | | | 0.200*** | 0.044 | |
| | (0.042) | | | (0.038) | (0.043) | |
| REER*ExportShare | 0.068 | 0.062 | | 0.068 | -0.032 | |
| | (0.051) | (0.051) | | (0.051) | (0.058) | |
| REER*ImportShare (sales) | | 0.402*** | | | | |
| | | (0.103) | | | | |
| REER*NetExposure | | | -0.111*** | | | -0.040 |
| | | | (0.033) | | | (0.034) |
| Tariff*ImportShare | | | | 0.003 | | |
| | | | | (0.005) | | |
| TFP | 0.117*** | 0.117*** | 0.117*** | 0.117*** | 0.306*** | 0.306*** |
| | (0.004) | (0.004) | (0.004) | (0.004) | (0.005) | (0.005) |
| Avg Markup | 0.22 | 0.22 | 0.22 | 0.22 | 0.25 | 0.25 |
| Fixed Effects | Firm, Year | Firm, Year | Firm, Year | Firm, Year | Firm, Year | Firm, Year |
| N | 29504 | 29504 | 29504 | 29504 | 29504 | 29504 |

This table examines the differential markup responses to foreign shocks depending on firm exposure. "Net Exposure" is the difference between the share of sales that are exported and the share of inputs that are imported. Since it is fixed over time for each firm, it is dropped from the specification. Dependent variable for the first 3 columns is the Lerner index, which the price-cost ratio measured using the procedure outlined in DeLoecker and Warzynski (2012) (DLW). TFP measurement also follows DLW. REER, TOT, and output tariffs are in logs. Columns (5)-(6) use a profit share measure of the markup. All columns include firm and year fixed effects (for industry-year interacted FEs see Appendix). I interact the following firm characteristics with the foreign shock to use as controls: capital intensity, a dummy if the firm is a multinational, the ratio of skilled to unskilled labor. The table only displays the results for the REER interaction. Standard errors are clustered at the firm level. I drop the basic metal industry (ISIC 27). $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

**Figure 2:** Markup Dispersion: Average Across Importing, Non-Importing, and All Sectors




Markup dispersion calculated for each sector by estimating the standard deviation (other methods available upon request). The connected line is the average across all sectors. The solid line takes the average standard deviation for sectors where less than 25% of firms are importers, while the dash line does the same for sector where more than 25% of firms are importers (half of sectors).

real exchange rate shock in Section 4.1. To preview those results, I report the dispersion of markups over time in Chile.

In Figure 2 the dispersion is calculated within each 2-digit sector and averaged (excluding basic metals) to exhibit the manufacturing industry as a whole. There are two main results. First, the middle line shows that there is an increase in markup dispersion in the 2003-2006

period, which is concurrent with the large exchange rate appreciation. Before then, the markup dispersion decreases, which is consistent with the depreciation. The second result is that the increase in dispersion of 2003 is driven entirely by importing industries, which is consistent with the story built in this paper that exchange rate movements will reallocate production in a way that a constant markup environment misses.

# 3 Structural Estimation of Allocative Inefficiency

## 3.1 Setup of Variable Elasticity Model

In this section I produce a structural estimate of allocative efficiency that can be taken to the data. I succinctly describe a framework with directly additive preferences that deliver variable demand elasticities, as fully laid out in Dhingra and Morrow (2019) and Zhelobodko et al. (2012). This sets up an environment in which markup heterogeneity is the driving factor behind allocative inefficiency.

The economy is made up of $L$ workers that supply one unit of labor inelastically. $M^e$ represents the mass of entering varieties, with each firm drawing $c$, its marginal cost or labor requirement to produce one unit, from a distribution $G(c)$, a continuously differentiable cumulative distribution. Then, $c_d$ is the highest possible cost with positive demand, so that active firms have costs in the range: $c \in (0, c_d]$ and $M^e G(c_d) = N$ represents the mass of varieties supplied. Firms are indexed by their cost, $c$, with the quantity sold to each (identical) consumer and price being $q(c)$ and $p(c)$ respectively. Preferences are given as follows:

$$U_j(M_j^e, q_j) \equiv M_j^e \int_0^{c_d^j} u_j(q_j(c)) dG_j(c) \tag{2}$$

$$\text{s.t} \sum_{j=1}^{J} M_j^e \int_0^{c_d^j} p_j(c) q_j(c) dG_j(c) = w \tag{3}$$

I assume a single sector to focus on the intrasector misallocation – and drop the $j$-sector subscript for the rest of the theory – but use this sectoral notation in the empirical application.[26] Utility within sectors takes a variable elasticity form and is *additively separable*

[26]In the empirical application, a sector will be comprised of products within a 2-digit ISIC code, with the assumption that each sector represents a constant weight $\beta_j$ of the economy. This is consistent with an economy where sectors $j$ are aggregated in a Cobb-Douglas fashion. Notice that Cobb-Douglas aggregation assumes no interesting sectoral interaction, although misallocation could also be present across sectors (as in Epifani and Gancia (2011)). Behrens et al. (2020) derive separate intra- and inter-sector allocative efficiency

*across products*. Although this allows for any range of demand elasticities, I restrict myself to preferences where the inverse demand elasticity is increasing with quantity.[27] For this reason more productive firms (producing a differentiated good with a lower marginal cost) will produce higher quantity, but have more market power and charge higher markups than their less productive counterparts.

For each variety there is inverse demand of, $p(q(c)) = \frac{u'(q(c))}{\delta}$, where the shadow price of income is $\delta = M^e \int_0^{c_d} u'(q(c))q(c)dG$. There is a competitive labor market with labor mobile across sectors, so that firms take as given a common wage, $w$. This common wage can thus be normalized to one. Firms pay a fixed entry cost, $f_e$, to choose a cost from the distribution, and then only active firms pay a fixed cost of production, $f$. These firms maximize profits, $\pi(c) = [p(q(c)) - c]\, q(c)L - f$. With monopolistic competition firms set their marginal revenue equal to marginal costs and the the markup rate is equal to the inverse demand elasticity: $\mu(q) = |\frac{qu''(q)}{u'(q)}| = |dlnp(q)/dlnq| = (p(c) - c)/p(c)$. The Lerner index, or the degree of market power, was my measure of markups in Table 2. Free entry implies the following sector-specific conditions: $\pi(c_d)) = 0$ and $\int \pi(c)dG = f_e$. Therefore, in the language of Dixit and Stiglitz (1977), the social optimum is a "constrained optimum" since firms need to be compensated for the chance of losing the entry cost.

In the market equilibrium, firms charge variable markups. The firms' first order conditions imply that for all firms: $u'(q(c)) + u''(q(c))q = \delta c$, or $u'(q(c)) = \frac{\delta c}{1-\mu(q(c))}$. Given that $p = u'(q(c))/\delta$:

$$p(q(c)) = \frac{1}{1 - \mu(q(c))} c \tag{4}$$

With non-homothetic preferences, the price is not a constant over marginal cost because $\mu(q(c))$ is a function of firm-varying productivity (or marginal cost). In other words, market power is heterogeneous across firms within a sector, and firms do not equate marginal rates of transformation.

## 3.2 Allocative Inefficiency

Dhingra and Morrow (2019) show that the model above leads to distortions not present in the standard CES model because the market equilibrium is socially optimal only when pref-

measures for a similar model. With the Cobb-Douglas upper-tier, the two inefficiencies can be studied independently. Chile's labor share of 2-digit industries are mostly constant during these 13 years.

[27] This is the case most often chosen in the literature, which Mrazova and Neary (2018) call "Marshall's Second Law of Demand". It is also the pro-competitive case in Krugman (1979). I am partial to Paul Krugman's words that to get reasonable results, "I make this assumption without apology".

erences are CES. Building on their work, this paper identifies the difference in the growth rate of revenue due to reallocation in the variable elasticity model relative to the commonly used CES framework. I motivate the importance of revenue growth in a welfare decomposition and use the definition of revenue (separating prices and quantity) to measure the bias inherent in the CES assumption relative to the generalized demand.

### 3.2.1 Utility with CES

I start by decomposing welfare when utility is homothetic, the knife-edge case where welfare is proportional to revenue, and compare that case to a generalization where utility is non-homothetic. If the sub-utility is assumed CES, aggregate real revenue is proportional to welfare because $u(q) \propto qu'(q)$, which means we can relate utility to aggregate real revenue ($qu'(q) \propto p(q)q$). From the definition of preferences and the consumer budget constraint, the following describes utility:

$$\begin{aligned} U = M^e \int u(q)dG &\propto M^e \int_0^{c_d} u'(q(c))q(c)dG(c) \\ &\propto \lambda L\Big(\int_0^{c_d} \frac{1}{1-\mu(q(c))} dG(c)\Big)\big(L - Nf - M^e f_e\big) \end{aligned} \tag{5}$$

where $N$ is once again the mass of varieties supplied and $\lambda$ is the Lagrange multiplier in the social problem of utility maximization. The last line uses the budget constraint (the total resources in the economy), and that $Cov(\frac{1}{1-\mu(q(c))}, cq(c)) = 0$. In this case, welfare is proportional to the average markup times the total labor used for production.

### 3.2.2 Utility with VES

I now generalize to the non-homothetic case where the subutility is not CES, which imples $Cov(\frac{1}{1-\mu(q(c))}, cq(c)) \neq 0$. In this case utility and aggregate revenue will diverge, and I show how to decompose this divergence. Since cost advantages are not fully passed through to prices, some firms under-produce and others over-produce, which distorts total revenue relative to the CES benchmark. [28] Furthermore, it has been known since at least Dixit and Stiglitz (1977) that an inefficiency exists even with homogeneous firms due to a distortion in the number of available varieties. I decompose the full welfare expression in the model to express clearly how the misallocation term in my model captures a distortion from the CES case and builds on the variety distortion described in this earlier work.

[28] Notice that this framework is consistent with the results of Edmond et al. (2015) and Arkolakis et al. (2019), who both find that it is the *joint distribution* of markups and production that matters. Alternatively, the intuition is that the whole distribution of markups matters, not the unweighted mean.

Aggregate revenue is defined as, $R = M^e L \int_0^{c_d} p(q(c))q(c)dG(c)$. I will work with the conditional distribution of $g(c)$ on $(0, c_d]$, defined as follows:

$$h_d(c)dc = \begin{cases} \frac{g(c)}{G(c_d)}dc & \text{if } c \leq c_d, \\ 0 & \text{if } c > c_d \end{cases} \tag{6}$$

It will be useful to define the average price level, $P \equiv \int_0^{c_d} p(q(c))h_d(c)dc$ and aggregate physical production sold, $Q \equiv NL \int_0^{c_d} q(c)h_d(c)dc$. Let the "elasticity of utility" be: $\epsilon(q) = \frac{\partial u(q)}{\partial q}\frac{q}{u(q)}$, the proportional increase in utility given an increase in the quantity of a variety. Then, as in Dhingra and Morrow (2019), the (utility-weighted) average elasticity of utility is $\bar{\epsilon} = \frac{\int \epsilon(q)u(q)}{\int u(q)}$. Using this definition, the indirect utlity function is defined as $V = \frac{1}{\bar{\epsilon}} M^e L \int u'(q(c))q(c)dG(c)dc$. I then plug in the inverse demand function, $u'(q(c)) = \delta p(q)$ (with $\delta$ as the marginal utility of income), and conduct algebraic manipulations on revenue, to decompose revenue within the indirect utility function:

$$V = NL\frac{\delta}{\bar{\epsilon}} \int_0^{c_d} p(q)q(c)h_d(c)dc$$

$$\Delta ln(V) = \Delta ln(1-\bar{\epsilon}) + \Delta ln(\delta) + \underbrace{\Delta ln\,(Q) + \Delta ln\,(P) + \Delta ln\left(\frac{\tilde{R}}{Q}\right)}_{\Delta ln(R)}, \tag{7}$$

where $\tilde{R} = \frac{R}{P}$. Vives (2001) on page 170 refers to $(1 - \epsilon(q))$ as "the proportion of social benefits not captured by revenues when introducing a new variety." Since the elasticity of utility is constant under CES preferences, in that case $\Delta ln(1-\bar{\epsilon})$ is zero.[29] Along with the change in the marginal utility, it will be a part of the change in indirect utility that I do *not* capture by focusing only on $\Delta ln\,(R)$, the part that is captured in the data. Note also that with a Pareto distribution of firm costs, entry is optimal (Arkolakis et al., 2019; Feenstra and Weinstein, 2017). Equation 7 motivates why we care about revenue: the change in revenue is a component of welfare growth.[30]

The central motive for this decomposition is to establish *the bias in revenue growth over time using CES demand relative to the generalized variable elasticity demand*, within the monopolistic competition framework described above. I argue that the last term is the bias in aggregate revenue that is not captured by the allocatively efficient case, which requires CES subutility. To get an intuition about the last term in 7, it is helpful to derive it from the

[29] In which case: $\frac{1}{\bar{\epsilon}} = \frac{1}{1-\bar{\mu}} = \frac{\sigma}{\sigma-1}$, with $\sigma$ the constant elasticity of substitution.

[30] Notice that the literature has mostly examined misallocation in the context of there being a non-optimal distribution of revenue across firms (i.e. Hsieh and Klenow (2009)).

aggregate revenue equation. I decompose aggregate revenue in terms of mean and variances using the covariance: $\text{Cov}(p,q) = \int_0^{c_d}(p(q(c)) - P)(q(c) - \frac{Q}{NL})h_d(c)dc$. Then,

$$\Delta ln\left(\frac{\tilde{R}}{Q}\right) \approx \Delta\left(\frac{\text{Cov}(\frac{1}{1-\mu}, l)}{\int_0^{c_d} p(q(c))h_d(c)dc \int_0^{c_d} q(c)h_d(c)dc}\right). \tag{8}$$

$\Delta \ln\left(\frac{\tilde{R}}{Q}\right)$ is therefore proportional to the covariance of the markup and labor allocation in each firm.[31]

In order for $\Delta \ln\left(\frac{\tilde{R}}{Q}\right)$ to represent the change in allocative efficiency captured by aggregate real revenue I will show that it is zero only in the case where there is no inefficiency, which is true when demand is CES. Furthermore, I eliminate the effects due to changes in the cost cutoff by assuming that $G(c)$ is a Pareto distribution with tail parameter $\kappa$.[32] In other words, the measure provides a sufficient statistic for the correction in real revenue due to reallocation that is not captured in the Melitz-Chaney framework. For this to be true, the following proposition is necessary:

**Proposition 1.** *In the VES directly additive framework described above, and if $G(c)$ is a Pareto distribution, then $\Delta \ln(\tilde{R}) = \Delta \ln(Q)$ if and only if demand is CES.*

*Proof.* In Appendix B.1 I take the case of CES preferences and Pareto distribution of costs and show that the right hand side of Equation 8 is zero.

The second part of the proof is to show that if $\Delta \ln\left(\frac{\tilde{R}}{Q}\right) = 0$ then preferences must be CES. Assume preferences are not the knife-edge CES case, then the within-sector preferences described in 2 are non-homothetic. Then, the price is a function of quantity and this contradicts that the left hand since of Equation 8 is equal to 0. ■

Given that the market power distortion exists only in the non-efficient market equilibrium, I label the change in the covariance term as $\Delta AE$:

$$\Delta(AE_j) = \Delta ln\left(\frac{\tilde{R}_j}{Q_j}\right) \tag{9}$$

Notice that this term is the log change of the *aggregate* markup, which depends on the joint distribution of markups and production. In the market allocation, high (low) markup

[31] Full details are in Appendix B.1. I write the covariance in terms of markups and labor by using $pq = \frac{p}{c}cq$, where $cq$ is the labor required to produce $q$ units.

[32] For this reason, the analysis should be viewed as reallocation across existing firms. Data availability would make it very difficult to capture the effect of entry on welfare without a more stylized model.

firms under- (over-) produce. *Reallocating production to the high-markup firms raises the aggregate markup and welfare.* The rise in welfare would be due solely to a compositional effect.[33] With constant markups this term is constant – in fact $\Delta \ln(V) = \Delta \ln(Q)$ in the CES case. Lastly, in a practical sense I take the level of aggregation to be an industry, so that this holds for each industry $j$ separately.

### 3.2.3 Discussion

ACDR propose a gains from trade decomposition with variable markups that is closest to the one in this paper, as it includes a misallocation distortion.[34] In that paper, a reduction in output tariffs has two effects: the distortion among domestic firms is *reduced* due to an increase in competition, but the distortion *increases* among foreign firms as they face lower marginal costs. Aside from providing a more direct measure of changes in allocative efficiency which is captured with aggregate data, in the next subsection I extend their work by capturing a particular foreign shock and isolate its effect on misallocation. I focus on an exchange rate shock because this reflects a shift in unit costs for importing firms. Therefore, I isolate the second channel in ACDR, but for domestic firms. I note that a similar analysis can be done for a rise in competition due to foreign entry, a demand shock that would also alter allocative efficiency through the compositional channel. In a very stylized model in Appendix D, I provide comparative statics for both supply and demand shocks on the *markup differences* between firms, with the expected result that an increase in foreign entry raises allocative efficiency in the domestic economy.

## 3.3 Quantitative Model of Importing with VES Preferences

In this subsection I highlight a mechanism that underlies how reallocation improves or worsens misallocation. I introduce an aggregate shock – in the form of an exchange rate shock – and show how the differential adjustment across firms sets off a reallocation that either increases or decreases misallocation. To connect the theoretical framework to the case of

[33] This is a result emphasized in recent papers: (Macedoni and Weinberger, 2019; Peters, 2020; Edmond et al., 2018; Baqaee and Farhi, 2017). However, the sufficient statistic that captures changes in this weighted markup is new. I will connect foreign shocks, firm reallocation, and misallocation transparently in 3.3.

[34] The measure is also similar to the Holmes et al. (2014) (HHL) allocative efficiency index that is separable from production efficiency to measure gains from trade. The features of that model are not geared towards how firms might pass-through costs shocks to prices, which has been shown to be a big part of short-term adjustments to trade liberalization (DeLoecker et al. (2016)). Misallocation in Edmond et al. (2015) is based on an aggregate TFP index due to homothetic demand, and is reduced through pro-competitive effects of greater competition (which can be incorporated in the VES framework above with a rise in the number of firms due to entry). The measure in Equation 9 can be viewed as a complement to these papers, based on a demand-side distortion.

