Markups and Misallocation with Evidence from an Exchange Rate Appreciation

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Abstract

With non-homothetic preferences, a monopolistic competition equilibrium is inefficient. In a setting with heterogeneous firms that charge variable markups, this paper finds a sufficient statistic for changes in allocative efficiency that can be directly measured with data. The model also predicts differential effects of competition and cost shocks on the reallocation across domestic firms, which I test empirically with firm and industry-level data in Chile, a country that has experienced large exchange rate shocks. I find important changes in misallocation over time due to the way firms pass-through productivity gains into markups. From industry-year variation, there is evidence that industries that import a larger share of their inputs become more misallocated as a result of exchange rate appreciations compared to open sectors whose output competition becomes fiercer. The observations of markup responses at the firm level are consistent with the aggregate measure of allocative efficiency.

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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 (2015) (DM) that non- constant markups in a monopolistic competition framework imply a sub-optimal allocation across firms, and 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 globalization events, with the objective of empirically showing 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. Higher markups by these firms map onto lower aggregate income relative to the allocatively efficient benchmark and thus creates an aggregate distortion.

The first contribution of this paper is to show that the aggregate distortion is captured

[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.

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.[3] 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. Furthermore, I connect allocative efficiency to trade policy by identifying the heterogeneous effects of aggregate shocks on firm market power. I use aggregate shocks to the open economy such as the exchange rate and import competition as a possible impetus for reallocation. The model yields comparative statics that allow me to make predictions about the way these shocks will show up as aggregate allocative efficiency changes.[4]

Globalization/trade policy has two separate – and possibly simulataneous – effects. One possibility is that there are more varieties that enter the domestic market (a competition effect), and this affects firm-level demand elasticities. A separate possibility is to lower marginal costs for domestic firms through cheaper intermediate inputs. Tougher competition results in initially high-markup firms lowering their prices relatively more, so that inputs must be reallocated to these firms. The latter shock allows firms to charge higher markups due to incomplete pass-through into prices, resulting in larger markup heterogeneity because pass-through is smaller for high-markup firms. In both cases, the pass-through heterogeneity yields a reallocation that affects total income. In the empirical framework I aim to separately control for the effects of both shocks, which differs from the more common exercise that explores lower output tariffs. However, I stress that I only find evidence for the case of cheaper inputs due to the large variation in the real exchange rate but very small reduction in output tariffs during this time.

I examine changes in this aggregate misallocation, measured at the industry level, and its relation to firm level reallocation, using both industry and firm-level panel data for Chile from 1995-2007. This period includes both large real exchange rate shocks – due mostly to changes in the price of copper (Chile's main export) – and a gradual continuation of Chile's past trade liberalization. To do so, I follow the recent literature's

[3] I do not necessarily measure *all* of the change in allocative efficiency as a component of welfare because it does not take into account optimal entry. I differentiate between revenue and the welfare component not captured by revenue (Vives (2001)).

[4] I point out that the limitation of my framework is that I will only explicitly model domestic producers (selling at home and abroad). This is suitable for my empirical analysis described below. Without customs data, I cannot know where the domestic firms are exporting (and value to each destination) nor where the imports are coming from (and value from each origin).

expanded view of globalization, which considers input costs together with import competition (Konings and Vandenbussche (2013)). I focus on the terms of trade gain because of the large magnitude of the appreciation, with the terms of trade shock interpreted as an exogenous exchange rate appreciation for non-copper manufacturing (as I eliminate the copper-based metal industries from the analysis). The exposure to exchange rate movements depends on the vulnerability to import competition versus reliance on imported inputs. [5] As predicted in the model, the exchange rate shock has heterogeneous effects on market power at the firm level, which is reflected in the changes in income at the industry level. Therefore, my data allows me to connect the firm level findings with the observed movement in the aggregate measures.

The main aggregate empirical results are that industries dominated by firms that rely on imported inputs become more misallocated in response to a positive terms of trade shock. Comparing the extreme case of an industry that imports 100% of inputs and does not export any of their products with an industry whose share of imports in inputs equals the share of exports to sales[6], a 1 percent increase in the growth rate of the terms of trade leads to a 4.24 percentage points smaller growth rate in allocative efficiency in the former industry relative to the latter. For sectors that compete in final goods (export-oriented and import-competing), the terms of trade gain leads to a modest increase in allocative efficiency. Those sectors are also the ones affected the most by trade liberalization. A sector that does not import, but exports all of its output, has allocative efficiency growth 1.14 percentage points larger than an industry whose share of imports in inputs equals the share of exports to sales, in response to a 1 percent decrease in the growth of output tariffs. Therefore, I conclude that real exchange rate shocks in Chile are important drivers of allocative efficiency.

Although the distortion I measure is at the industry level, it is the product of aggregating firm-level responses. For this reason I start by showing at the firm-level that the terms of trade appreciation raises markups more for importers. The response is largest for the most productive (and largest) firms, which implies the overall market power distortion increases. In fact, the terms of trade shock is followed by a large rise in the dispersion of markups, and the evidence suggests that importing sectors drive this result. I show that the reallocation witnessed at the firm level is consistent with allocative efficiency findings at the industry level.

The theoretical and empirical contributions should be viewed relative to numerous

[5] I can confirm that importers reduce costs with an appreciation. Exporters and other domestic producers face stricter competition in this case, as well as when output tariffs are reduced.

[6] In Section 6 I delineate the reasons for this definition

recent papers. Dhingra and Morrow (2015) characterize qualitative properties of this misallocation and investigate the case where market size increases. Arkolakis et al. (2015) 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. Furthermore, I bring in firm-level data and show how real exchange rate shocks in Chile had distortionary effects.

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, I suggest a measure separate from firm TFP in Section 3.2 that is based on the change in the covariance of prices and quantities, an interesting statistic that has not been explored in this literature.[7] This feature also differentiates my measure to that in Holmes et al. (2014) which holds only for homothetic preferences.[8] 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. (2012) 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

[7] In future work, this covariance measure could bridge the misallocation measures between models of a supply-side focus and those that rely on non-homothetic demand for variable elasticities. For example, Arkolakis et al. (2015) relate the monopolistic competition distortion to changes in the revenue shares for markup aggregates. 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.

[8] I maintain the monopolistic competition environment as in Krugman (1979) and Melitz (2003) but generalize the prefereces within the boundaries of separable utility and log-concave demand.

degree of misallocation because productive firms raise their markups the most. My empirical results are related to Berman et al. (2012) who show that exchange rate movements tend to affect markups and not export volumes.[9] I focus on how this markup effect relates to the way the trade literature measures reallocation instead of the implications on export volumes. On the efficiency side, theoretical models have explored variety and scale trade-offs (Chamberlin, 1933; Vives, 2001), but not necessarily misallocation of quantity among existing producers, which requires firm heterogeneity.

The rest of this paper is organized as follows. The next section is a literature review. Section 3 sets up the theoretical framework and differentiates between growth in real income in the CES and VES models. Section 4 provides predictions for aggregate movements in misallocation based on two distinct ways that open economy shocks drive reallocation at the firm level. Section 5 describes the data and Section 6 presents the empirical results. Section 7 concludes and discusses the composition of importers and exporters at the country level in relation to misallocation.

2 Related Literature

Theoretical trade models have explored variable markups to generalize welfare gains from trade, though the earlier literature concentrates on the decrease in the average markup in search of a "pro-competitive" effect as in Krugman (1979). When there is free entry, competition decreases average markups and increases aggregate productivity as firms increase their scale and move down their average cost curves. This is possible with symmetric firms and for this reason should be separated from the distortion present in this paper that is the result of the interaction of non-homothetic demand (with separable preferences) and firm heterogeneity. Feenstra and Weinstein (2010) use a homothetic (with non-separable preferences) framework to measure the pro-competitive plus variety effects from increased global competition. Bertoletti et al. (2017) examine pro-competitive effects when preferences are non-homothetic but not additively separable. Within the directly additive non-homothetic preference framework, Behrens et al. (2014) have investigated the pro-competitive effect of trade liberalization, while Simonovska (2015) establishes the existence of price discrimination across destinations with heterogeneous incomes. Cavallari and Etro (2017) have applied non-homothetic preferences to the study of business cycles using a functional form introduced in Bertoletti et al. (2008). Finally.

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

Arkolakis et al. (2015) (ACDR) look at a broader class of variable markup models and point out that with non-homothetic demand there is an extra welfare term that is the average markup elasticity with respect to costs. Demidova (2016) studies a similar framework and introduces trade policy to the qualitative statements about welfare gains from trade.