Chile, which experienced large real exchange rate variation during the sample period highlighted above, I introduce an importing margin to a framework that features consumers with an explicit form of non-homothetic preferences nested in the general environment of Section 3.1. Although I choose one specific functional form for preferences, the advantage of the decomposition above is that it holds for any structure with VES preferences and the assumed Pareto distribution of firm productivity (e.g. Behrens et al. (2014), Melitz and Ottaviano (2008)).

### 3.3.1 Closed Economy

**Consumer Problem** Preferences will now take the specific functional form:

$$U = \int_{\omega \in \Omega} \ln(q(\omega) + \bar{q}) d\omega, \tag{10}$$

where $q(\omega)$ is individual consumption, $\Omega$ is the set of potentially produced goods, and $\bar{q} > 0$ is a constant. These preferences are detailed in Simonovska (2015), and can be interpreted as a restricted version of the "generalized" CES that have been applied recently by Jung et al. (2019) and Arkolakis et al. (2019).[35] For $\bar{q} = 0$, the utility function is homothetic, but a positive $\bar{q}$ implies that firms face less elastic demand as their sales increase. I make the latter assumption to guarantee that more productive firms have larger markups and higher sales, as is clear in the data.

**Firm Problem** Aside from the ability to import, the supply side is mostly identical to the setup in Section 3.1. However, to simplify the estimation, I drop the production fixed cost. The preferences outlined above feature a bounded marginal utility, which means that consumers do not have positive demand for all potentially produced goods. Firms pay an entry cost to draw their intrinsic productivity from a Pareto distribution with $\kappa$ the shape parameter of that distribution. Given the attributes of demand, there exists a choke price such that demand is zero for goods whose price exceed it. Since details of this model can be found in Simonovska (2015), I relegate large parts to Appendix B.2 and include only the most important components in the main text.

Given the preferences above and the setup described, the consumer first order conditions imply an inverse demand function that sets up the following firm profit equation (where

[35] In Appendix B.3 I show the more general model where the elasticity of substitution across varieties ($\sigma$) is allowed to vary. The restricted case examined here restricts $\sigma \to 1$, but either parameterization is consistent with the VES structure of the previous subsection.

firms are identified from their cost draw, $c$):

$$\pi(c) = \frac{L}{\lambda}\left(\frac{q(c)}{q(c)+\bar{q}}\right) - Lq(c)wc, \tag{11}$$

where the aggregate environment is taken as given for each firm and summarized by $\lambda = \int_0^{c^d} \frac{q(c)}{q(c)+\bar{q}} dG(c)$[36], and $w$ represents the real wage (once again normalized to one). Firms choose $q(c)$ to maximize profits, and setting quantity equal to zero yields the cutoff cost draw with positive demand:

$$c^d = (\lambda w \bar{q})^{-1} \tag{12}$$

As is common in the literature (e.g. (Arkolakis et al., 2019; Jung et al., 2019)), the competitive environment is summarized by a single aggregator, the market determined cost cutoff. Quantity demanded, price, and revenue can be written as a function of the the firms' cost relative to the market cutoff:

$$p(c) = wc \underbrace{\left(\frac{c^d}{c}\right)^{\frac{1}{2}}}_{\text{markup}} \tag{13}$$

$$q(c) = L\bar{q}\left[\left(\frac{c^d}{c}\right)^{\frac{1}{2}} - 1\right] \tag{14}$$

$$r(c) = L\bar{q}w\left[c^d - \left(c^d c\right)^{\frac{1}{2}}\right] \tag{15}$$

### 3.3.2 Importing

The ability to import inputs will generate interesting implications from a shock to the relative price of foreign and domestic goods. I introduce the ability to import in the simplest way possible, by making the assumption that the share of foreign inputs in the total input cost is proportional to firm productivity.[37] Although this is a stark assumption, it generates the differential response to a shock in the cost of imports, which is clearly enough to highlight the mechanism through which this shock generates changes in allocative efficiency.

[36] A useful feature of this framework is that it will not be necessary to solve for the general equilibrium term, $\lambda$, as is clear below.

[37] This restricts the set of firms to have positive imports. Although not modeled explicitly, it is consistent with conditioning on the firms that have paid a fixed entry cost for importing. A full structural model with non-importers and importers would include the entry cost $f_e$ above, plus a second fixed cost to enter the import market (akin to the export fixed cost in Melitz (2003)). However, with non-homothetic preferences, the decision to pay the second entry cost becomes burdensome, and would not add any insight in terms of generating changes in allocative inefficiency when all firms respond to the aggregate shock. The general model would produce *quantitatively* different results as only a subset of firms would receive a cost shock (the original importers plus any firm that enters/exits the import market).

I incorporate imports by differentiating between the intrinsic cost $c$, and a unit cost, $u$, which includes the cost reductions that result from importing. To model the cost reductions, I rely on the theoretical results of Blaum et al. (2018) which allows me to skip the sourcing decision. They show that in a variety of structural models[38], the unit cost is proportional to the domestic share of inputs. Directly from their results, I take the following specification for unit costs:

$$u(c) = wc(s_D(c))^{\gamma}, \qquad s_D(c) = \alpha(\tau^I)^{\beta}c^{1/\theta}. \tag{16}$$

$s_D$ is the share of inputs that are sourced domestically and $\gamma > 0$ reflects that a lower domestic share raises unit costs. The imported input share $(1 - s_D)$ differs across firms based on their heterogeneous cost draws, and is also a function of aggregate parameters. $\tau^I$ is the relative price of imports, $\beta$ is the elasticity of the domestic share with respect to the relative price of imports, and $\alpha$ scales the domestic share. $w$ captures the domestic input costs which I set to one as the numeraire. $c$ continues to be the firm cost draw, but the unit cost is now given by $u$, which can be computed by substituting in the expression for the domestic input share. Notice that the inverse of the domestic share is proportional to the cost draw of the firm, which captures the fact that there is a sorting in the data where more productive and larger firms have larger import shares.[39] To quantify the model, I set $\tau^I = 1$ to start and then vary it to mimic the exchange rate volatility. An appreciation lowers the relative price of imports and therefore $\tau^I$.

The firm problem follows the domestic economy case, where firms still draw their intrinsic cost from the same distribution, but now $u(c) = wc^{\frac{\gamma+\theta}{\theta}}(\alpha\tau^{\beta})^{\gamma}$. Thus, the new firm profit equation is given by, $\pi(c) = \frac{L}{\lambda}\left(\frac{q(c)}{q(c)+\bar{q}}\right) - Lq(c)w(\alpha\tau^{\beta})^{\gamma}c^{\frac{\gamma+\theta}{\theta}}$, where the general equilibrium object, $\lambda$, is identical to the closed economy case. Once again using the profit equation to solve for the marginal firm yields the new cost cutoff:

$$c^* = (w\lambda\bar{q})^{-\frac{\theta}{\gamma+\theta}}\left(\alpha(\tau^I)^{\beta}\right)^{\frac{-\theta\gamma}{\gamma+\theta}}. \tag{17}$$

Given the new unit cost of the firm, the aggregate environment can be expressed as a function of $\tau^I$. As the ability to import affects unit costs, firms now produce when $u(c) < c^*$, where the composition of firms is determined also by the importing environment. Since I am

[38] Halpern et al. (2015), Gopinath and Neiman (2014), Antras et al. (2017), Kasahara and Rodrigue (2008), Lu et al. (2016), Goldberg et al. (2010), Amiti et al. (2014).

[39] This assumption allows for a parsimonious framework to incorporate imports. One could combine a fixed importing cost with a separate draw from a distribution of domestic input shares. This structure could be used to create a closer relationship with the correlation of sales and imports in the data (by breaking the sorting that happens due to my assumption), but would only alter the results quantitatively.

interested only in deviations of aggregate measures with respect to a shock to the relative price of imports, without loss of generality, I set $c^d = 1$ and allow the composition of firms to change based on changes in $\tau^I$. To see the firm-level effect, for example take the case when the relative price of imports, $\tau^I$, is lower. $c^*$ increases as firms source more products from abroad and reduce their unit costs, production and revenues increase, and markups increase for all firms because the lower costs are only partially passed-through to prices.

Finally, one can solve for the aggregate statistics (see Appendix B.2) and then express the measure of misallocation as in Section 3:

$$\frac{\tilde{R}}{Q} = \left(\hat{c^*}(\tau^I)\right)^{-\frac{1}{2}(\frac{\gamma}{\theta}+1)} \left[ \frac{1 - \frac{\kappa}{\frac{1}{2}(\frac{\gamma}{\theta}+1)+\kappa}}{\frac{\kappa}{\frac{1}{2}(\frac{\gamma}{\theta}+1)+\kappa}\left(\frac{\kappa}{\kappa-\frac{1}{2}(\frac{\gamma}{\theta}+1)} - 1\right)} \right]$$

$$\Delta \ln\left(\frac{\tilde{R}}{Q}\right) = -\frac{1}{2}(\frac{\gamma}{\theta}+1)\Delta \ln(\hat{c^*}(\tau^I)) \tag{18}$$

A convenient feature of this formulation is the expression of the cutoff, $\hat{c^*}(\tau^I) = \frac{c^*(\tau^I)}{c^*(\tau^I=1)}$. In the quantitative analysis, the left hand side of (18) is set to one when $\tau^I = 1$, to measure *deviations* in allocative efficiency in response to exchange rate shocks. With importing, $\hat{c^*}(\tau^I)$ varies with $\tau^I$, as the competitive environment changes in the domestic economy. This is what leads to changes in allocative efficiency, scaled by parameters.

Why does this matter? The ratio of aggregate real revenue relative to aggregate production, or the aggregate markup, decreases with $\tau^I$, which I show quantitatively below.[40] The intuition is simple: responses to the shock are heterogeneous as they depend of the firm-specific ratio of their cost to the cutoff. More productive firms import more and are larger, hence have larger markups, so the differential response to changes in the aggregate environment result in a reallocation of labor. In Section 4.2, I estimate the model and simulate firms in this economy to show that a drop (rise) in $\tau^I$ generates relatively greater (smaller) increases in labor in firms with initially lower markups. This is the compositional change that drives Equation 9. As production is reallocated to lower markup firms, aggregate real revenue increases more slowly than production.

[40] In addition, markup dispersion increases, although this is not sufficient to measure misallocation in this model.

# 4 Allocative Efficiency in Response to Exchange Rate Shocks

A REER shock will induce the compositional effect in (9). In this section I conduct empirical exercises to quantify the effect. First, a reduced form specification suggests that the real exchange rate variation led to relatively different changes in allocative efficiency in industries depending on their exposure to imported inputs. I clarify the mechanisms at work by estimating the VES framework with imported inputs, which is disciplined with the Chilean data. For the same exchange rate variation observed in the data, the model generates changes in misallocation comparable to the reduced form findings.

## 4.1 Empirical Evidence

### 4.1.1 Measures of the Aggregate Economy

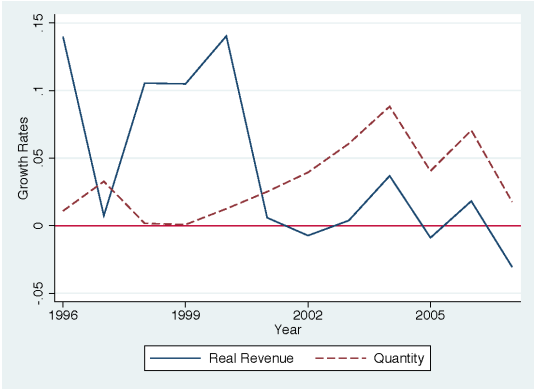
Before the difference-in-difference specification, I introduce the implications of the underlying markup heterogeneity by asking: during the period explored in Section 2, what was the performance of Chile's manufacturing sector? The time series of real income growth does not mirror that of physical production. Instead, real income growth was much smaller in the 2003-2007 period, and higher from 1997-2001, than would be expected given the rise in production. I compare two industry-level (2-digit ISIC) measures: the aggregate productivity growth (APG) defined in Petrin and Levinsohn (2012), which is equivalent to $\tilde{R}$, and the growth of total physical production ($Q$) as computed by the ENIA survey of firms (both measures defined in the data description above).

Figure 3 shows the growth rate of the two aggregates at the manufacturing level.[41] A complication is that the physical production index does not necessarily include all producing firms because it is based on a survey that chooses representative firms in the base year (though these firms make up 80% of manufacturing output). In addition it does not pick up entering firms (most likely small) between the two base periods. In the attempt to make the data as comparable as possible, I produce a revenue growth measure that only includes firms that are in the database for 7 years or longer. As a robustness check, I also compare results when the census of firms are included in the revenue measure. The aggregate data implies that revenue productivity grew much faster than physical productivity up until 2001. This

[41] Each is calculated at the 2-digit sector level and I aggregate to the manufacturing level using value added shares by sector. The results above allow for value added weights to change, but I have also used constant shares to eliminate across sector reallocation effects. The growth rates look almost identical, which reflects the fact that there is very little across sector reallocation.

trend was reversed after the terms of trade shock. The structural model in the next section describes how reallocation explains the difference between these two measures, and why this is entirely consistent with the markup heterogeneity explored above.

**Figure 3:** Real Income Growth versus Physical Production




Real revenue is the growth in the sum of deflated value added (minus primary input growth) at the 2-digit ISIC level. Economy-wide average taken by weighting each 2-digit group by its value added share. I allow for value added shares to change over time, although constant shares results in almost identical growth rates. Quantity growth is taken from the physical manufacturing index provided by the ENIA at the 2-digit ISIC level with same weighting scheme. Sector 27 is eliminated as in the rest of the analysis since this sector is made up mostly of copper.

I stress that the divergence in these two measures is large in economic terms. Take the following thought experiment: given a starting point for aggregate value added, what would be the implied real revenue at the end of a period if it is assumed to grow proportionally with physical output versus using the growth rate of the actual revenue growth? Using the respective growth rates aggregated to the manufacturing level, and aggregate value added in manufacturing in 1995 and 2002, I examine two sub-periods: a) Starting from 1995, ignoring the growth rate of misallocation results in revenue that is 41% below actual revenue in 2002 (translates to 2.3 trillion Chilean pesos, or 3.3 billion US dollars); b) Starting in 2002, ignoring misallocation results in revenue that is 22% greater than actual revenue in 2007 (translates to 2.5 trillion Chilean pesos, or 4.8 billion US dollars).[42] Given that these two measures move together absent any misallocation in the economy, these two separate sub-periods provide evidence that changes in allocative efficiency can provide either an amplification or dampening effect on aggregate income depending on whether the economy is becoming more or less resource efficient. [43]

[42] Manufacturing valued added accounts for 20% of the economy in 2002, and 13% of the economy in 2007.

[43] Using the full sample of firms for revenue growth slightly reduce the difference between these two measures but the signs remain the same.

### 4.1.2 Difference-in-Difference Analysis

To identify the aggregate allocative efficiency responses to Chile's exchange rate volatility, I estimate a difference-in-difference specification in which industries are treated differentially based on their exposure to the real exchange rate shock. This is analogous to the specification in Section 2.3, now measuring the aggregate response of the same shock, allowing for reallocation across firms with heterogeneous markups:

$$\Delta AE_{jt} = \alpha_j + \alpha_t + \psi \Delta REER_t * Expos_j + \zeta \Delta Z_{jt} + u_{jt}, \tag{19}$$

The main outcome is $\Delta AE$, the misallocation measure introduced in Section 3.2. I also check $\Delta cov(markup, inputs)$, which should move in conjunction with allocative efficiency given in (8).[44] $\alpha_t$ and $\alpha_j$ represent time (t) and industry (j) fixed effects respectively. $]REER$ represents the aggregate shock, but in the appendix results are reported for TOT.[45] $\psi$ measures the differential effect on industries "exposed" to the shock relative to other industries. The question is: "do industries that are more exposed to the large terms of trade appreciation have relatively lower growth in allocative efficiency?" Once again the baseline measure of exposure is the share of imported inputs, fixed to the beginning of the sample. I also control for export exposure as the fraction of sales that are exported. The industry exposure measure is constructed by averaging the firm-level shares across each industry. Given the results in the previous section, I expect that a REER appreciation will have a larger impact on the allocative efficiency of industries with a larger share of importers.

**Results** Table 3 displays the results for industry level outcomes in response to variability in the REER. The first two columns illustrate that industries with a higher exposure to importing intermediates than exporting their final product become more misallocated in response to an increase in the terms of trade. The second column reports the same specification with the alternative import share measure. Notice that by normalizing the maximum import share to one, the coefficients can be interpreted as the differential growth in allocative efficiency in a fully treated industry (the most import intensive) relative to a non-treated industry (import share of zero). The results in column (1) and (3) suggest a treated industry

[44] I calculate the covariance of the markup with both material inputs and labor costs. In the theory, labor is the only input (costing $cq$), so my reported results reflect the covariance of the markup with wages paid.

[45] One might worry about an omitted variable bias as exchange rates respond endogenously to other macro shocks. In Chile, the appreciation in 2003-2006 is plausibly exogenous as it is due to an unexpected boom in copper prices. I eliminate all copper-related industries from the regressions and interpret the copper price shock as exogenous to other industries. I also include various controls for possible simultaneous shocks that affect exposed industries differentially.

has about a 1.64-1.67 percentage points lower growth rate in response to a 1% increase in the growth of the real effective exchange rate. As expected, the importing industries become more misallocated with a REER appreciation.[46] In columns (5) and (6), the signs are consistent when replacing the allocation efficiency measure with the covariance of markups and labor expenditure. The interpretation of these columns is consistent with higher misallocation as a result of allocating inputs away from the more productive firms. The lower input costs allow for productivity gains, but more productive firms pass-through relatively more of their cost reductions to markups, thus raising misallocation.

The strength of the baseline result depends on the plausibility of the identifying assumptions. First, that there are no contemporaneous shocks that affect high-exposure industries differentially, and second that exposed and non-exposed industries are on parallel trends prior to the REER shock (and would have continued on these trends but for the shock). To check the first identifying assumption, I focus on possible omitted variables that might be correlated with the exposure measure (the treatment). These include growth rates of important industry-level time-varying characteristics: the industry output tariff, the average revenue productivity (TFP estimated with revenue data), and the ratio of unskilled workers to employment. Furthermore, I add an interaction of a post-2002 indicator with a time-invariant measure of the copper exposure of an industry. The copper share is computed using the input-output tables, and captures how each industry is used as *an input* to the production of copper. I limit the analysis to the inclusion of this short list of controls as they capture a wide variety of potential shocks that might also explain the reallocation process that leads to changes in $\Delta AE$. Trade liberalization can have important effects on import competition to domestic industries and could affect the access to inputs. I use the TFP measure to capture demand shocks, as a TFP measure estimated with revenue data is correlated with demand shocks (see Foster et al. (2008)). The copper measure interaction is added for a similar reason. There is a huge demand shock for copper internationally after 2002 (as discussed above), which mechanically raises the demand of any input to copper.[47] The skill ratio has been shown to respond to technology and trade shocks, and so captures whether these occur in the exposed industries. However, these controls do not seem to alter how the interaction with REER shocks moved allocative efficiency. Columns (3) and (4) report the same specification as the first two columns, adding these possibly omitted shocks as controls.

[46]Tables 14-16 in the Appendix provide robustness checks. I check that these results hold for varying exposure shares, when exposure is expressed as fraction if importing (but not exporting) firms, and using TOT variation instead of the REER.

[47]Foreign competition and demand shocks lead to changes in $\Delta AE$, as discussed above. Aside from the controls discussed here, robustness checks in the appendix check for alternative outcome measures in (19) and do not suggest that demand shocks simultaneous to the REER shocks affect treated industries (Table 11.

As in any study of this nature, there are potential unobservables that are not captured by the set of controls discussed above. To identify the differential $\Delta AE$ across industries of differing exposure, the argument is that the divergence would not have occurred *but for* the unexpected REER shock. I now test the second identifying assumption using a dynamic analysis of the outcome, comparing treated and untreated industries. As I have argued previously, although I use all the time series variation in the REER, the cleanest shock happens after 2002 with the sharp increase in the terms of trade (Figure 1). Figure 4 plots the $\Delta AE$ responses of treated firms *across time*. The coefficients (plotted on the y-axis) reflect the interaction of the treatment with each year dummy, dropping 2002, where the treatment varies between 0 and 1 as I normalize the import share of each industry by the maximum import share. For example, in 2003, 2005, and 2006, the growth in allocative efficiency is 1 percentage point lower in a fully treated industry relative to a non-treated industry. The figure is consistent with the story advanced thus far: the large TOT appreciation after 2002 reflects a shock that acts upon $AE$ in treated (importing) industries relative to non-treated ones. Finally, essential for the test of the parallel trend assumption, there is no appearance of a pre-trend prior to 2002. There is strong evidence that the assumption that treated and non-treated industries would have followed paths of $\Delta AE$, but for the unexpected appreciation after 2002, is valid.

**Robustness** Appendix C.1 contains further robustness checks that I summarize in that section. First, C.1.1 includes various outcomes that could represent shocks that are simultaneous to the REER variation. Second, I note that standard errors are clustered at the sector level (Bertrand et al., 2004), but in Subsection C.1.2 I also conduct various checks related to the possibility that standard errors are under-estimated. To account for serial correlation, I present several specification where standard errors are corrected for autocorrelation. I also eliminate serial correlation altogether by taking long differences and estimating a triple differences specification that assumes the REER shock can be separated between a pre-period (1995-2002) and a post-period (2003-2007). Finally, I conduct a randomization inference test where the treatment is randomly assigned, and I obtain placebo estimates of the interaction of the placebo treatment and the REER growth. I provide strong evidence that the effect captured in the baseline specification would not appear by chance.

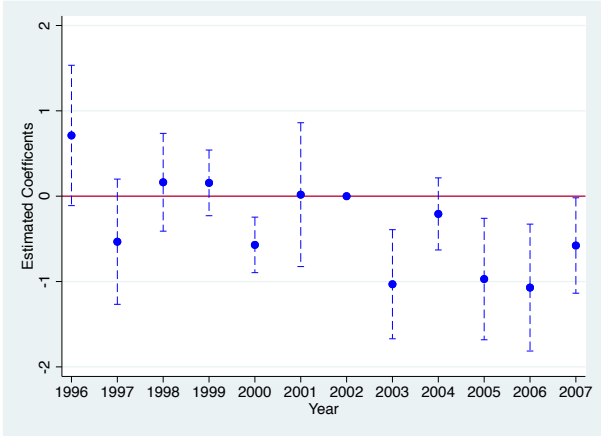
In summary, I have provided evidence for the differential growth in allocative efficiency between importers and non-importers in response to real exchange rate shocks. Still, the measure of misallocation derived in this study admittedly picks up possible within-industry reallocations for reasons that I cannot account for, and with a small number of sectors, fully tackling the error of serially correlated errors is difficult. However, it is important

**Table 3:** Industry Responses to Exchange Rate Shock: Fixed Exposure Shares

| | Δ AE | | | | Δ Cov(markup,inputs) | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Δ REER*Imported Share | -1.635*** | | -1.673*** | | -1.170 | |
| | (0.506) | | (0.425) | | (0.675) | |
| Δ REER*Imported Share (sales) | | -1.393*** | | -1.439*** | | -0.960 |
| | | (0.374) | | (0.322) | | (0.571) |
| Δ REER*Exported Share | -0.547 | -0.404 | -0.645 | -0.498 | 2.029** | 2.145** |
| | (0.915) | (0.866) | (0.708) | (0.679) | (0.906) | (0.880) |
| Year ≥ 2003*Copper Share | | | -0.423 | -0.404 | 0.534 | 0.529 |
| | | | (0.530) | (0.532) | (0.483) | (0.485) |
| Δ Tariff | | | 0.028 | 0.029 | -0.009 | -0.009 |
| | | | (0.023) | (0.023) | (0.035) | (0.035) |
| Δ Ratio Unskilled L | | | 1.270** | 1.266** | 0.080 | 0.079 |
| | | | (0.578) | (0.578) | (0.475) | (0.475) |
| Δ Avg TFP | | | 0.795 | 0.797 | -0.679** | -0.678** |
| | | | (0.531) | (0.530) | (0.255) | (0.256) |
| Fixed Effects | Year,Sector | Year,Sector | Year,Sector | Year,Sector | Year,Sector | Year,Sector |
| $R^2$ | 0.243 | 0.243 | 0.295 | 0.295 | 0.339 | 0.338 |
| N | 192 | 192 | 192 | 192 | 176 | 176 |

This Table reports the response in aggregate industry allocative efficiency in response to REER shocks, where industry exposure is based on the share of inputs imported, controlling also for share of sales exported. Dependent variables are $\Delta AE$ (columns (1)-(4)), and Δ Cov(markup,inputs) (columns (5)-(6)). Columns (1), (3) and (5) use the share of imports in material costs, while the other columns use share of imported inputs in total sales. These shares are fixed over time and normalized by the maximum import share, so that the treatment exposure varies from 0 to 1. Outcomes and exposure measures are at the 2-digit ISIC level of aggregation. For the covariance I use first differences, while the first 4 columns are growth rates. $\Delta REER$ is a one year growth rate. Industry controls are shown in the table. All regressions include sector and year fixed effects and standard errors clustered at the 2-digit industry level (in parenthesis). All regressions are weighted by value added across sectors, which gives an empirical counterpart to the model if utility is assumed to be a Cobb-Douglas aggregate of industries. As in 4.1.1, I eliminate firms that do not produce for 6 consecutive years. In results that do not eliminate these entering firms, the regression results are very similar both qualitatively and quantitatively. I drop the basic metal industry (ISIC 27). $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

**Figure 4:** Dynamic Effects: Annual $\Delta AE$ Responses of Treated Firms (Import Share)




This specification follows 19, but interacts the exposure treatment by separate year dummies instead of the REER. I normalize the exposure to be between 0 and 1 by normalizing each industry's import share by the maximum import share. I drop the interaction with year=2002. The coefficients are interpreted as the difference (relative to 2002) in the growth of allocative efficiency in a fully treated industry relative to a non-treated industry. The import share is calculated as total imported inputs relative to input expenditure at the firm level, then averaged across firms for each 2-digit industry. We drop the variable interacted with the year 2003 dummy. Dashed vertical bars represent 95% confidence intervals. All regressions include sector and year fixed effects and standard errors clustered at the 2-digit industry level. I drop the basic metal industry (ISIC 27).

to note with respect to inference that OLS is still unbiased and consistent if one accepts the diff-in-diff design. Although there are no studies I am aware of that connect exchange rates to misallocation, the effect I highlight is fully consistent with studies of incomplete pass-through such as Berman et al. (2012), Amiti et al. (2014), and DeLoecker et al. (2016). Theoretically, Arkolakis et al. (2019) also show that the covariance between markups and labor (the only input in their model) tracks allocative efficiency, and my interpretation of allocative efficiency as "unrealized differences in aggregate productivity growth" tracks Petrin and Sivadasan (2013). The reduced form evidence connect these literatures. In the next subsection I confirm the underlying mechanism with a quantitative analysis of the model where firms can reduce unit costs by importing inputs. The ability to isolate the compositional channel strengthens the claim that the specific channel which I claim drives the results above is present.

## 4.2 Quantitative Analysis

To shed light on the underlying mechanism through which exchange rate variation impacts allocative efficiency, I evaluate counterfactual changes in $\tau^I$ through the model in Section 3.3. The first step is to estimate 4 parameters that govern novel moments of the model: $(\alpha, \gamma, \theta, \beta)$.[48] For the shape of the Pareto distribution, $\kappa$, I set a value of 4 which is now standard in the literature (Simonovska and Waugh (2014)).

I use a simulated method of moments (SMM) approach and target 4 moments from the data, all described in Section 2.3. Two of the moments concern the aggregate import data. The average firm import share is used to discipline $\alpha$. $\beta$ governs the aggregate change in imports with respect to a change in import costs, which affects all firms equally. For that reason I match the log change of the aggregate import share with respect to the log change in the REER, an elasticity equal to -3.98.[49] The final two moments relate to the relationship between the import share and unit costs. Although costs are not available in the data, they determine sales and markups in the model so instead I match the firm-level statistics presented in Table 1. The cross-sectional relationship between relative sales and import shares (column (6) in the Table) will identify $\theta$, while the average change in the lerner markup with respect to changes in the import share within firms (columns (1)) identifies

[48] In Appendix B.3, I report how a model could be generalized to parameterize demand curvature, with an extra parameter. It does not feature the closed form solutions of the restricted version I use in this paper, but can be solved numerically. Qualitatively it shares the same features in terms of the relationship between productivity and markups, but quantitatively it affects the correlation between sales and productivity as the parameter governs the level of market power for each firm.

[49] As described in Section 2.3, I take the change in the aggregate import share after the terms of trade shock relative to the import share before the shock.

$\gamma$. Notice that the parameter $\bar{q}$, which governs the "love of variety" in the model, is not necessary to estimate the model. This is because the parameter would only be needed for the *level* of the cost cutoff, and cancels out in all the moments targeted.

I solve the model via simulation because the moments in the model that pin down the parameters require a distribution of firms. The procedure consists of simulating a large enough number of draws so as to best approximate the entire continuum of firms that exist in the model. I follow the application in Jung et al. (2019), and relabel firm-level indicators that can be simulated from a parameter-free uniform distribution. Recall that the pdf of the cost distribution is given by $h(c) = \frac{\kappa}{c^{-\kappa-1}}$. I draw one million realizations of the uniform distribution on the domain, $U \sim [0; 1]$, order them in decreasing order, and find the maximum realization, denoted by $u_{max}$. Then, the firm cost is $c = (u/u_{max})^{1/\kappa}\, \hat{c^*}$. I normalize $(\hat{c^*})$ equal to $\alpha^\gamma$ in the case where $\tau^I = 1$, so that $(w\lambda\bar{q})^{-\frac{\theta}{\gamma+\theta}} = 1$. This is without loss of generality, as all moments can be written without these parameters.[50]

The simulated firms are used to construct the model-implied moments described above, which are matched to their counterpart in the data. Let $F_i^m(\alpha, \gamma, \theta, \beta)$ be the vector of model generated moments, where $i$ represents each moment, and let $F_i^d$ denote the corresponding value of the empirical moments.[51] Identification consists of choosing the parameter set that minimizes the sum of the squared errors between empirical and theoretical moments:

$$\min_{\alpha,\gamma,\theta,\beta} \sum_{i=1}^{4} \left(F_i^d - F_i^m(\alpha, \gamma, \theta, \beta)\right)^2. \tag{20}$$

The cross-sectional moments are computed at $\tau^I = 1$, with the response of aggregate imports as well as firm markups and import share then computed after a drop in $\tau^I$ to 0.90. The model moments match the data exactly in this exact-identification procedure. After calibrating the parameters, I study the implications for allocative efficiency when $\tau^I$ varies between 0.8 and 1.2.[52]

Table 4, Panel A, displays the parameter estimates in an exactly-identified estimation as well as the moments targeted. The parameters mostly do not have close comparisons in the literature, but are based on reasonable data moments established in the summary statistics. For example, a trade elasticity around -4 is very slightly smaller than Blaum et al. (2018). Qualitatively, the fact that markups increase as importing is cheaper, and that larger firms import more, is well established (Berman et al., 2012; Amiti et al., 2014).

[50] For changes in $\tau^I$, I re-compute the set of firms.

[51] Appendix C.2 provides details on this estimation procedure.

[52] The parameters are fixed based on the response to a 10% depreciation.

**Table 4:** Calibration Results

Panel A: Moments and Parameter Estimates

| Moments (targeted) | Data | Model | $\hat{\alpha}$ | $\hat{\gamma}$ | $\hat{\theta}$ | $\hat{\beta}$ |
|---|---|---|---|---|---|---|
| Mean Import Share | 0.19 | 0.19 | 1 | 0.17 | 1.41 | 0.92 |
| Relative Sales-Import Share Coeff. | 0.83 | 0.83 | | | | |
| Change in Markup w.r.t. Import Share | 0.095 | 0.095 | | | | |
| Aggregate Trade Elasticity | -3.98 | -3.98 | | | | |

Panel B: Out of Samples Moments

| Moments | Data | Model |
|---|---|---|
| Import Share, $\tau^I$ 1 to 0.9 | 0.161-.237 | 0.151-0.239 |
| Mean Markup | 0.22 | 0.12 |
| SD of Log Sales | 1.60 | 1.40 |
| Markup-Import Share Coeff. | 0.056 | 0.84 |
| Change in Sales w.r.t. Import Share . | 0.23 | 0.1 |

Panel A reports the parameter estimates as well as the data moments that I target in the model estimation. The data moments are all reported in Section 2.3. In all cases with the import share, I take the measure which normalizes with total input costs (results are very similar with the other measure). In Panel B, I compute moments in the data and using the simulated firms. The import share change is compute with a 10% reduction in $\tau^I$ to reflect the shock to real exchange rates in the data. $\kappa$ is fixed to the value of 4.

Panel B reports out of sample moments from the import, markup and sales distributions in order to highlight some restrictions of the model. The model matches well the rise in the average import share from the pre- to post-period (first row). The average markup across simulated firms is about 12%, versus 22% in the data, while the standard deviation of sales is slightly smaller in the model than the data (although both would increase with a lower fixed $\kappa$).[53] The last three rows are based on columns (3)-(5) of Table 1. There are two important ways the model is overly restrictive in the cross-sectional relationships. First, the sorting in the data between importing and firm markups/sales is clearly not due only to differences in intrinsic productivity. Therefore, the cross-sectional relationship between imports and firm outcomes is weak in the data as seen in the fourth row. Sales are slightly more responsive to changes in import share in the data but the model does well in this regard. Second, the assumption of log-linear demand preferences restricts the markup and sales distributions to be the same.[54] In Appendix C.2 I show how generalized preferences, with a parameter for demand curvature which lowers the markup-sales correlation and raises

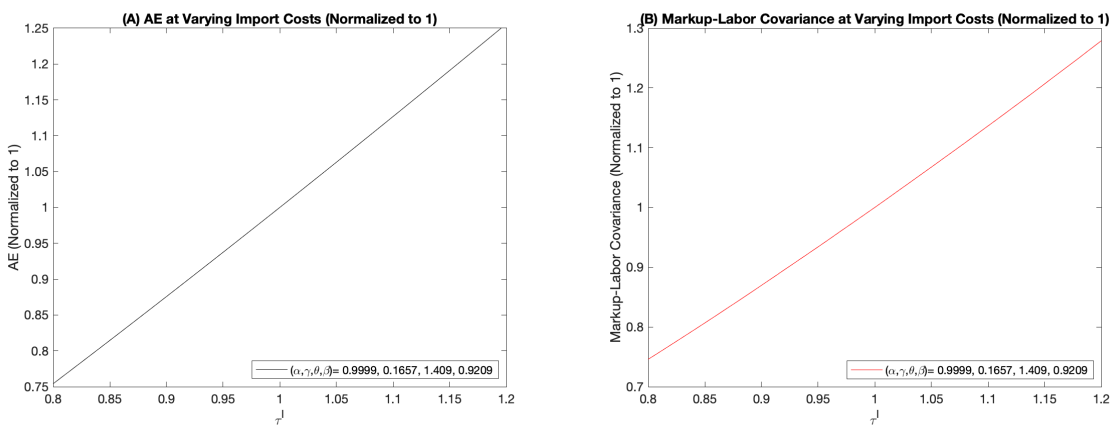
[53] A lower $\tau^I$ raises firm markups and raises markup dispersion – consistent with Table 2.

[54] This is the reason the model yields the same relationship of import share with markups and sales both in the cross-sectional and with respect to change in import share. In the data, these are clearly not the same.

the sales heterogeneity, affects the results. Reproducing all the interactions between sales, markup, and import distributions is beyond the scope of this paper, but the ability to reproduce much of the qualitative relationships will allow this model to generate a large share of the changes in allocative efficiency observed in the data.

**Counterfactual** With the necessary parameters in hand, I next investigate how changes in $\tau^I$ affect the allocative efficiency of the economy. Consider a counterfactual where $\tau^I$ ranges between 0.8 and 1.2, where $\tau^I > 1$ reflects a depreciation in the real exchange rate and $\tau^I < 1$ an appreciation. Panel A of Figure 5 displays the aggregate real income to quantity ratio, $\left(\frac{\tilde{R}}{Q}\right)$, at varying $\tau^I$'s. As an example, a 10% appreciation, which reduces the relative price of foreign goods, generates a reduction in allocative efficiency of 13%. Although aggregate revenues *increase* due to an appreciation, the rise in welfare is dampened by the welfare-reducing reallocation.