Misallocation has recently been introduced into models with CES preferences and heterogeneous firms in oligopolistic competition based on Bernard et al. (2003) and Atkeson and Burstein (2008). de Blas and Russ (2015), Peters (2011), Holmes et al. (2014) and Edmond et al. (2015) all focus on welfare gains of tougher competition when the distribution of markups plays a key role. In my model with VES preferences and monopolistic competition, misallocation is due to non-homotheticity on the demand side. It allows for more flexible demand, a distortion that maps to the aggregate productivity literature, and an intuitive application to incomplete pass-through. The latter feature not only receives empirical support, but opens up the possibility of cost shocks that lower allocative efficiency in addition to tougher competition lowering the market power of high-markup firms.

Epifani and Gancia (2011) also relate markup heterogeneity to misallocation. In that paper an aggregate distortion is due to heterogeneity in markups, so that markups above (below) the mean are due to having too few (many) workers and imply under- (over-) production for an industry. In fact they demonstrate a similar result of how trade liberalization can reduce welfare by raising markup differences across sectors. In contrast to my study, they focus on inter-sectoral inefficiency and limit their empirical results to aggregate data. The mechanism through which welfare can be reduced is also different as it is not related to incomplete pass-through which is complete in their model. Although I view the inter-sector inefficiencies as another important component, my empirical identification of exchange rate exposure is a better fit for examining variation across firms. Trade liberalization exercises have examined "traded" versus "non-traded" sectors before, but it is hard to rationalize such extreme cases when you account for intermediate inputs.

The relation of markups and misallocation has also been a focus outside of the trade literature. The distortions present in this model will remind the reader of Hsieh and Klenow (2009) (HK), which models firms' production choices given they face output and capital distortions. In their framework markups are constant due to CES preferences but the distortions mean 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, as the non-equalization of firms' marginal rates of transformation occurs endogenously through non-homothetic preferences. Consistent with the aggre-

gate productivity literature, a distortion inflicts a wedge between total revenues and total output, and leads to an inefficient allocation of resources.

The closest fit to this paper theoretically might be the Aggregate Productivity Growth (APG) literature that decomposes APG into growth in average firm productivity and reallocation. Basu and Fernald (2002), Petrin and Levinsohn (2012) and Basu et al. (2010) argue that reallocation increases welfare if inputs are reallocated to where they have the highest social valuation in terms of marginal utility. In those papers, the markup is the gap between marginal revenue productivity of an input and the cost share of that input in the total input cost. There is aggregate productivity growth when inputs are reallocated towards firms with markups above the mean markup. I incorporate the same type of welfare gain into a trade model that is an extension of Melitz (2003).

Empirically, my results are closest to DeLoecker et al. (2016) and Berman et al. (2012), as mentioned above. It is evident a CES model would over-state the gains from trade given their incomplete pass-through findings. This is what I find, that firm-level productivity gains are not necessarily passed through to aggregate real income. 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 their Olley and Pakes (1996) decomposition, aggregate productivity is the sum of unweighted average productivity and the covariance of market share and firm productivity (which is the Melitz-type reallocation). This method is consistent with aggregate Solow residuals, so it misses the part of reallocation that is due to misallocation (captures only the selection effects). 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. I show that this was true also for Chilean firms.

3 Structural Estimation of Allocative Inefficiency

3.1 Setup of Variable Elasticity Model

In this section I succinctly describe the framework with non-homothetic, directly additive preferences that is fully laid out in Dhingra and Morrow (2015) and Zhelobodko et al. (2012). I add an upper tier to describe the interaction across sectors, but focus on the intra-sector action. 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. Preferences are given by the following aggregation across and within sectors, j:

$$U \equiv \prod_{j=1}^{J} U_j^{\beta_j} \tag{1}$$

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

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

Notice the first line assumes that there is Cobb-Douglas aggregation across sectors. This will allow me to focus on the intrasector misallocation and assign each sector a constant weight β_j.[10] I assume that utility within sectors takes a variable elasticity form and is *additively separable 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.[11] 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 the rest of this section I mostly drop the subscript j to concentrate on the within-sector analysis and return to the definition of industries in the empirical framework (below I will selectively use j subscripts in some equations to highlight that they hold at sector level). Notice that the Cobb-Douglas aggregation assumes there will be no interesting sectoral interaction, although misallocation could also be present across sectors.[12][13]

[10] To tie this to the empirical application, a sector will be comprised of products within a 2-digit ISIC code. Aggregate measures will be constructed and vary at this level.

[11] This is the case most often chosen in the literature, which Mrazova and Neary (2013b) 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".