**Figure 5:** Effects of a Cost Shock on Allocative Efficiency




Panel A reports the allocative efficiency statistic (normalized to 1 when $\tau^I = 1$) as $\tau^I$ varies between 0.8 and 1.2. Panel B reports the markup-labor covariance, once again normalized to one. These are calculated using the parameter estimates from Table 4. $\kappa$ is fixed at 4.

Panel B of Figure 5 plots the markup-labor covariance for $\tau \in (0.8, 1.2)$, which is proportional to allocative efficiency in (8) and responds similarly to the shock in Table 3 (last two columns). A real exchange rate appreciation, which lowers the cost of imported inputs and raises markups, also reduces the markup-labor covariance. This reflects the fact that there is a reallocation of labor from high-markup to low-markup firms relative to the case where all firms choose a constant markup. It is the mechanism through which exchange rate shocks affect the allocative efficiency of the economy. The opposite effect is true for an exchange rate depreciation, where Figure 5 reports that the markup-labor covariance and allocative efficiency both increase.

The counterfactual can be compared to the reduced form regressions that measure the changes in allocative efficiency in response to changes in the REER. In this simplified model, on average each 1% appreciation generates a reduction in allocative efficiency of 1.27 percentage points in an industry where the import share is equal to the mean in the data. The reduced form results in Table 3 (column (3)) suggest that each 1% increase in the growth of the real exchange rate reduce allocative efficiency by 0.65 percentage points in an industry where the import share of inputs is equal to the mean import share, 0.19.[55] The model therefore captures twice the change in allocative efficiency implied by the reduced form analysis. There are a few possible reasons for the discrepancy. First, the reduced form results could be capturing counteracting effects on allocative efficiency not included in the model. To show the mechanisms transparently, I simplify the model such that all firms import and one parameter maps productivity to import shares. Furthermore, the way that changes in the cutoffs lead to more or fewer firms in the model might be missed by the limited entry in the data (maybe due to the censoring of firms). Second, although Chile experiences a depreciation from 1998-2002, Figure 4 suggests $\Delta AE$ does not increase as significantly, which is consistent with contemporaneous shocks during this period creating a downward bias. Overall, it is reassuring that the model-simulated effect on misallocation is in the quantitative vicinity of the reduced form estimate.

In robustness results in Appendix C.2, I check sensitivity to deviations in the calibrated parameters. First, I re-estimate the model under a slight change in the data moments. Since changes in allocative efficiency are most sensitive to $\beta$ and $\gamma$, I start by targeting a higher change in markups with respect to the import share (raise it to 0.14), but otherwise keep the same moments. Allocative efficiency drops more with an appreciation due to the larger $\gamma$. Re-calibrating with a trade elasticity assumed to equal to -5, thus mainly raising $\beta$, leads to a larger drop in $AE$. Second, I assume preferences take a more generalized form, with a parameter that governs demand curvature, and estimate allocative efficiency for a rise in this parameter. In this case, the drop in $AE$ is very slightly *smaller*, the average markup is lower, and the sales dispersion is larger. As firms have less ability to price discriminate (because consumers are more price sensitive as $\sigma$ increases), the compositional effect due to changes in $\tau^I$ is smaller. In this case, the correlation between sales and markups decreases to just 0.33 (recall it is one in the benchmark model).

[55] Since the exposure is constructed as relative to the maximum import share, which is equal to 0.49, this hypothetical industry has an "exposure" equal to 0.39. This is multiplied by 1.675, the coefficient reported in column (3) of the table.

# 5 Conclusion

This study examines how changes in allocative efficiency can be a result of shocks that alter the relative price of foreign and domestic goods. The distortion that keeps the market economy away from allocative efficiency is the heterogeneity in market power. In this framework, exchange rate shocks are passed through to prices differentially across firms and I show this effect can have important welfare effects using the case of Chile. Chile experiences large exchange rate variations, partly due to demand shocks for its commodities. In response, exposed firms respond by varying their markup and this generates a reduction in markup dispersion during the depreciation period and an increase in dispersion during the appreciation period. In this context, the mechanism I find most compelling is incomplete pass-through of revenue productivity gains that are heterogeneous across the firm distribution within an industry. Changes in misallocation suggest that the assumption of preferences that yield constant markup would result in a mismeasurement of how reallocation impacts real revenue growth.

Chile can be characterized as an exporter of natural resources, especially copper, and importer of intermediate goods. It is therefore not surprising that there is a significant benefit for Chilean firms in terms of cheaper imported inputs. On the other hand, it is not clear how much its domestic producers are affected by an increase in global competition. Other countries could have a very different composition of exports and imports. They might import mostly final goods and export goods higher up in the vertical specialization ladder. This would mean that trade liberalization can have a more dramatic effect in terms of increasing competition in the manufacturing sector, as is convincingly shown in Feenstra and Weinstein (2017). Future research should consider the importance in the composition of imports and exports to how domestic firms respond to global shocks.

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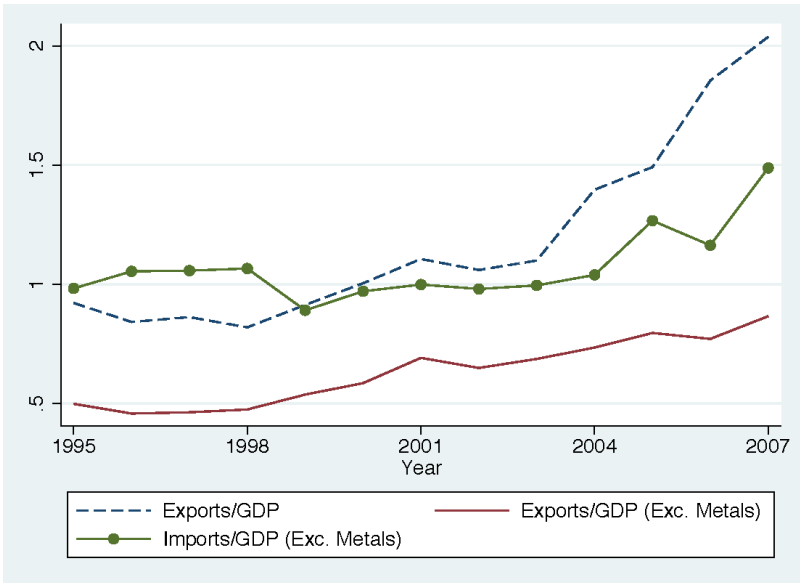
# Appendices

## A Open Economy Data and Firm Level Responses

### A.1 Open Economy Trends

**Figure 6:** Exports and Imports as a share of GDP, 1995-2007



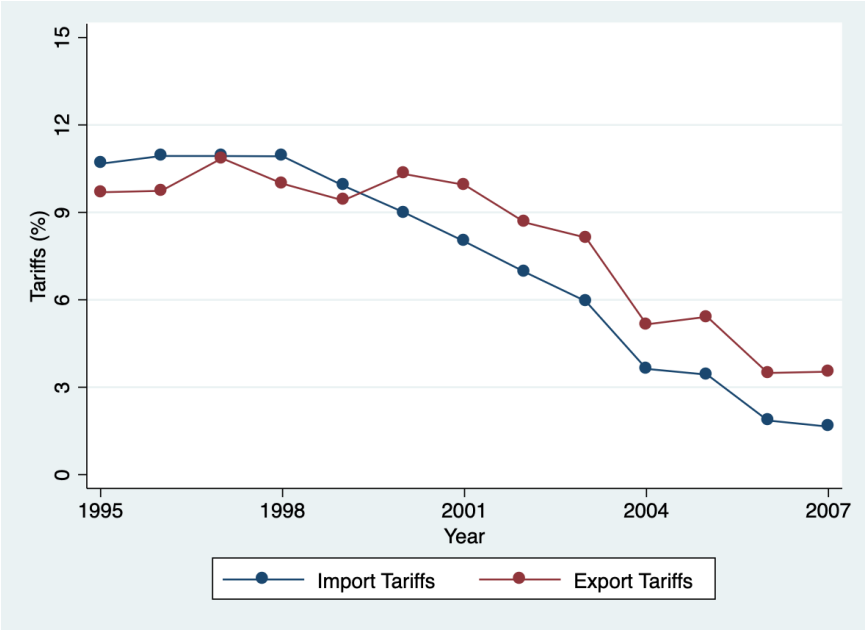

*Sources: Trade data from Feenstra et al. (2005), and manufacturing GDP from Banco Central de Chile.* Manufacturing GDP and manufacturing exports/imports are both in thousands of current US dollars.

### A.2 Aggregate Data Definitions

Here I describe the measures constructed from the right hand side of Equation 9. $\tilde{R}$ equivalent to the Aggregate Productivity Growth (APG) that is used in Petrin and Levinsohn (2012) and Basu and Fernald (2002), which tracks welfare without taking into account variety. In words, $\tilde{R}$ is the sum of deflated value added, subtracting out the growth in inputs. $\Delta ln(\tilde{R}_t) = \Delta ln(Y_t) - \Delta ln(L_t)$, where $Y_t$ (sum of deflated value added) is real revenue if all production income goes towards final demand. $\Delta ln(L_t)$ corrects for changes in expenditure on labor (wage growth in the data) so that the APG measure is not driven by differential wage trends across sectors or labor reallocating across sectors.

*Measurement of* $Y_t$ ("Final Demand"): At the firm ($i$) level, $Y_i = Q_i - \sum_j X_{ji}$, where $X_{ji}$ are inputs sourced from some firm, $j$. By the National Accounting Identity, aggregate final demand is equal to aggregate value added: $\sum_i P_i Y_i = \sum_i VA_i \ = \sum_i P_i Q_i - \sum_i \sum_j P_{ij} X_{ji}$.

**Figure 7:** Average Applied Import and Export Tariffs 1995-2007




*Source: Comtrade Database, downloaded from World Integrated Trade Solution (WITS).* Bilateral tariffs are aggregated to 4-digit level using an unweighted average of 6-digit tariff lines, and then weighted by trade shares to get an average applied tariff rate across all trade partners. Export tariffs are an average of tariffs charged by all importers of Chilean goods.

Information on the construction of aggregate price indices can be found at: `http://www.ine.cl/canales/chile_estadistico/estadisticas_economicas/industria/enia/pdf/deflactor_dos_completo_07_09.pdf` (Note: This is in Spanish). The index is calculated using a Laspeyres index and is aggregated to the 4 digit ISIC using data on 7-digit products. Deflators are constructed for both output and input prices, so that the value added is "double deflated."

Information on the construction of the quantity index can be found at: `http://www.ine.cl/canales/chile_estadistico/estadisticas_economicas/industria/series_estadisticas/archivos/base2002/manufacturera_metodologico_base_promedio_2002.pdf` The goal as described by the INE is to "measure the evolution of quantities and qualities at the product level by eliminating the influence of prices." They sample a set of firms from 1989-2002 and 2001-2007 (the overlap makes it possible to have a continuing time series of growth rates). Although the sampled firms are not the universe of firms in the census, they do make up about 80% of manufacturing value added. However, it does mean I am not picking up the smallest firms and some new enterers, which is why I only use firms that exist for more than 6 years in the construction of real income (though the results look similar without dropping these firms). As with the price indices, the INE constructs a Laspeyeres index with value of

sales as weights at a disaggregated product level and then aggregate up to the 3 digit level.

## A.3 Production Function and Markup Estimation

The production function must follow the following functional form:

$$Y_{it} = F(L_{it}, X_{it}, K_{it}; \beta)exp(\omega_{it})$$

$\beta$ is the vector of output coefficients, $\omega_{it}$ is a firm's $(i)$ productivity at time $t$, $\epsilon_{it}$ the measurement error, and $\{L_{it}, X_{it}\}$ are the set of variable inputs (labor and materials). Given data constraints, $Y_{it}$ is deflated total sales.[56] I take logs and use a Gross Output, Translog production function:

$$y_{it} = \beta_l l_{it} + \beta_{ll} l_{it}^2 + \beta_k k_{it} + \beta_{kk} k_{it}^2 + \beta_x x_{it} + \beta_{xx} x_{it}^2 + \beta_{lk} l_{it} k_{it} + \beta_{lx} l_{it} x_{it} + \beta_{kx} k_{it} x_{it} + \beta_{lkx} l_{it} k_{it} x_{it} + \omega_{it} + \epsilon_{it}$$

$l, k, x$ refer to the logged value of labor, capital and intermediate inputs respectively. I estimate each 2-digit industry separately, using 4-digit industry input and output deflators provided by the Chilean Statistics Institution (INE). Notice that this Translog production specification allows for heterogeneous firm level output coefficients.[57] Importantly, I incorporate exporter and importer dummies into the ACF methodology as state variables to the firms' production decisions. This allows exporters and importers to follow a different production technology, following the strategy of Kasahara and Rodrigue (2008) (they add an importer dummy as a state variable), and DeLoecker and Warzynski (2012) (they use export status similarly). Specifically, in the first step of the ACF procedure for the production function estimation, I add imports and exports into the intermediate input demand function of the firm.[58][59] Furthermore, these dummy variables are used in the estimation of survival probabilities (using a Probit function) that control for non random exit of firms as a determinant of next-period productivity.[60]

[56] Labor is the number of total workers. I combine skilled and unskilled although they can be split up using a subjective classification of labor categories. Capital and materials are both expressed as total deflated value of the input.

[57] Given the production function above, the output elasticity of materials for example is: $\theta_{it}^x = \beta_x + 2\beta_{xx} x_{it} + \beta_{lx} l_{it} + \beta_{kx} k_{it} + \beta_{lkx} l_{it} k_{it}$. $\beta$s are constant by sector for all years, however notice that $\theta_{it}^x$ depends on firm and year specific input values. Output elasticities are therefore firm and year specific.

[58] For a full account of the 2-step procedure see Olley and Pakes (1996), Levinsohn and Petrin (2003), or Ackerberg et al. (2015).

[59] Or in the Olley and Pakes (1996) framework, the investment demand function. This gets inverted to get a non-parametric function for the unobserved productivity shock.

[60] See Olley and Pakes (1996) for a full discussion about the necessity to account for exit/survival.

**Table 5:** Factor Coefficients and Markups by 2-digit ISIC Sectors

| | | | | (1) | | |
|---|---|---|---|---|---|---|
| | Obs | $\theta_L$ | $\theta_K$ | $\theta_M$ | Ret Scale | Median Markup |
| Food products and beverages | 19475 | 0.218 | 0.073 | 0.757 | 1.048 | 1.192 |
| Manufacture of textile | 3462 | 0.336 | 0.083 | 0.666 | 1.085 | 1.206 |
| Wearing apparel | 3846 | 0.349 | 0.047 | 0.665 | 1.062 | 1.219 |
| Tanning and leather | 2095 | 0.433 | 0.054 | 0.657 | 1.145 | 1.034 |
| Manufacture of wood | 4382 | 0.240 | 0.051 | 0.773 | 1.064 | 1.264 |
| Manufacture of paper | 1803 | 0.187 | 0.089 | 0.745 | 1.020 | 1.358 |
| Publishing, printing | 3017 | 0.285 | 0.111 | 0.633 | 1.029 | 1.323 |
| Manufacture of chemicals | 3740 | 0.283 | 0.105 | 0.667 | 1.055 | 1.360 |
| Manufacture of rubber and plastics | 4085 | 0.221 | 0.072 | 0.734 | 1.027 | 1.352 |
| Other non-metallic mineral products | 2837 | 0.191 | 0.064 | 0.802 | 1.057 | 1.540 |
| Manufacture of basic metals | 1503 | 0.128 | 0.139 | 0.747 | 1.015 | 1.412 |
| Fabricated metal products | 4760 | 0.243 | 0.059 | 0.675 | 0.977 | 1.189 |
| Machinery and equipment | 2923 | 0.508 | 0.098 | 0.489 | 1.095 | 0.993 |
| Electrical machinery | 1199 | 0.246 | 0.074 | 0.682 | 1.002 | 1.260 |
| Manufacture of instruments | 365 | 0.178 | 0.046 | 0.778 | 1.002 | 1.774 |
| Manufacture of motor vehicles | 752 | 0.490 | 0.091 | 0.656 | 1.237 | 1.529 |
| Manufacture of other transport | 595 | 0.338 | 0.074 | 0.603 | 1.016 | 1.119 |
| Manufacture of furniture | 3229 | 0.180 | 0.033 | 0.812 | 1.025 | 1.544 |

Production function coefficients and median markups calculated using the methods of Ackerberg et al. (2015) and DeLoecker and Warzynski (2012) as described in the text. The production function is estimated with past export and import status (as well as exit probability) as state variables. Robustness analysis has also been done by excluding import and export status from the production function.