[12] See Epifani and Gancia (2011) for a nice application of inter-sector misallocation. I view my contribution as complementary to theirs in examining separately within-sector efficiency. This is a reasonable application for Chile, where the labor share of 2-digit industries are remarkably constant during the 13 years I study.

[13] Behrens et al. (2016) derive separate intra-sector and inter-sector allocative efficiency measures for a similar model. With the Cobb-Douglas upper-tier, the two inefficiencies can be studied independently. Their paper focuses on quantifying the inefficiencies using calibration.

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 firns 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 marignal costs and the the markup rate is equal to the inverse demand elasiticity: $\mu(q) = |\frac{qu''(q)}{u'(q)}| = |dlnp(q)/dlnq| = (p(c) - c)/p(c)$. I refer to this Lerner Index as the degree of market power, though in the data I use the price-cost ratio for markups (defined below). Free entry implies the following sector-specfic 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 and not producing.

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 $u'(q(c)) = \frac{\delta c}{1-\mu(q(c))}$, where μ is the Lerner Index. 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.[14] As in Basu and Fernald (2002), when market power is heterogeneous firms do not equate marginal rates of transformation. As expressed in DM and related to Feenstra and Kee (2008), the social and market allocations are aligned only when utility is defined by CES preferences, where the market allocation mirrors a constrained optimum.

3.2 Allocative Inefficiency

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

[14] In this decreasing demand elasticity case, more productive firms have more market power and higher markups.

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 subutility 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 in each sector j:

$$\begin{aligned} U_j &= M_j^e \int u_j(q_j) dG_j \propto M_j^e \int_0^{c_d^j} u_j'(q_j(c)) q_j(c) dG_j(c) \\ &\propto \lambda_j M_j^e \int_0^{c_d^j} \frac{1}{1-\mu_j(q_j(c))} c q_j(c) dG_j(c) \\ &\propto \lambda_j L_j \big(\int_0^{c_d^j} \frac{1}{1-\mu_j(q_j(c))} dG_j(c) \big) \big(L_j - N_j f - M_j^e f_e \big) \end{aligned} \tag{5}$$

where N_j is once again the mass of varieties supplied and λ_j is the Lagrange multiplier in the social problem of utility maximization.[15] The last line uses the budget constraint (the total resources in the economy), and that $Cov(\frac{1}{1-\mu(q(c))}, cq(c)) = 0$ when the sub-utility function is homothetic. 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. Below, I will work to get a measure of this misallocation that is possible to track in the data by comparing growth in revenue in the socially optimal and market allocation. Notice that this framework is consistent with the results of Edmond et al. (2015) and Arkolakis et al. (2015), who both find that it is the *joint distribution* of markups and production that matters.[16]

[15] A sector aggregate that represents the shadow value of resources.

[16] Alternatively, the intuition is that the whole distribution of markups matters, not the unweighted mean.

It has been known since Dixit and Stiglitz (1977), summarized in Vives (2001), and expanded in Mrazova and Neary (2013a) that an inefficiency exists even with homogeneous firms due to a distortion in the number of available varieties.[17][18] I decompose the full welfare expression in my 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.

Let aggregate revenue, $R = M^e L \int_0^{c_d} p(q(c))q(c)dG(c)$. 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, $Q \equiv NL \int_0^{c_d} q(c)h_d(c)dc$. $q(c)$ stands for the consumption of an individual variety by identical consumers. 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 (2015), 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 δ as the marginal utility of income), to decompose revenue within the indirect utility function:

$$\begin{aligned} V &= NL\frac{\delta}{\bar{\epsilon}} \int_0^{c_d} p(q)q(c)h_d(c)dc \\ &= \frac{\delta}{\bar{\epsilon}} R \\ \Delta ln(V) &= \Delta ln(\delta) - \Delta ln(\bar{\epsilon}) + \Delta ln\,(R) \end{aligned} \tag{7}$$

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 $-\Delta ln(\bar{\epsilon})$ is zero.[19] 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. However, Equation 7 does

[17]These studies all establish allocative inefficiency with symmetric firms, in contrast to my focus on the allocative inefficiency due solely to firm heterogeneity.

[18]Chamberlin (1933) also argued for "excess capacity" which resulted in excess entry.

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

motivate why we care about revenue: the change in revenue is a component of welfare growth.

At this point I have reached the central purpose for this decomposition, which is to ask, *how biased are changes in revenue over time using CES demand relative to the generalized variable elasticity demand?*

I use some algebraic manipulations to rewrite the revenue term in Equation 7:

$$\Delta ln(V_j) = \Delta ln(1-\bar{\epsilon}_j) + \Delta ln(\delta_j) + \underbrace{\Delta ln\left(P_j\right) + \Delta ln\left(Q_j\right) + \Delta ln\left(\frac{\tilde{R}_j}{Q_j}\right)}_{\Delta ln(R_j)} \tag{8}$$

where I denote $\frac{R}{P}$, real revenue, with $\tilde{R}$. 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 8, it is helpful to derive it from the 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, the aggregate revenue equation can be manipulated in the following way:

$$\frac{R}{P} = NL\int_0^{c_d} q(c)h_d(c)dc + NL\left[\text{Cov}(p,q)/\int_0^{c_d} p(q(c))h_d(c)dc\right] \tag{9}$$

The last term is a residual that represents the deviation of real revenue from physical production. Equation 9 can be further expanded substituting for $\tilde{R}$ and Q, and then taking logs to get growth rates:

$$\begin{aligned} \frac{\tilde{R}}{Q} &= 1 + \frac{\text{Cov}(p,q)}{\int_0^{c_d} p(q(c))h_d(c)dc \int_0^{c_d} q(c)h_d(c)dc} \\ \Delta ln\left(\frac{\tilde{R}}{Q}\right) &\approx \Delta\left(\frac{\text{Cov}(p,q)}{\int_0^{c_d} p(q(c))h_d(c)dc \int_0^{c_d} q(c)h_d(c)dc}\right) \end{aligned} \tag{10}$$

The last line uses the approximation that $ln(1+x) \approx x$.

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.[20] In other words, the measure provides a sufficient statistic for the correction in real revenue due to reallocation

[20]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.

that is not captured in the Melitz-Chaney framework. For this to be true, the following proposition is necessary:

Proposition 1. *In the VES framework described above, and if $G_j(c)$ is a Pareto distribution, then $\Delta \ln(\tilde{R}_j) = \Delta \ln(Q_j)$ if and only if demand in sector j is CES.*

Proof. In Appendix A I take the case of CES preferences and Pareto distribution of costs and show that the right hand side of Equation 10 is zero.

The secod 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 10 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 ΔAE:

$$\Delta(AE_j) = \Delta ln\left(\frac{\tilde{R}_j}{Q_j}\right) \tag{11}$$

Notice that this term is the log change of the aggregate markup and with heterogeneous firms depends on the joint distribution of markups and production. With constant markups it is intuitive that it is constant. Furthermore, it is straighforward to show that $\Delta \ln(V) = \Delta \ln(Q)$ in the CES case since the price index is proportional to the inverse of the Lagrange multiplier. With variable markups, "technology" will not necessarily capture productivity (Basu and Fernald (2002)). Lastly, notice that this holds for each industry j and does not account for inter-sectoral allocations.

3.3 Discussion

Equation 11 measures the real revenue change due to a change in the distribution of the price-cost ratios, holding productive efficiency comstant. This measure is therefore similar to the Holmes et al. (2014) (HHL) allocative efficiency index that is separable from production efficiency to measure gains from trade. However that index only holds for homothetic tastes. The features of that model make it very useful for analyzing the effects of a symmetric trade cost, but not for taking into consideration 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)) (DGKP). The comprehensive studies of misallocation in Edmond et al. (2015) (EMX) and Hsieh and Klenow (2009) (HK) also focus on an aggregate TFP index due to homothetic demand. I see the measure

in Equation 11 as a complement to those papers because Sections 4 and 6 will establish evidence consistent with recent firm-level empirical work (DGKP, Berman et al. (2012), Chatterjee et al. (2013)) that cannot necessarily be tied to HHL, EMX, and HK. My measure is not tied to an aggregate TFP measure but instead non-homothetic preferences result in a welfare distortion in market allocations – differentiated from the supply-side interpretation of those papers.

In the case of directly additive preferences and a variable elasticity of substitution, "over/under-producing" is a result of market power and pass-through. Due to incomplete pass-through, some of the cost advantages are passed through to markups instead of prices, which is why low cost firms have higher markups and lower production than under the optimal allocation. For example, take the case of two heterogeneous firms indexed by c and c′, with $c < c'$. Then, with incomplete pass-through: $\frac{p}{p'} > \frac{c}{c'}$, in clear contradiction to the socially optimal condition present in the CES that $\frac{p}{p'} = \frac{c}{c'}$. This is why there are extra terms that need to be accounted for to measure welfare gains.