I estimate firm level markups from the gap (or "wedge") between the output elasticity of materials ($\theta^x_{it}$) and the cost share of materials ($\alpha^x_{it}$) in total costs. The only assumption necessary is that firms minimize costs, so that the output elasticity is then set equal to its cost share. Markups could also be estimated using the same gap in the labor input, though labor requires more adjustment costs than materials and is less variable. This would make it a worse measure of markups, but I do compare some results to using the labor "wedge" as well. Specifically, my markup measure, at the firm-time level, is represented by:

$$\frac{1}{1-\mu_{it}} = m_{it} = \frac{\theta^x_{it}}{\alpha^x_{it}} \tag{21}$$

## A.4 Robustness Regressions: Firm Responses to Exchange Rate Shock

**Table 6:** Firm Markups and Characteristics: All Characteristics Shown

| | Markup (Lerner) | | | | Relative Sales | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Import Share | 0.095*** | | 0.046*** | | 0.233* | 0.837*** |
| | (0.006) | | (0.006) | | (0.122) | (0.241) |
| Import Share (sales) | | 0.181*** | | 0.066*** | | |
| | | (0.014) | | (0.015) | | |
| Export Share | 0.038*** | 0.036*** | 0.048*** | 0.048*** | 0.042 | 0.100 |
| | (0.010) | (0.010) | (0.010) | (0.010) | (0.145) | (0.485) |
| TFP | 0.127*** | 0.130*** | 0.103*** | 0.104*** | 0.504*** | 1.707*** |
| | (0.004) | (0.004) | (0.005) | (0.005) | (0.057) | (0.281) |
| Employment | 0.027*** | 0.028*** | 0.012*** | 0.013*** | 0.553*** | 1.469*** |
| | (0.003) | (0.003) | (0.002) | (0.002) | (0.038) | (0.183) |
| Capital Intensity | 0.008*** | 0.008*** | 0.000 | 0.001 | 0.062*** | 0.242*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.008) | (0.037) |
| Multinational | 0.007 | 0.007 | -0.010 | -0.007 | 0.050 | 0.215 |
| | (0.006) | (0.006) | (0.007) | (0.007) | (0.132) | (0.260) |
| Ratio Unskilled L | 0.000 | 0.000 | 0.006* | 0.006 | -0.054* | -0.794*** |
| | (0.003) | (0.003) | (0.004) | (0.004) | (0.030) | (0.211) |
| Fixed Effects | Firm, Year | Firm, Year | Sector-Year | Sector-Year | Firm, Year | Sector-Year |
| $R^2$ | 0.79 | 0.78 | 0.57 | 0.56 | 0.94 | 0.30 |
| N | 29504 | 29504 | 29462 | 29462 | 29504 | 29462 |

This table measures the relationship of firm outcomes with its characteristics. The benchmark Lerner markups is the outcome in the first four columns. The outcome in the last two columns is relative sales, or firm sales relative to mean sales in the industry in that year. In columns (1), (2), and (5), I take firm and year fixed effects to capture the effect of changes in the outcome with respect to changes in firm characteristics within firms over time. In columns (3), (4), and (6), I add sector-year fixed effects to capture the cross-sectional relationship across firms within sectors. Standard errors (in parenthesis) are clustered at the firm level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

**Table 7:** Firm Level: Differential Effect on Markup by Degree of Exposure: Shows All controls

| | Markup (Lerner) | | | | Markup (Profit) | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| REER*ImportShare | 0.209*** | | | 0.200*** | 0.044 | |
| | (0.042) | | | (0.038) | (0.043) | |
| REER*ExportShare | 0.068 | 0.062 | | 0.068 | -0.032 | |
| | (0.051) | (0.051) | | (0.051) | (0.058) | |
| REER*ImportShare (sales) | | 0.402*** | | | | |
| | | (0.103) | | | | |
| REER*NetExposure | | | -0.111*** | | | -0.040 |
| | | | (0.033) | | | (0.034) |
| Tariff*ImportShare | | | | 0.003 | | |
| | | | | (0.005) | | |
| TFP | 0.117*** | 0.117*** | 0.117*** | 0.117*** | 0.306*** | 0.306*** |
| | (0.004) | (0.004) | (0.004) | (0.004) | (0.005) | (0.005) |
| REER*MNC=1 | 0.108** | 0.124*** | 0.147*** | 0.108** | -0.089* | -0.087* |
| | (0.046) | (0.046) | (0.045) | (0.046) | (0.049) | (0.047) |
| REER*Kintensity | -0.025*** | -0.023*** | -0.018*** | -0.025*** | -0.071*** | -0.071*** |
| | (0.006) | (0.006) | (0.005) | (0.006) | (0.006) | (0.006) |
| REER*Ratio Unskilled L | -0.118*** | -0.120*** | -0.106*** | -0.118*** | 0.002 | 0.003 |
| | (0.024) | (0.024) | (0.024) | (0.024) | (0.026) | (0.026) |
| Capital Intensity | 0.122*** | 0.113*** | 0.091*** | 0.122*** | 0.320*** | 0.319*** |
| | (0.026) | (0.026) | (0.025) | (0.026) | (0.028) | (0.027) |
| Ratio Unskilled L | 0.544*** | 0.553*** | 0.489*** | 0.544*** | -0.007 | -0.009 |
| | (0.109) | (0.109) | (0.109) | (0.109) | (0.121) | (0.120) |
| Multinational | -0.484** | -0.560*** | -0.664*** | -0.486** | 0.410* | 0.402* |
| | (0.213) | (0.210) | (0.206) | (0.214) | (0.227) | (0.218) |
| Avg Markup | 0.22 | 0.22 | 0.22 | 0.22 | 0.25 | 0.25 |
| Fixed Effects | Firm, Year | Firm, Year | Firm, Year | Firm, Year | Firm, Year | Firm, Year |
| N | 29504 | 29504 | 29504 | 29504 | 29504 | 29504 |
| $R^2$ | 0.78 | 0.78 | 0.78 | 0.78 | 0.75 | 0.75 |

This table is a duplicate of Table 2, but reports all controls. All regressions include firm and year fixed effects and standard errors clustered at the firm level (in parenthesis). I drop the basic metal industry (ISIC 27). $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

**Table 8:** Firm Level: Differential Effect on Markup by Degree of Exposure to Competition: Alternative Specifications

| | Markup (Lerner) | | | | | |
|---|---|---|---|---|---|---|
| | (Sector-Year) | (Region-Year) | (Sector-Year) | (Year≥2001) | (Year≥2001) | (Year≤2000) |
| REER*ImportShare | 0.177*** | 0.206*** | | 0.125*** | | 0.199*** |
| | (0.041) | (0.043) | | (0.045) | | (0.049) |
| REER*ExportShare | -0.054 | 0.040 | | | | |
| | (0.057) | (0.052) | | | | |
| REER*NetExposure | | | -0.140*** | | -0.127*** | |
| | | | (0.034) | | (0.031) | |
| REER*MNC=1 | 0.025 | 0.103** | 0.037 | -0.059 | -0.054 | 0.077 |
| | (0.041) | (0.046) | (0.040) | (0.044) | (0.043) | (0.049) |
| TFP | 0.071*** | 0.117*** | 0.071*** | 0.092*** | 0.090*** | 0.122*** |
| | (0.004) | (0.004) | (0.004) | (0.005) | (0.005) | (0.004) |
| REER*Kintensity | -0.021*** | -0.023*** | -0.019*** | 0.014** | 0.019*** | -0.033*** |
| | (0.006) | (0.006) | (0.006) | (0.007) | (0.007) | (0.007) |
| REER*Ratio Unskilled L | -0.028 | -0.112*** | -0.026 | 0.104*** | 0.117*** | -0.138*** |
| | (0.021) | (0.024) | (0.021) | (0.028) | (0.028) | (0.030) |
| Capital Intensity | 0.098*** | 0.113*** | 0.088*** | -0.061* | -0.080*** | 0.155*** |
| | (0.028) | (0.026) | (0.027) | (0.032) | (0.031) | (0.031) |
| Ratio Unskilled L | 0.128 | 0.517*** | 0.117 | -0.469*** | -0.528*** | 0.641*** |
| | (0.097) | (0.108) | (0.097) | (0.126) | (0.126) | (0.141) |
| Multinational | -0.105 | -0.463** | -0.159 | 0.270 | 0.246 | -0.351 |
| | (0.191) | (0.212) | (0.186) | (0.201) | (0.196) | (0.228) |
| Import Share | | | | -0.481** | | -0.820*** |
| | | | | (0.204) | | (0.227) |
| NetExposure | | | | | 0.518*** | |
| | | | | | (0.141) | |
| Fixed Effects | Firm, Sector-Year | Firm, Region-Year | Firm, Sector-Year | Firm, Sector, Year | Firm, Sector, Year | Firm, Sector, Year |
| $R^2$ | 0.859 | 0.781 | 0.859 | 0.878 | 0.877 | 0.831 |
| N | 29393 | 29504 | 29393 | 22536 | 22536 | 23757 |

This table conducts alternative specifications of the baseline results. The first three columns are as in Table 2, but with industry-year (columns 1 and 3) and region-year (column 2) fixed effects. The last two columns repeat the benchmark firm and year fixed effects specification but only after 2000 and before 2001. Note that only in these cases I allow the exposure measure to vary, so that it is different in the two time periods. Dependent variable is log markup measured using the procedure outlined in DeLoecker and Warzynski (2012) (DLW). All regressions include standard errors clustered at the firm level (in parenthesis). I drop the basic metal industry (ISIC 27). $***p < 0.01$, $**p < 0.05$, $*p < 0.1$.

**Table 9:** Firm Level: Differential Effect on Markup by Varying Exposure to Competition

| | Markup (Lerner) | | | | Markup (Profit) | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| REER*ImportShare | 0.116*** | | | 0.130*** | -0.034 | |
| | (0.037) | | | (0.035) | (0.050) | |
| REER*ExportShare | 0.041 | 0.034 | | 0.040 | -0.124* | |
| | (0.047) | (0.048) | | (0.047) | (0.072) | |
| REER*ImportShare (sales) | | 0.247*** | | | | |
| | | (0.092) | | | | |
| REER*NetExposure | | | -0.063** | | | -0.024 |
| | | | (0.029) | | | (0.042) |
| Tariff*ImportShare | | | | -0.005 | | |
| | | | | (0.005) | | |
| TFP | 0.120*** | 0.122*** | 0.116*** | 0.120*** | | |
| | (0.004) | (0.004) | (0.004) | (0.004) | | |
| Import Share | -0.436** | | | -0.492*** | 0.189 | |
| | (0.171) | | | (0.160) | (0.230) | |
| Export Share | -0.145 | -0.115 | | -0.144 | 0.489 | |
| | (0.217) | (0.218) | | (0.217) | (0.333) | |
| NetExposure | | | 0.225* | | | 0.066 |
| | | | (0.134) | | | (0.194) |
| Fixed Effects | Firm, Year | Firm, Year | Firm, Year | Firm, Year | Firm, Year | Firm, Year |
| $R^2$ | 0.78 | 0.78 | 0.78 | 0.78 | 0.57 | 0.57 |
| N | 29504 | 29504 | 29504 | 29504 | 29504 | 29504 |
| Avg Markup | 0.22 | 0.22 | 0.22 | 0.22 | 0.25 | 0.25 |

This table examines the differential markup responses to foreign shocks depending on firm exposure. In comparison to Table 2, net exposure is allowed to vary over time (so the term is also used as a control). Dependent variable for the first 3 columns is the Lerner index, which the price-cost ratio measured using the procedure outlined in DeLoecker and Warzynski (2012) (DLW). TFP measurement also follows DLW. REER, TOT, and output tariffs are in logs. Column (4) uses a profit share measure of the markup: "Markup (Profit)" $= \frac{Sales_{it} - wages_{it} - capitalcosts_{it} - inputscosts_{it}}{Sales_{it}}$.

The last column uses a Lerner index of the inverse labor share: "Markup (Lshare)" $= \mu^{Lshare}$. The last two columns *do not* include TFP as a control as they are not constructed using the productivity estimation procedures. All columns include firm and year fixed effects (for industry-year interacted FEs see Appendix). I interact the following firm characteristics with the foreign shock to use as controls: capital intensity, a dummy if the firm is a multinational, the ratio of skilled to unskilled labor. The table only displays the results for the REER interaction. Standard errors are clustered at the firm level. I drop the basic metal industry (ISIC 27). $***p < 0.01$, $**p < 0.05$, $*p < 0.1$. $***p < 0.01$, $**p < 0.05$, $*p < 0.1$.

**Table 10:** Alternate Firm Markups and Characteristics

| | Markup (Lerner) | Markup (Profit) | Markup (Lshare) |
|---|---|---|---|
| | (1) | (2) | (3) |
| Import Share | 0.046*** | 0.016*** | 0.051*** |
| | (0.006) | (0.006) | (0.008) |
| Export Share | 0.048*** | 0.005 | 0.015 |
| | (0.010) | (0.009) | (0.011) |
| TFP | 0.103*** | 0.355*** | 0.247*** |
| | (0.005) | (0.006) | (0.008) |
| Employment | 0.012*** | 0.014*** | 0.004* |
| | (0.002) | (0.001) | (0.002) |
| Capital Intensity | 0.000 | -0.006*** | 0.035*** |
| | (0.001) | (0.001) | (0.001) |
| Multinational | -0.010 | -0.031*** | -0.025*** |
| | (0.007) | (0.006) | (0.008) |
| Ratio Unskilled L | 0.006* | 0.020*** | 0.006 |
| | (0.004) | (0.003) | (0.005) |
| Fixed Effects | Sector-Year | Sector-Year | Sector-Year |
| $R^2$ | 0.57 | 0.63 | 0.46 |
| N | 29462 | 29462 | 29462 |
| Avg Markup | 0.22 | 0.25 | 0.63 |

I construct markups three ways. (1)"Markup (Lerner)" $= \mu_{it}$, where $\frac{1}{1-\mu}$ is the price-cost ratio, or ratio of material output elasticity and material cost share ($\frac{\theta^m}{\alpha^m}$) estimated using (DeLoecker and Warzynski, 2012); (2) "Markup (Profit)" $= \frac{Sales_{it} - wages_{it} - capitalcosts_{it} - inputscosts_{it}}{Sales_{it}}$, constructed using sales and input data; (3) "Markup (Lshare)" $= \mu_{it}^{Lshare}$, where $\mu^{Lshare}$ is a Lerner index from the inverse labor share of value added. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

# B Structural Model Appendix

## B.1 Price-Quantity Covariance

This appendix shows the derivation of Equation 8 and establishes the result that it is zero in the case when the sub utility function is CES and the added assumption of Pareto distribution of marginal costs.

First, I start by decomposing revenue using the definition of the covariance. The aggregate revenue equation can be manipulated in the following way:

$$R = NL \int_0^{c_d} q(c)h_d(c)dc \int_0^{c_d} p(c)h_d(c)dc + NL\left[\text{Cov}(p,q)\right], \tag{22}$$

where I use the definition of the covariance: $\text{Cov}(p,q) = \int_0^{c_d}(p(q(c)) - P)(q(c) - Q)h_d(c)dc$. The last term is a residual that represents the deviation of aggregate revenue from physical production. Equation 22 can be further expanded substituting for $\tilde{R}$ and $Q$, and then taking logs to get growth rates:

$$\begin{aligned} \frac{\tilde{R}}{Q} &= 1 + \frac{\text{Cov}(p,q)}{\int_0^{c_d} p(q(c))h_d(c)dc \int_0^{c_d} q(c)h_d(c)dc} \\ \Delta ln\left(\frac{\tilde{R}}{Q}\right) &\approx \Delta\left(\frac{\text{Cov}(p,q)}{\int_0^{c_d} p(q(c))h_d(c)dc \int_0^{c_d} q(c)h_d(c)dc}\right) \end{aligned} \tag{23}$$

The last line uses the approximation that $ln(1+x) \approx x$. In the main text, I rewrite the covariance using markups and labor, which is equivalent to the equation above.

Next, I show that (23) is zero in the case where preferences are CES and costs are drawn from a Pareto distribution. This is the first part of the proof necessary for Proposition 1. Using the definition of the covariance above:

$$\Delta\left(\frac{\text{Cov}(p,q)}{\int_0^{c_d} p(q(c))h_d(c)dc \int_0^{c_d} q(c)h_d(c)dc}\right) = \Delta\left(\frac{\int_0^{c_d} p(q(c))q(c)h_d(c)dc}{\int_0^{c_d} p(q(c))h_d(c)dc \int_0^{c_d} q(c)h_d(c)dc} - 1\right) \tag{24}$$

When preferences are CES, $p(c) = \frac{1}{1-\mu}c$ with $\mu$ constant, and $q(c) = c^{-\sigma}\left(\frac{1}{1-\mu}\right)^{-\sigma}\left(\frac{R}{\tilde{P}}\right)$ with $\tilde{P}$ the aggregate "ideal" price index and $R$ the aggregate revenue. Additionally, $h_d(c)dc = \frac{g(c)}{G(c_d)} = \kappa c^{\kappa-1}c_d^{-\kappa}$. Thus I can input all this information into Equation 24 and reduce the

numerator and denominator separately:

$$\int_0^{c_d} p(q(c))q(c)h_d(c)dc = \left(\frac{R}{\tilde{P}}\right)\frac{1}{1-\mu}\left(\frac{1}{1-\mu}\right)^{-\sigma}\int_0^{c_d} cc^{-\sigma}\kappa c^{\kappa-1}c_d^{-\kappa}dc$$

$$= \left(\frac{R}{\tilde{P}}\right)\left(\frac{1}{1-\mu}\right)^{1-\sigma}\left(\frac{\kappa}{\kappa-\sigma+1}\right)c_d^{1-\sigma} \tag{25}$$

$$\int_0^{c_d} p(q(c))h_d(c)dc = \frac{1}{1-\mu}\int_0^{c_d} c\kappa c^{\kappa-1}c_d^{-\kappa}dc$$

$$= \frac{1}{1-\mu}\frac{\kappa}{\kappa+1}c_d \tag{26}$$

$$\int_0^{c_d} q(c)h_d(c)dc = \left(\frac{R}{\tilde{P}}\right)\left(\frac{1}{1-\mu}\right)^{-\sigma}\int_0^{c_d} c^{-\sigma}\kappa c^{\kappa-1}c_d^{-\kappa}$$

$$= \left(\frac{R}{\tilde{P}}\right)\left(\frac{1}{1-\mu}\right)^{-\sigma}\left(\frac{\kappa}{\kappa-\sigma}\right)c_d^{-\sigma} \tag{27}$$

Next, combining the three above terms into Equation 24:

$$\Delta\left(\frac{\int_0^{c_d} p(q(c))q(c)h_d(c)dc}{\int_0^{c_d} p(q(c))h_d(c)dc\int_0^{c_d} q(c)h_d(c)dc} - 1\right) = \Delta\left(\frac{(\kappa+1)(\kappa-\sigma)}{\kappa(\kappa-\sigma+1)}\right) \tag{28}$$

where the term inside the parenthesis on the RHS is constant. Therefore, under the case of CES sub utility and Pareto $G(c)$, the terms in Equation 8 are zero.

## B.2 Importing with VES Preferences

In this Appendix I provide details of the specific VES model with stone-geary preferences. First, using the assumptions on unit costs and the mapping from the cost draw to import shares, I can write unit costs:

$$u(c) = wc(s_D(c))^{\gamma}, \qquad s_D(c) = \alpha(\tau^I)^{\beta}c^{1/\theta}. \tag{29}$$

I set $w = 1$ as domestic inputs remain unchanged in the model. The parameters are detailed in the main text.

From the first order conditions, we can use the inverse demand function to get:

$$\pi(c) = \frac{L}{\lambda}\left(\frac{q(c)}{q(c)+\bar{q}}\right) - Lq(c)w(\alpha(\tau^I)^{\beta})^{\gamma}c^{\frac{\gamma}{\theta}+1}, \tag{30}$$

where the aggregate environment is taken as given for each firm and summarized by $\lambda = \int_0^{c^d}\frac{q(c)}{q(c)+\bar{q}}dG(c)$. A useful feature of this framework is that it will not be necessary to solve

for the general equilibrium term, $\lambda$. This is because I normalize the relative cutoffs to the case where $\tau^I = 1$ and simply measure *deviations* in the allocative efficiency relative to that case. Essentially, in addition to setting wages to one, I also set $\lambda$ and $\bar{q}$ equal to one.[61].

Firms choose $q(c)$ to maximize profits, which yields the following solution:

$$q(c) = L\bar{q}\left[\left(\frac{1}{\lambda w\bar{q}}(\alpha(\tau^I)^\beta)^\gamma c^{-(\frac{\gamma}{\theta}+1)}\right)^{\frac{1}{2}} - 1\right] \tag{31}$$

The key then is to set quantity equal to zero, which yields the cutoff cost draw with positive demand. Then, price, quantity, profits, and revenues for a firm can all be written strictly as a function of their cost relative to the cutoff:

$$c^* = (\lambda w\bar{q})^{\frac{-\theta}{\gamma+\theta}}\left(\alpha(\tau^I)^\beta\right)^{\frac{-\gamma\theta}{\gamma+\theta}} \tag{32}$$

$$p(c) = wc^{\frac{\gamma}{\theta}+1}(\alpha(\tau^I)^\beta)^\gamma\left[\underbrace{(c^*c)^{\frac{1}{2}(\frac{\gamma}{\theta}+1)}}_{\text{markup}}\right] \tag{33}$$

$$q(c) = L\bar{q}\left[\left(\frac{c^*}{c}\right)^{\frac{1}{2}(\frac{\gamma}{\theta}+1)} - 1\right] \tag{34}$$

$$\pi(c) = L\bar{q}w(\alpha(\tau^I)^\beta)^\gamma\left[(c^*)^{(\frac{\gamma}{\theta}+1)} - 2\,(c^*c)^{\frac{1}{2}(\frac{\gamma}{\theta}+1)} + c^{(\frac{\gamma}{\theta}+1)}\right] \tag{35}$$

$$r(c) = L\bar{q}w(\alpha(\tau^I)^\beta)^\gamma\left[(c^*)^{(\frac{\gamma}{\theta}+1)} - (c^*c)^{\frac{1}{2}(\frac{\gamma}{\theta}+1)}\right] \tag{36}$$

Notice that plugging in the solution for $c^*$, one can get, for example, the markup: $m(c) = (\lambda w\bar{q})^{-1/2}(\alpha(\tau^I)^\beta)^{-\frac{\gamma}{2}}$. Thus, $\frac{\partial m(c)}{\partial \tau^I} = -\frac{\gamma}{2}\alpha(\tau^I)^{\frac{-3\gamma}{2}}(\lambda w\bar{q})^{-1/2} < 0$.

Then, the aggregates are computed by assuming a Pareto distribution of costs, where $\kappa$ the shape parameter of the Pareto cost distribution Let $\hat{c^*}(\tau^I) = \frac{c^*(\tau^I)}{c^*(\tau^I=1)}$. The set of producing firms is in the range $(0, \hat{c^*})$. I therefore integrate across producing firms, and

[61] Although $\bar{q}$ is important in that it parameterizes "love of variety", the level of of this parameter will *not* affect local changes in $AE$, just as it does not affect local changes in welfare in ACDR (see Jung et al. (2019) and Arkolakis et al. (2019))

write aggregate production as a function of this new general equilibrium cutoff.

$$
\begin{aligned}
R &= N \int_0^{\hat{c^*}(\tau^I)} r(c) c^{\kappa-1} (\hat{c^*}(\tau^I))^{-\kappa} \kappa dc \\
&= N L \bar{q} w (\alpha(\tau^I)^\beta)^\gamma \left[ \left(\hat{c^*}(\tau^I)\right)^{(\frac{\gamma}{\theta}+1)} - \frac{\kappa}{\frac{1}{2}(\frac{\gamma}{\theta}+1)+\kappa} \left(\hat{c^*}(\tau^I)\right)^{(\frac{\gamma}{\theta}+1)} \right] \qquad (37) \\
Q &= N L \bar{q} \left[ \frac{\kappa}{\kappa - \frac{1}{2}(\frac{\gamma}{\theta}+1)} \left(\hat{c^*}(\tau^I)\right)^{\frac{1}{2}(\frac{\gamma}{\theta}+1)} - \left(\hat{c^*}(\tau^I)\right)^{\frac{1}{2}(\frac{\gamma}{\theta}+1)} \right] \qquad (38) \\
P &= w (\alpha(\tau^I)^\beta)^\gamma \left[ \frac{\kappa}{\frac{1}{2}(\frac{\gamma}{\theta}+1)+\kappa} \left(\hat{c^*}(\tau^I)\right)^{(\frac{\gamma}{\theta}+1)} \right]. \qquad (39)
\end{aligned}
$$

$N$ is the total number of producing firms, which depends on entry and the Pareto shape and scale parameters, but notice it cancels out when we take the ratio of aggregate revenue and quantity. Then, one can write the ratio for aggregate markups, which determines allocative efficiency, as relative to the case when $\tau I$ is one:

$$
\frac{\tilde{R}}{Q} = (\hat{c^*}(\tau^I)^{-\frac{1}{2}(\frac{\gamma}{\theta}+1)} \left[ \frac{1 - \frac{\kappa}{\frac{1}{2}(\frac{\gamma}{\theta}+1)+\kappa}}{\frac{\kappa}{\frac{1}{2}(\frac{\gamma}{\theta}+1)+\kappa} \left( \frac{\kappa}{\kappa - \frac{1}{2}(\frac{\gamma}{\theta}+1)} - 1 \right)} \right] \qquad (40)
$$

Notice that since $c^d = (\lambda w \bar{q})^{\frac{-\theta}{\beta+\theta}}$ (without importing), it is a function of a general equilibrium object, $\lambda$. Without solving for the object, I set it equal to one and capture *deviations* in the cutoff as $\tau I$ changes. To solve for the cutoff, one could use the free entry condition: $\bar{\pi} = f_e$, where $f_e$ is the entry cost parameter. This allows one to solve for $\lambda$ and plug into $c^*$, which results in:

## B.3 Generalized CES Preferences

A related, but more general formulation of the preferences I assume in this paper are explored in Jung et al. (2019) and and Arkolakis et al. (2019). The more general preferences are written as:

$$
U = \left( \int_{\omega \in \Omega} (q(\omega) + \bar{q})^{\frac{\sigma-1}{\sigma}} d\omega \right)^{\frac{\sigma}{\sigma-1}}, \qquad (41)
$$

where $q(\omega)$ is individual consumption, $\Omega$ is the set of potentially produced goods, $\bar{q} > 0$ is a constant, and $\sigma \geq 1$ governs curvature. These preferences are a type of "generalized" CES that correspond to a Dixit-Stiglitz utility function with a displaced origin.

The estimation in the main text is conducted assuming a restricted version of the Generalized CES (GCES) preferences, where $\sigma \to 1$. The general preference structure allows for flexibility in the curvature of demand, which will affect average markups in the economy, but

requires a value for for $\sigma$.[62] For the sake of showing the qualitative effects on misallocation in this model, demand curvature is not important and therefore I essentially set $\sigma \to 1$. However, in robustness exercises I explore the effect of raising $\sigma$, where I take the value of $\sigma$ as given and re-rerun the couterfactual.

In this section I also summarize the equilibrium of the general model, with the quantitative implications below. Notice that there do not exist reduced form expressions in the general case, but the aggregates can be produced numerically.

First, the behavior of the cutoff cost is identical in GCES preferences. Equation (20) in Jung et al. (2019) shows the cost cutoff with GCES preferences in a model with multiple countries. They also show that the cutoff cost is proportional across all preferences with directly separable demand, only differentiated by the demand parameters. Hence, the cutoff in the GCES will follow exactly from the case where $\sigma = 1$ above.

For $\sigma \neq 1$, no closed form solution exist for prices and therefore sales. However, one can solve for these numerically, as laid out in Jung et al. (2019). As in the previous subsection, there is a cutoff cost at which demand is zero and given this cutoff cost there is the following implicit function for prices:

$$(1-\sigma)p(c) + \sigma u(c) = p(c)^{\sigma+1}(c^*)^{-\sigma}, \tag{42}$$

where $u$ is the unit cost of the firm (which in this case might differentiate from the cost draw $c$). Given prices, one case solve for quantity and sales:

$$q(c) = L\bar{q}\left[\left(\frac{c^*}{p(c)}\right)^{\sigma} - 1\right] \tag{43}$$

$$r(c) = L\bar{q}w(\alpha(\tau^I)^{\beta})^{\gamma}\left[(c^*)^{\sigma}\, p(c)^{1-\sigma} - p(c)\right] \tag{44}$$

I then use numerical methods to aggregate these and compute $\tilde{R}$ and $Q$. Although there is no closed form analogue to (40), I compute it numerically and plot it with $\sigma > 1$ in the robustness exercises of the quantitative analysis below. As the general CES fits within the VES framework described in Section 3.2, the interpretation of allocative efficiency is identical to the more restrictive preferences, and misallocation increases with an appreciation. Quantitatively, the magnitude of changes in misallocation are affected by $\sigma$.

[62] For more details on the advantages of this preference specification, see Jung et al. (2019).

# C Changes in Allocative Efficiency as a Response to an Exchange Rate Shock: Empirics and Structural Estimation

## C.1 Robustness: Empirics

### C.1.1 Alternative Outcomes

Table 11 below includes various outcomes that could represent shocks that are simultaneous to the REER variation. In this case I check whether there are *time-varying* outcomes that might be correlated with the interaction of the growth in the REER with international exposure. For example, If my results are due to demand shocks, one would expect the REER shock to importing industries to also lead to significant increases in average TFP, average markups, and average employment per firm (columns (1)-(3)). Unlike the misallocation measure, these measures don't capture compositional changes since they are unweighted means. To see why this is important, take the average markup measure. A rise in the markup of individual firms *lowers welfare* as consumers pay more for the same products, however a rise in allocative efficiency reflects a rise in the aggregate markup, through compositional changes. In columns (4) and (5) of Table 11 I show that factor allocations do in fact change in imported industries with REER shocks. The ratio of unskilled labor decreases, and capital intensity decreases – likely importing firms hire more skilled workers to work with the new inputs. I the ratio of unskilled labor as a control to the baseline specification, but do not include capital intensity in the main text since it didn't seem to provide any extra information (results as I incrementally add controls available upon request). Column (6) reports results with the *standard deviation* of employment as an outcome, since changes in size-dependent policies would change the distribution of employment, but there is also no evidence that changes in employment dispersion are correlated with the coefficient of interest. The last column of Table 11 suggests that there was no differential growth in non-tariff measures (NTMs) in importing industries during the time of REER variations. Non-tariff measures usually impose fixed costs on firms, which can reallocate production across firms of varying quality (**?**).

### C.1.2 Robustness on Inference

The checks above pertain to the *bias* in the coefficient of interest and confirm that treating the specification as a difference-in-difference with an exogenous shock to treated industries is valid. A separate concern pertains to inference when errors might be serially correlated. I

**Table 11:** Miscellaneous Industry Responses to Exchange Rate Shock

| | Δ Avg TFP | Δ Avg Markup | Δ Avg L | Δ Ratio Unskilled L | Δ Log Kint | Δ SD L | Δ Log NTMs |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Δ REER*Imported Share | 0.385 | 0.310 | -0.086 | -0.167*** | -1.906*** | -0.045 | 0.268 |
| | (0.297) | (0.219) | (0.128) | (0.054) | (0.502) | (0.117) | (1.268) |
| Δ REER*Exported Share | -0.623 | -0.427 | 0.279 | 0.507*** | -0.206 | 0.022 | 4.953** |
| | (0.456) | (0.337) | (0.307) | (0.087) | (0.858) | (0.159) | (1.817) |
| Δ Tariff | -0.008 | -0.007 | -0.005 | 0.005 | -0.007 | 0.012* | -0.032 |
| | (0.009) | (0.006) | (0.017) | (0.007) | (0.035) | (0.006) | (0.058) |
| Fixed Effects | Year,Sector | Year,Sector | Year,Sector | Year,Sector | Year,Sector | Year,Sector | Year,Sector |
| $R^2$ | 0.360 | 0.374 | 0.510 | 0.716 | 0.511 | 0.642 | 0.365 |
| N | 192 | 192 | 192 | 192 | 192 | 192 | 192 |

I check whether there are *time-varying* outcomes that might be correlated with the interaction of the growth in the REER with international exposure. The main interactions (first two rows), plus changes in tariffs, are the same as in column (3) of Table 3. Outcomes are described above. Firm level TFP and markups are estimated as in Section 2.3, and I use a simple mean at the industry level to compute the growth rate of these aggregates. NTMs are a time-varying industry level measure of non-tariff measures that is taken from **?**. In that paper, we use a comprehensive database constructed by TRAINS that reports all the domestic regulations that fit within the definition of santitary and phytosanitary (SPS) and technical barriers to trade (TBT). We construct a frequency index at the industry-year level. Standards are reported at the HS6 product level, so I then aggregate these to the 2 digit industry as the total number of non-tariff measures imposed relative to the number of products in the industry.

conduct several robustness checks that pertain to the possibility of incorrect inference.

- There exists negative autocorrelation in the error terms, as is common in first-differenced specifications. When I predict the errors of the baseline specification (Column (3) in Table 3 of the paper), the Arellano-Bond test for autocorrelation results rejects the null for no autocorrelation in the first lag at the 2.3% level ($\chi^2$=5.3).[63] A regression of the residual on its lag has a coefficient of -0.42. Some of the autocorrelation is due to large changes in the outcome for a few observations. I drop observations where $\Delta AE$ is more than 50% or less than -50%, and the hypothesis of no serial correlation can only be rejected at the 5.9% level ($\chi^2$=3.6).

  To check whether the standard errors are too small due to the presence of autocorrelation, in Table 12 below I report results with autocorrelation robust standard errors.[64] In all these cases I assume there is one lag of dependence. The first column replicates the first column of Table 3 in the main text, with autocorrelation corrected standard errors, but the standard errors are of similar size as the baseline analysis. In the second column I eliminate the observations with very large changes in AE, and in the third column I add the "small sample" correction to check whether the small number of clusters is a problem. The results are still significant at the 1% level. In Column (4)

[63]Specifically, I use the more general Cumby-Huizinga general test in STATA. I cannot reject the null for no autocorrelation in the second lag at the 10% level, so I assume my model is an AR(1).

[64]Specifically, these are Driscoll-Kraay standard errors, which are robust to general forms of cross-sectional dependence. It is implemented using the ivreg2 command in STATA, with a bandwidth equal to two (because I assume one lag).

I add the set of controls as in the paper. The standard error does increase, but stays significant at the 5.7% level. Finally, in the last column I add lags of the the REER. The results are robust to their inclusion.

- Given that my specification follows a difference-in-difference research design, I next focus on the seminal work by Bertrand et al. (2004) to run further robustness checks that check the possibility of underestimated standard errors in this type of identification.[65]

  First, one important conclusion from Bertrand et al. (2004) is that it is important to cluster standard errors at the correct level of aggregation when there is a possibility that the errors are autocorrelated. I highlight in my discussion of the results that errors are clustered at the sector level in my analysis. Since the variation in my analysis comes from differences in exposure *across sectors*, I argue that this is the correct way to conduct inference.

- Bertrand et al. (2004) find that ignoring time series information altogether is a successful strategy to get correct standard errors. I can do this in my analysis by taking long differences in two separate periods and comparing the differences in those periods with in a triple differences design. Let's take the case again where there is a major shock after 2002, the time when the terms of trade starts to grow. Then, I can eliminate time series information by running:

$$\Delta_1 AE - \Delta_0 AE = \alpha + \psi Expos_{j0}(\Delta_1 REER - \Delta_0 REER) + \zeta(\Delta_1 Z_j - \Delta_0 Z_j) + \varphi Z_{j0} + \nu_j, \tag{45}$$

  where the time periods $t = \{0, 1\}$, reflect the pre-period (1995-2002) and the post-period (2003-2007). As in the baseline specification, the exposure is fixed to the base period (here labeled 0). I control for changes in other possible time series variables labeled $Z_j$ and fixed industry characteristics labeled $Z_{j0}$. The results for this specification are reported in the Appendix of the paper and Table 13 below. Of course, with all variation now being across sectors, N is very low. However, it is evident that the relationship between allocative efficiency and the REER still holds. Even as I add controls, $\psi$ stays large, with a *total* of a 6 percentage point difference in $AE$ between a fully treated industry and a non-treated industry.[66]

  I should note that as in a large part of the robustness conducted, the analysis relies

[65] Notice that here I once again assume away any potential the bias in the coefficient.

[66] I normalize the growth rates in each time period by the number of years in each period since the pre period is longer.

on thinking about an exogenous shock to treated industries pre- and post-2002. My main specification in the paper uses the growth rate of the REER as the "shock" on treated industries, and this allows me to use all the variation of the REER across time. However, I emphasize that I find similar results if I use the TOT as the shock (which varies much less than the REER before 2003), and I have also shown results using a "post-2002" dummy interacted with the treatment measure. It is clear that my main results are driven by the large reduction of allocative efficiency in treated industries after the terms of the trade shock.

- Permutation test. Although above I have argued that my standard errors seem reasonable, I also conduct a randomization inference test. Here, the treatment is randomly assigned, and I then obtain placebo estimates of the interaction of the placebo treatment and the REER growth. In the words of Bertrand et al. (2004), the goal is to ask "If a thousand researchers analyzed the effects of REER fluctuations on AE, what fraction would find a significant effect even when there should be no effect?" (since the exposure is randomly assigned). Figure 8 below plots the coefficients of 1000 regressions, where in each regression I choose import shares and export shares for each industry from a uniform distribution that has the same range of shares as the data. Using the randomly generated import and export shares, I create the interaction of REER growth with the "fake" shares, and run the same specification as in Table 3 of the main text. The red line of the figure represents the coefficient in the "real" regression (column (3) of Table 3 in the text). Only 1.3% of placebo coefficients are more negative than the "real" one.[67] This suggests that the real distribution of my treatment is driving the effect on allocative efficiency, and that the effect I find is not mere chance. A p-value of 0.013 is slightly higher than the one in my estimation (0.002), but the difference is not very large.

I do highlight that with a small N, fully tackling the error of serially correlated errors is difficult. With that in mind, it is important to note that OLS is still unbiased and consistent (if one buys the diff-in-diff design). I therefore still see the connection to the quantitative exercise as valid. If we believe that the research design is picking up a correct coefficient on the interaction between REER growth and import exposure, then we can compare that to the negative relationship between $\Delta AE$ and $\Delta REER$ that is highlighted in the quantitative exercise. Furthermore, it still allows me to compare the magnitude of the effect that I find in the model to coefficient in my empirical analysis.

[67] I have also done this without controls, so that the regression includes only the REER growth interaction with the import and export shares (plus fixed effects). The results are similar: in that case 2% of placebo

**Table 12:** Robustness: Driscoll-Kray Autocorrelation Corrected Standard Errors

| | Δ AE | | | | |
|---|---|---|---|---|---|
| | (1) | (No Outliers) | (Small Sample) | (4) | (5) |
| Δ REER*Imported Share | -1.635*** | -1.888*** | -1.888*** | -1.673* | -2.747** |
| | (0.447) | (0.450) | (0.510) | (0.878) | (1.185) |
| Δ REER*Exported Share | -0.547 | 0.114 | 0.114 | -0.645 | -0.867 |
| | (1.709) | (1.641) | (1.861) | (.) | (.) |
| Year ≥ 2003*Copper Share | | | | -0.423 | 1.772 |
| | | | | (1.403) | (1.526) |
| Δ Tariff | | | | 0.028 | 0.019 |
| | | | | (0.055) | (0.075) |
| Δ Unskilled L Ratio | | | | 1.270** | 1.472** |
| | | | | (0.561) | (0.601) |
| Δ Avg TFP | | | | 0.795** | 0.873*** |
| | | | | (0.338) | (0.261) |
| L.Δ REER*Imported Share | | | | | -0.638 |
| | | | | | (1.358) |
| L.Δ REER*Exported Share | | | | | -0.223 |
| | | | | | (1.065) |
| Fixed Effects | | | | | |
| $R^2$ | 0.243 | 0.267 | 0.267 | 0.295 | 0.325 |
| N | 192 | 185 | 185 | 192 | 176 |

In this table I replicate the industry specification in the paper, but with Driskoll-Kray autocorrelation corrected standard errors. The first column replicates the first column of Table 3 in the main paper, with AC corrected standard errors. In the second column I eliminate the observations with very large changes in AE, and in the third column I add the "small sample" correction to check whether the small number of clusters is a problem. In Column (4) I add the set of controls as in the paper. Finally, in the last column I add lags of the exposure measure, the REER. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

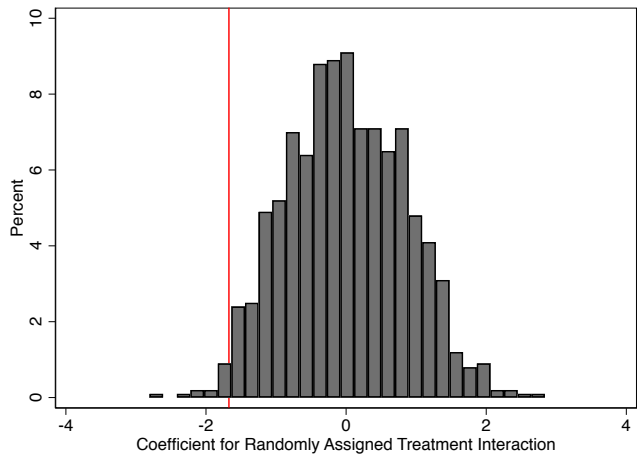
**Table 13:** Industry Responses to Exchange Rate Shock: Long Differences (Post-2002 relative to Pre-2002)

| | (Δ(2003 − 2007) - Δ(1995 − 2002))AE | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| (Δ(2003 − 2007) - Δ(1995 − 2002))REER*Import Share | -6.033* | -5.826 | -5.939 |
| | (3.294) | (3.370) | (3.482) |
| Δ(2003 − 2007) - Δ(1995 − 2002))Tariff | | 0.231 | 0.179 |
| | | (0.327) | (0.388) |
| Export Share | | | -0.170 |
| | | | (0.179) |
| Copper Share | | | -0.009 |
| | | | (0.337) |
| N | 18 | 18 | 18 |

In this table I regress the long difference of $\Delta AE$ on the long difference of the exchange rate, interacted with the import exposure measure. To calculate long differences, I take the total growth rate of the outcome, as well as the REER, from 1995-2002 (pre-period) and 2003-2007 (post-period). The I subtract the pre-period from the post-period so that there is one "difference-in-difference" measure for both the outcome and shock measure. Since I interact the shock with the import exposure measure, the coefficient is then a triple-difference. Sector and year fixed effects are differenced out, with only a constant regressor left. I add sector specific controls which are export share, copper share, and log capital intensity of an industry in the base year. This follows the main specification in Ekholm et al. (2012). ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

coefficients are more negative than the "real" one.

**Figure 8:** Placebo Test: Distribution of $\psi$ Coefficient when Treatment Randomly Assigned



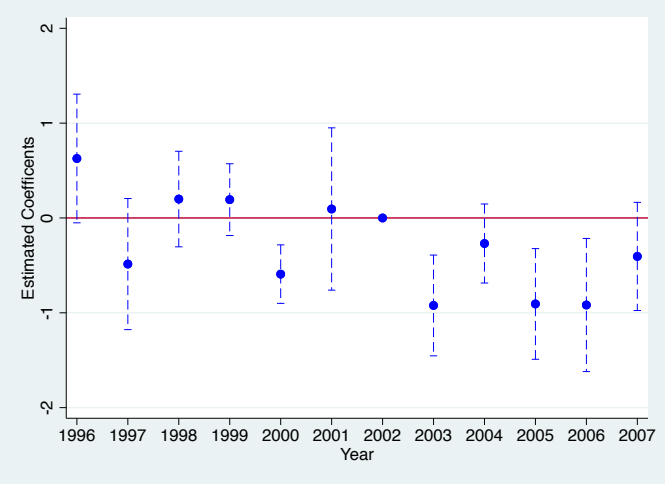

This histogram plots the coefficients from 1000 placebo regressions of the baseline specification, but with the import and export share exposure of each industry randomly generated for each regression. Therefore, the main interaction is created with fake exposure measures, while the rest of the data is the same. Each regression includes the same controls, fixed effects, and is clustered at the same level as the baseline specification. The red line is added to the value of the "real" coefficient using the industry exposure measures in the data. The cumulative fraction of placebo coefficients *more negative* than the real one in the above histogram is 0.02.

### C.1.3 Other Robustness

The following Figures and Tables relate to alternative measures of exposure, as well as the shock. First, Figure 9 repeats the dynamic effects analysis from the main text, but with the exposure measure instead of the import exposure. Note that I normalize the most *negative exposed* (highest import share relative to export share) to be equal to one (as "treated"). Export-exposed industries will therefore have negative exposure. In this way, the coefficient across years can be compared to the figure in the text, where treated industries are expected to see a *reduction* in allocative efficiency. Table 14 replicates the main analysis, but replaces $\Delta REER$ with $\Delta TOT$, using the terms of trade data described in Section 2. In Table 15, I use a difference exposure measure: the fraction of firms in the industry that are importers *but not exporters* (the reason for this is similar to the "net exposure" measure, which corrects for the fact that many importing firms are also large exporters). In Table 16 I repeat the analysis with *varying* exposure shares, instead of fixing them to the base year. Finally, Figure 10 reiterates that only the industries with exposure to importing are responding to the terms of trade shocks with the expected sign. I separate industries into a binary "negative" exposure if industries are below the median of exposure across all industries, with the rest being "positive". I then take the average $\Delta AE$ for all industries in each category per year (weighting by value added), and plot this against the change in the terms of trade. Each point represents one year (for each type of industry). $\Delta AE$ has a clear negative relationship with changes in the terms of trade *only for* negatively exposed industries, while this relationship

is horizontal for the other industries.

**Figure 9:** Dynamic Effects: Annual $\Delta AE$ Responses of Treated Firms (By Net Exposure)




This specification follows 19, but interacts the exposure treatment by separate year dummies instead of the REER. I normalize the exposure by normalizing each industry's exposure by the *minimum* exposure, so that a positive 1 is the most import-exposed. For this reason the coefficients are interpreted as the difference in the growth of allocative efficiency in a fully treated industry relative to a non-treated industry. Net is calculated as the difference in total imported inputs relative to input expenditure at the firm level and the export share of sales, then averaged across firms for each 2-digit industry. We drop the variable interacted with the year 2003 dummy. Dashed vertical bars represent 95% confidence intervals.

**Table 14:** Industry Responses to Terms of Trade Shock with Fixed Exposure Shares

| | Δ AE | | | | Δ Cov(markup,inputs) | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Δ TOT*Imported Share | -1.245*** | | -1.321*** | | 0.034 | |
| | (0.334) | | (0.383) | | (0.106) | |
| Δ TOT*Imported Share (sales) | | -1.046*** | | -1.096*** | | 0.035 |
| | | (0.257) | | (0.315) | | (0.082) |
| Δ TOT*Exported Share | -0.878 | -0.763 | -0.603 | -0.479 | 0.749** | 0.748** |
| | (0.519) | (0.480) | (0.483) | (0.456) | (0.289) | (0.279) |
| Δ Tariff | | | 0.021 | 0.021 | -0.023 | -0.023 |
| | | | (0.025) | (0.025) | (0.032) | (0.032) |
| Δ Ratio Unskilled L | | | 1.126* | 1.119* | 0.356 | 0.358 |
| | | | (0.627) | (0.631) | (0.398) | (0.398) |
| Δ Avg TFP | | | 0.839 | 0.834 | -0.789** | -0.789** |
| | | | (0.534) | (0.533) | (0.297) | (0.296) |
| Fixed Effects | Year,Sector | Year,Sector | Year,Sector | Year,Sector | Year,Sector | Year,Sector |
| $R^2$ | 0.262 | 0.262 | 0.311 | 0.311 | 0.317 | 0.317 |
| N | 192 | 192 | 192 | 192 | 176 | 176 |

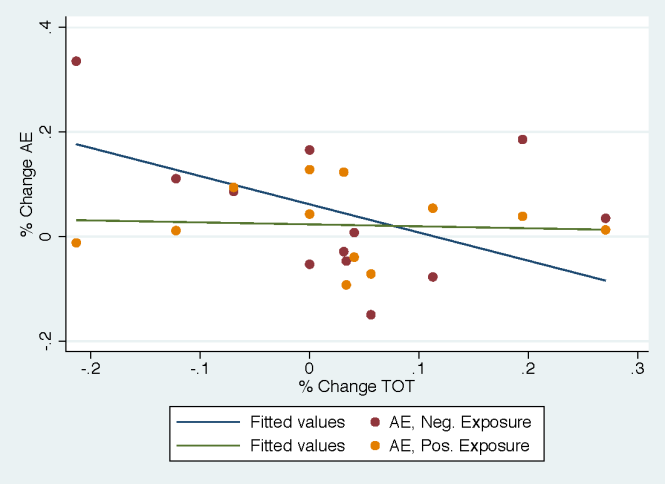
This Table reports the response in aggregate industry measures in response to TOT shocks instead of REER shocks. The table follows the same specifications as Table 3 in the main text.

**Table 15:** Industry Responses to Exchange Rate Shock: Fixed Importer Dummy (Average across Sector)

| | Δ AE | Δ Cov(markup,inputs) |
|---|---|---|
| | (1) | (2) |
| Δ REER*Importer | -5.737*** | -1.201 |
| | (1.395) | (1.353) |
| Δ REER*Exporter | -8.361 | 11.192** |
| | (5.157) | (5.196) |
| Δ Tariff | 0.033 | -0.016 |
| | (0.022) | (0.034) |
| Δ Ratio Unskilled L | 1.307** | 0.129 |
| | (0.589) | (0.452) |
| Δ Avg TFP | 0.778 | -0.716** |
| | (0.529) | (0.252) |
| Fixed Effects | Year,Sector | Year,Sector |
| $R^2$ | 0.295 | 0.339 |
| N | 192 | 176 |

This Table repeats the specifications from Table 3, but with fixed import and export dummies. The dummies are at the firm level, so I take an average for the sector measure. All regressions include sector and year fixed effects and standard errors clustered at the 2-digit industry level (in parenthesis). I drop the basic metal industry (ISIC 27). $***p < 0.01$, $**p < 0.05$, $*p < 0.1$.

**Figure 10:** Δ AE vs Δ TOT for Positively Exposed vs Negatively Exposed Industries




Industry categorized as "Negatively Exposed" if the average net exposure variable is less than the median across all industries. Within each year, I take the average Δ AE for the two categories by aggregating using value added shares. Each point represents a combination of the change in the terms of trade and change in allocative efficiency in a year, for each type of industry.

**Table 16:** Industry Responses to Exchange Rate Shock: Varying Exposure Shares

| | Δ AE | | | | Δ Cov(markup,inputs) | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Δ REER*Imported Share | -2.672* | | -3.238*** | | -1.760** | |
| | (1.262) | | (0.831) | | (0.698) | |
| Δ REER*Imported Share (sales) | | -2.541** | | -3.182*** | | -1.585* |
| | | (1.143) | | (0.778) | | (0.879) |
| Δ REER*Exported Share | 0.451 | 0.349 | 0.292 | 0.146 | 1.304 | 1.503 |
| | (1.088) | (1.091) | (0.882) | (0.882) | (1.118) | (1.074) |
| Δ Tariff | | | 0.042* | 0.042* | -0.017 | -0.014 |
| | | | (0.020) | (0.023) | (0.039) | (0.043) |
| Δ Ratio Unskilled L | | | 1.009* | 1.072* | 0.034 | 0.017 |
| | | | (0.536) | (0.538) | (0.477) | (0.461) |
| Δ Avg TFP | | | 0.864 | 0.889* | -0.652** | -0.652** |
| | | | (0.522) | (0.505) | (0.244) | (0.255) |
| Imported Share | 0.543 | | 0.507 | | -0.340 | |
| | (0.392) | | (0.322) | | (0.394) | |
| Exported Share | -0.363 | -0.273 | -0.308 | -0.198 | -0.271** | -0.267* |
| | (0.232) | (0.188) | (0.245) | (0.185) | (0.112) | (0.126) |
| Imported Share (sales) | | -0.040 | | -0.094 | | -0.106 |
| | | (0.234) | | (0.248) | | (0.179) |
| Fixed Effects | Year,Sector | Year,Sector | Year,Sector | Year,Sector | Year,Sector | Year,Sector |
| $R^2$ | 0.256 | 0.255 | 0.307 | 0.310 | 0.346 | 0.343 |
| N | 192 | 192 | 192 | 192 | 176 | 176 |

This Table reports the response in aggregate industry measures in response to REER shocks as in Table 3 but with varying exposure shares. Dependent variables are $\Delta AE$ (columns (1)-(4)), and Δ Cov(markup,inputs) (columns (5)-(6)). All regressions include sector and year fixed effects and standard errors clustered at the 2-digit industry level (in parenthesis). I drop the basic metal industry (ISIC 27). $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

## C.2 Simulated Method of Moments Estimation

In this section, I provide more details on the estimation the parameters of the structural model described in Section 3.3, and provide results with alternative parameter specifications.

The goal is to estimate the parameter set $(\alpha, \gamma, \theta, \beta)$. I solve the model via simulation because the moments in the model that pin down these parameters are created using simulated firms. In other words, for a guess of the parameters, I simulate firm-level outcomes and attempt to reproduce moments from the data, which includes firm sales, firm imports relative to total intermediate use, and firm markups. The moments in the data are constructed using the Chilean data described in the main text.

The theoretical moments are matched to their counterpart in the data in order to identify the model parameters. The moments above can be constructed using the same census of Chilean firms used in the reduced form estimation. The sample is the same set of firms used for Tables 1 and 2. This includes the set of firms where I can set a fixed import share in the base year, and drops firms with price-minus-cost markups of less than 0 or above 1 in any of the 3 markup estimates. For firm sales, I normalize by average sales in order to create a scale-free measure. Markups are estimated using the DLW procedure described in Section 2. I construct firm-level import shares as imported inputs relative to firm material costs, as well as import shares relative to sales. The data import share matched in the estimation is the average of the mean import share with each type of import measure. I calculate the average across all firms for two time periods. The time period that corresponds to $tau^I = 1$ is 1995-2002. The second time period, used is 2003-2007.

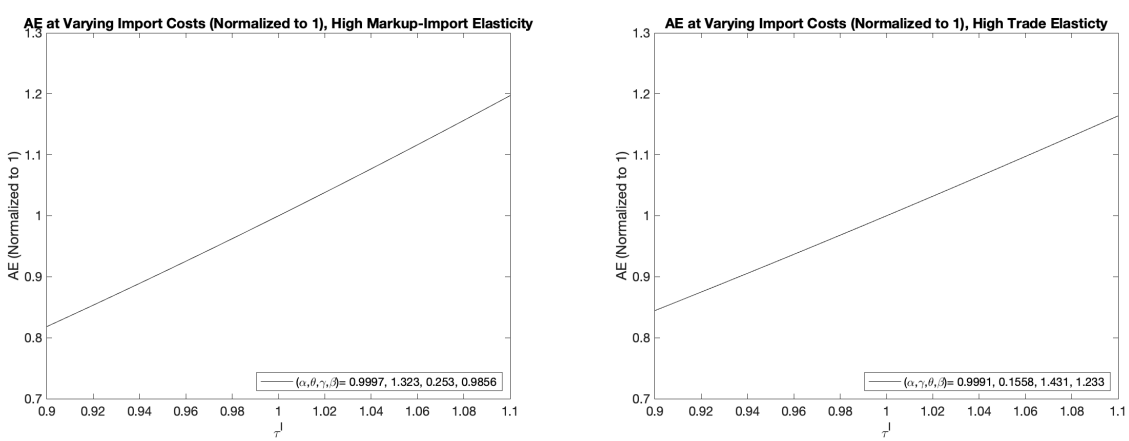
### C.2.1 Alternative Specifications

Next, I reproduce the results on how allocative efficiency varies with $\tau^I$, for varying specifications. First, I estimate the model with the same moments, but I match a higher change in markups with respect to the import share (which is identified by $\gamma$). The top left quadrant of Figure 11 reproduces $AE$ for the parameters when the change in the markup with respect to the import share is equal to 0.14 and all other moments are the same. Second, I raise the trade elasticity and re-estimate the model. The top right quadrant reproduces $AE$ for the parameters when the trade elasticity is equal to -5 and all other moments are the same. The new parameter estimates are reported on the bottom right of each figure. As expected, raising the markup response to the import share has a large effect on $\gamma$, which increases to 1.32, and $\theta$ drops. $AE$ now drops 1.6 percentage points in response to a 1% appreciation. The average markup also increases, to 14% when $\tau^I = 1$. This has little effect on other moments such as the average import share.

In the case of a higher trade elasticity, $\beta$ increases, while the other parameters are very slightly affected. As expected, the drop in $AE$ is also larger in the case, as a 1% appreciation leads to a 1.37 percentage point drop in allocative efficiency. The average markup is unchanged. Overall, we see how the magnitudes are slightly affected by changing the model moments, but the relationship is unchanged. Lowering $\gamma$ and $\beta$ would merely make the $AE$ change with respect to the exchange rate smaller.

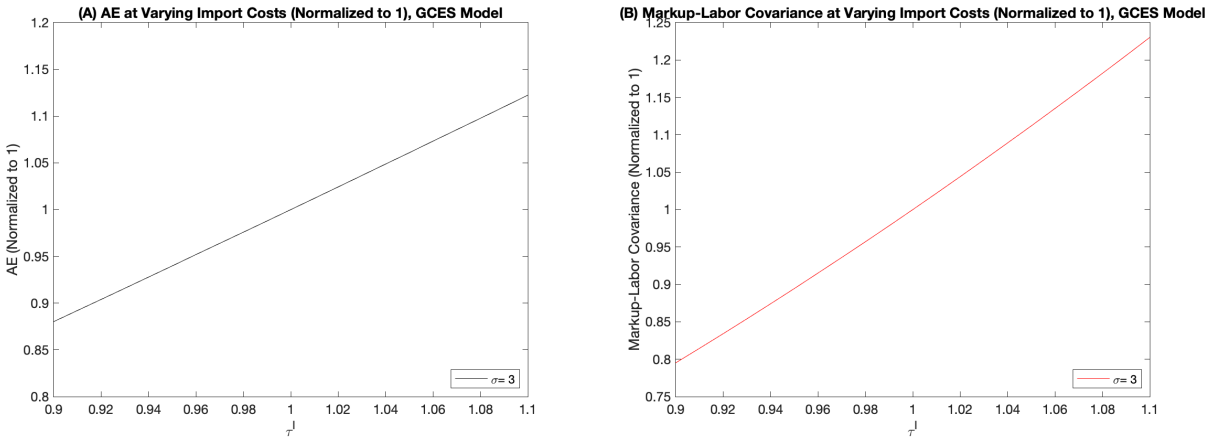
Finally, in the bottom right quadrant I take the parameters from the baseline estimation but compute the allocative efficiency assuming general CES demand. I set the $\sigma$ equal to 3, on the upper end estimated by Jung et al. (2019). As described in Appendix B.3, a higher $\sigma$ lowers the market power of each firm, but also raises the sales dispersion as consumers are less inclined to vary their consumption across varieties. Figure 12 reports both the changes in allocative efficiency and the markup-labor covariance, as in the main text, but with the larger demand curvature. The drop in $AE$ is very smaller, with a 1.2pp drop for every 1% appreciation. The average markup is lower (10% at $\tau^I = 1$), and the sales dispersion is larger (1.45). This is based on a $\sigma$ equal to 3, but the differences relative to the preferences in the main text simply increase with $\sigma$, and as $\sigma \to 1$, the results converge. As a higher $\sigma$ reflects firms having less ability to price discriminate (because consumers are more price sensitive as $\sigma$ increases), the compositional effect due to changes in $\tau^I$ decreases, although little. The big difference relative to the restrictive version is that eliminating log-linear demand allows the correlation between markups and sales to drop below one. In this parameterization it is equal to 0.39, still larger than what is observed in the data (0.11). A full estimation would require one to re-estimate the model to match this moment, allowing the rest of the parameters to adjust as well.

**Figure 11:** Effects of a Cost Shock on Allocative Efficiency: Alternative Moments




These figures replicate Panel (A) in (5, for alternative parameterizations.

**Figure 12:** Effects of a Cost Shock on Allocative Efficiency: General CES Model




Panel A reports the allocative efficiency statistic (normalized to 1 when $\tau^I = 1$) as $\tau^I$ varies between 0.9 and 1.1. Panel B reports the markup-labor covariance, once again normalized to one. These are calculated using the parameter estimates from Table 4. $\kappa$ is fixed at 4. $\sigma$, defined in Appendix B.3, is fixed to 3.

# D Global Shocks and Reallocation

In this Appendix section, I investigate how separate foreign shocks affect the reallocation of production and the implications for allocative efficiency. My strategy is to fit into a reduced-form approach two separate aggregate shocks that are generally confounded when trade costs are reduced. Globalization can affect firms through either i) their residual demand curve or ii) their marginal cost.[68] An example of the former effect is competition through foreign entry, which I show in Section D.1 reallocates production from less to more productive firms because more productive firms lower their markup relatively more. The latter case can occur through a higher terms of trade or lower input tariffs, and in this case more productive firms are able to increase their markup relatively more which reallocates production to the less efficient firms.

## D.1 Global Shocks and Markups

The average productivity/selection responses from the two shocks outlined above have been studied extensively in the canonical trade model. I differentiate how the shocks can increase

[68]Focusing exclusively on output tariffs can confound the two channels since they have opposite effects. Below I outline how each channel affects the markup distribution. Though the two shocks can happen simultaneously, in the empirical section I identify the shock using the firm or industry's expected exposure. For a separate perspective on how output tariffs can be tied to welfare gains from trade in a similar model, see Demidova (2017).

allocative efficiency ($\Delta AE_j > 0$), or dampen welfare gains by reducing allocative efficiency ($\Delta AE_j < 0$), purely through reallocation. My goal is to have a clear and intuitive demonstration of how a shock manifests itself through the change in relative markups, which can be interpreted as a reallocation that either increases or reduces allocative efficiency.

Consider an import competition shock that occurs with a one-time increase in entry ($M_e$). More entry implies an increase in the marginal utility of income — taken as given by the firm – and since $p(c) = \frac{u'(q(c))}{\delta}$, prices decrease for all firms. Let $p_i(\delta', c_i)$ represent the price decision of firm $i$ after an entry shock.

Separately, consider a shock that lowers costs of importing inputs.[69] To examine this case, I introduce imported inputs as a source of production with a constant labor requirement. To give the firm marginal cost more structure, for each firm $i$, let the production of one unit of output require one unit of a domestically produced task at cost: $c_i(\varphi_i) = \frac{a}{\varphi_i}$. $a$ is a constant, and $\varphi_i$ the firm's draw from a productivity distribution. With trade, firms can also import inputs with the cost of one unit of an imported task equal to $\frac{a(\tau^{\kappa_i}-1)}{\varphi_i}$ with $\tau^{\kappa_i} > 1$. The total marginal cost of production is then $c_i(\tau, \varphi_i, \kappa_i) = \frac{a\tau^{\kappa_i}}{\varphi_i}$, where $\tau$ is a scalar in the marginal cost curve that represents the cost of importing inputs and allows for a productivity shock that lowers production cost and raises markups due to incomplete pass-through (as is found in DeLoecker et al. (2016)). $\kappa_i > 1$ and is firm specific to allow the magnitude of the import shock to be heterogeneous across firms.[70] A shock that lowers the cost of imported inputs scales down $a\tau^{\kappa_i}$. The impetus for this mechanism can be a terms of trade gain or lower input tariffs.[71]

Taking both effects into consideration, price is represented by $p_i(\delta, a\tau^{\kappa_i}/\varphi_i)$ and Equation 4 is rewritten to express the markup as:

$$\frac{p_i(\delta, a\tau^{\kappa_i}/\varphi_i)}{a\tau^{\kappa_i}/\varphi_i} = \frac{1}{1-\mu(\delta, \tau^{\kappa_i}, \varphi_i)} = m_i(\delta, \tau^{\kappa_i}, \varphi_i) \tag{46}$$

Markups are a function of one firm primitive and two aggregate variables that identify the domestic environment. $\kappa_i$ is allowed to vary across firms, but I will compute comparative statics using changes in $\tau$ only, while controlling for firm specific effects in the empirical analysis. For the rest of this section, I set $\kappa_i = 1\ \forall i$.[72]

[69] DeLoecker and Goldberg (2014) differentiate between shocks to the residual demand curve and shocks to the marginal cost curve as responses to output and input tariffs changes respectively.

[70] For example bigger firms might be more sensitive to changes in import prices that small firms.

[71] Since $-1 < \frac{\partial q}{\partial c}\frac{c}{q} < 0$, a reduction in marginal costs will increase the equilibrium individual consumption of each variety and increase its markup.

[72] For example, in the empirical analysis I control for firm size, and interact it with the terms of trade (the $\tau$ shock).

To relate changes in allocative efficiency to reallocation, I concentrate on the second case from above which is also the focus of the empirical analysis of Chile. The firm-level responses to an input shock are given by $\frac{\partial m_i(\delta,\tau,\varphi_i)}{\partial \tau}$, and the reallocation effects can be interpreted as $\frac{\partial m_i^2(\delta,\tau,\varphi_i)}{\partial \tau \partial c_i}$. The first comparative static is trivial: the direction of the markup for each firm after the shock. The interpretation for the latter is the firm-specific sensitivity of the markup in response to the shock holding $\delta$ constant. The thought experiment is as follows: at a new equilibrium with a new $\tau$, has the markup difference between (the same) two firms increased or decreased? Going back to Equation 46, $\frac{\partial m_i(\delta,\tau,\varphi_i)}{\partial \tau} < 0$, or markups decrease with $\tau$. With the assumption of decreasing demand elasticity made in Section 3.1, it can be shown that $\frac{\partial m_i^2(\delta,\tau,\varphi_i)}{\partial \tau \partial c_i} > 0$.[73] Therefore at lower $\tau$'s, there is a *bigger* markup difference between a low cost and a high cost firm meaning that inputs are reallocated relatively to initially low markup firms. Intuitively, more productive firms pass-through relatively more of the cost reductions to markups.[74] At the industry level it shows up as a reduction in allocative efficiency as real revenues grow more slowly when there is a reallocation to low-markup firms.

I also explore a Krugman (1979) type globalization episode with tougher competition but relegate it mostly to the appendix since I cannot explore plausibly exogenous variation in competition in Chile using my data. In this case, at higher levels of competition the markup differences between two firms (which differ in their productivity) get *smaller*. Higher markup firms increase productions relatively more as they move down their demand curve and this shows up as an increase in aggregate allocative efficiency.

The details of these super/sub modularity arguments, and the derivations, are below. First, I summarize some testable predictions of the findings above.

## D.2 Testable Predictions

Incorporating the global shocks allows for testable predictions. The main question of interest is how the distinct aggregate shocks, either through a cost shifter or competition, affect aggregate misallocation at the industry level. With the assumptions on demand, reallocation of production can be inferred from the observed markup response and this allows for the channel that links the shocks to aggregate misallocation. There are therefore 2 connected predictions:

**Hypothesis 1.** *(Firm-level) A "favorable" cost shock in intermediate inputs increases markups due to incomplete pass-through, and also reallocates production to initially low markup firms*

[73] In Mrazova and Neary's terminology, this is equivalent to markups being super-modular with respect to trade costs when demand is "less convex" than CES.

[74] I have also checked that, as expected, CES demand implies both of these derivatives are equal to 0.

*because they increase markups by less. Increased import competition reduces markups, and this effect is larger for firms with initially higher markups because production is reallocated to high markup firms.*

**Hypothesis 2.** *(Industry-level) A terms of trade appreciation or decrease in input tariffs (reduction in the cost of imported inputs) reduces allocative efficiency. Increased import competition (through a reduction in output tariffs) increases allocative efficiency.*

I use Chilean data to measure growth in allocative efficiency at the 2-digit industry level as well as firm level markups using production function estimation. I argue that the real exchange rate shock – interpreted as a cost shock – is consistent at the micro level with the predicted changes in markups and at the macro level with the implied changes in allocative efficiency.

## D.3 Markup Heterogeneity: Super/Sub Modularity

### D.3.1 Markup Differences in response to more entry

A shock to the residual demand curve can be produced by assuming a higher level of entry, $M_e$, which will increase the marginal utility of income, $\delta$. $\frac{\partial q_i}{\partial M_e}\frac{M_e}{q_i} < -1$ (equilibrium consumption of each variety decreases), which raises the marginal utility of income. Using the same super/sub-modularity argument as in the main text (and shown in detail below), and once again assuming that demand elasticities decreases with sales, tougher competition not only lowers the average markup but also leads the lower cost firms to decrease their markup more than high cost firms.[75]. In this case we start with $\frac{\partial m_i(\delta, c_i(\tau,\varphi_i))}{\partial \delta} < 0$, so that a competition shock, or an increase in $M_e$, lowers the markup of each firm. To see the reallocation effects let $c_i = \frac{a\tau}{\varphi_i}$ be constant for each firm as there is no shock to $\tau$. Then, $\frac{\partial m_i^2(\delta, c_i(\tau,\varphi_i))}{\partial \delta \partial c_i} > 0$, which means that at higher levels of competition the markup differences between two firms get *smaller*. Higher markup firms increase productions relatively more as they move down their demand curve.

### D.3.2 The sub/super modularity argument

In general, the function $m_i(\delta, \tau, \varphi_i)$ is supermodular in $\tau$ and $\varphi_i$ (for a given $\delta$) if:

$$\Delta_{\varphi_i} m_i(\delta, \tau_1, \varphi_i) \leq \Delta_{\varphi_i} m_i(\delta, \tau_2, \varphi_i) \text{ when } \tau_1 \geq \tau_2 \tag{47}$$
$$\text{where } \Delta_{\varphi_i} m_i(\delta, \tau, \varphi_i) = m_1(\delta, \tau, \varphi_1) - m_2(\delta, \tau, \varphi_2) \text{ for } \varphi_1 \geq \varphi_2$$

[75] A result similar to Melitz and Ottaviano (2008)

In the main text I define $m_i(\delta, \tau, \varphi_i) = \frac{p_i(a\tau/\varphi_i)}{a\tau/\varphi_i}$. Let $a = 1$ in this section. Super-modularity holds when $\frac{\partial m_i^2(\delta,\tau,\varphi_i)}{\partial\tau\partial\varphi_i} > 0$. Therefore the markup difference between two firms differentiated by their productivity/marginal cost gets smaller or larger depending on the change in $\tau$. Below, as in the main text, I use *cost differences* instead of productivity differences to calculate supermodularity but the same intuition holds.

To show the results in the previous subsection, I will examine two unique example of the VES utility system of Dhingra and Morrow (2019). They show in their paper that distortions are determined by two elasticities: the demand elasticity and the elasticity of utility (which determines the social markup). Therefore there are 4 different possibilities: demand elasticity and elasticity of utility both increase in production, both decrease in production, and one increases and the other decreases (2 separate cases). My paper actually eliminates two of these cases by considering only decreasing demand elasticities as that is consistent with the Chilean data (and every other firm data I am aware of).

Therefore, I take one functional form example of each possible case. This is sufficient to show that the results are general for the whole VES class I explore in this paper. Although alternative functional forms for preferences within each case have different implications for equilibrium price, quantity, markup, etc., the changes in markups in response to the shocks must move in the same direction for a unique assumption on the sign of i) change in the elasticity of utility with quantity; and ii) change in demand elasticities with quantity.

**Case 1: Stone-Geary preferences (social markup decreases with quantity)**

$$u(q) = (q + \alpha)^{\rho}\,, \tag{48}$$

where $\alpha > 0$. In order to get an analytical solution I follow Simonovska (2015) and take the special case for $\rho$ such that $u(q) = \log(q + \alpha)$. Furthermore, for this example assume that $\alpha = 1$. This example is consistent with a decreasing social markup and decreasing demand elasticity, plus the necessary conditions that $u'(q) > 0$, $u''(q) < 0$, and $\mu(q) < 1$.

First order conditions for the firm satisfy $u'(q) + qu''(q) = \delta\tau c$. After calculating the first and second derivatives of the utility function allows me to solve for $q$ and the markup:

$$q = (\delta\tau c)^{-1/2} - 1, \text{ where } c \in \left(0, \frac{1}{\delta\tau}\right) \tag{49}$$

$$m = \frac{p}{\tau c} = \frac{u'(q)}{\delta\tau c} = (\delta\tau c)^{-1/2}\,, \tag{50}$$

Finally, the above expressions allow me to verify that: $\frac{\partial m(\delta,\tau,\varphi)}{\partial\tau} < 0$, $\frac{\partial m(\delta,\tau,\varphi)}{\partial\delta} < 0$, $\frac{\partial m(\delta,\tau,\varphi)^2}{\partial\tau\partial c} > 0$, and $\frac{\partial m(\delta,\tau,\varphi)^2}{\partial\delta\partial c} > 0$.

**Case 2: HARA or "bipower" preferences (social markup increases with quantity)** The HARA system is the specific utility system explored by Dhingra and Morrow (2019) and is also used in Cavallari and Etro (2017):

$$u(q) = aq^{\rho} + bq^{\alpha}, \tag{51}$$

where $\rho \neq \alpha$, $a < 0$, and $b > 0$ to satisfy the conditions that the social markup increases with quantity and the demand elasticity decreases with quantity. An example that satisfies the necessary restrictions and is easy to work with is: $\rho = 3$ and $\alpha = 1$.

Again, the first order conditions for the firm satisfy $u'(q) + qu''(q) = \delta\tau c$ which allows me to solve for $q$ and the markup:

$$q = \sqrt{\frac{\delta\tau c - b}{9a}}, \text{ where } c \in \left(0, \frac{b}{\delta\tau}\right) \tag{52}$$

$$m = \frac{p}{\tau c} = \frac{1}{3} + \frac{2}{3}\left(\frac{b}{\delta\tau c}\right) \tag{53}$$

Once again this allows me to verify that $\frac{\partial m(\delta,\tau,\varphi)}{\partial \tau} < 0$, $\frac{\partial m(\delta,\tau,\varphi)}{\partial \delta} < 0$, $\frac{\partial m(\delta,\tau,\varphi)^2}{\partial \tau \partial c} > 0$, and $\frac{\partial m(\delta,\tau,\varphi)^2}{\partial \delta \partial c} > 0$.