ACDR propose a gains from trade decomposition with variable markups that also includes a misallocation distortion.[21] The focus of this paper is on this distortion applied to an environment with domestic firms only: the last term in Equation 8. In ACDR, 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. In the next section I incorporate trade policy by introducing competition and cost shocks separately, unlike a reduction in output tariffs that can lead to both of these happening simultaneously. Trade shocks can have either of the two effects on domestic firms: an increase in competition will lead to a reallocation that lowers misallocation, while a reduction in marginal costs results in a reallocation that raises misallocation among domestic firms.

4 Global Shocks and Misallocation

The model above is informative about the firm-level distortions that cause misallocation and how to reallocate production to reduce this distortion. Next, I investigate how trade policy affects 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

[21] They show that this distortion is proportional to the covariance of markups and firm-level employment shares (of domestic firms).

through either i) their residual demand curve or ii) their marginal cost.[22] An example of the former effect is competition through foreign entry, which I show in Section 4.1 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. Although the two reallocation results are not necessarily surprising in light of the recent work in non-homothetic models (e.g, Arkolakis et al. (2015)), this section provides a useful transition to connect separate aggregate shocks that we might observe in the data with the micro reallocations and aggregate allocative efficiency implications that have not been explored elsewhere.[23] To make this clear, I adopt a method in Mrazova and Neary (2013b) that compares the distributional changes from an old to the new equilibrium.

4.1 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 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.[24] 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

[22]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 exposure to globalization. For a separate perspective on how output tariffs can be tied to welfare gains from trade in a similar model, see Demidova (2016).

[23]Edmond et al. (2015) is an exception, but the supply side inefficiency in their paper is different than the inefficiencies in this paper. Demidova (2016) explores a change in output tariffs only.

[24]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.

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 φ_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 τ 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.[25] 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.[26]

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:

$$\frac{p_i(\delta, a\tau^{\kappa_i}/\varphi_i)}{a\tau^{\kappa_i}/\varphi_i} = \frac{1}{1-\mu(\delta, \tau^{\kappa_i}, \varphi_i)} = m_i(\delta, \tau^{\kappa_i}, \varphi_i) \tag{12}$$

Markups are a function of one firm primitive and two aggregate variables that identify the domestic environment. κ_i is allowed to vary across firms, but I will compute comparative statics using changes in τ only, while controlling for firm specific effects in the empirical analysis. For the rest of this section, I set $\kappa_i = 1 \; \forall i$.[27]

To relate the pro- and anti-allocative reallocation effects to misallocation I start with the second case from above. 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 δ constant. The thought experiment is as follows: at a new equilibrium with a new τ, has the markup difference between (the same) two firms increased or decreased?[28] Going back to Equation 12, $\frac{\partial m_i(\delta,\tau,\varphi_i)}{\partial \tau} < 0$, or markups decrease with τ. With the assumption of decreasing demand elasticity made in Section 3.1, it can be shown that $\frac{\partial m_i^2(\delta,\tau,\varphi_i)}{\partial \tau \partial c_i} > 0$.[29] Therefore at lower τ's, there is a *bigger* markup difference between a low

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

[26]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.

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

[28]This follows the method of Mrazova and Neary (2013b), who use the second derivative to establish super/sub-modularity. Details are provided in Appendix C.

[29]In Mrazova and Neary's terminology, this is equivalent to markups being super-modular with respect

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.[30]

The comparative statics make the simplifying assumption that importing requires a constant labor requirement as in Acemoglu et al. (2012),[31] but I should point out some alternative frameworks. A conceivable alternative is that of Gopinath and Neiman (2012) with a fixed import cost, which allows for non-homothetic import demand. Their paper focuses on productivity changes in response to shocks in the ability to import, and not market power or allocative efficiency. Additionally, in Amiti et al. (2012) larger firms import more and are the most likely to take advantage of a reduction in τ. In the empirical section I use information about the share of imports in a firm's material cost and study the distributional effects of market power for a given share of imports. To control for the differences in κ_i, I conduct robustness checks with firm controls such as TFP, size, and foreign ownership that are interacted with the trade shock.

In a Krugman (1979) type globalization episode with tougher competition, $\frac{\partial q_i}{\partial M_e}\frac{M_e}{q_i} < -1$ (equilibrium consumption of each variety decreases), which raises the marginal utility of income. Using the same super/sub-modularity argument as above 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.[32]. 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 τ. 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.

4.2 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. In the empirical section I establish that the observed firm level reallocation is consistent with the observed growth rate in

to trade costs when demand is "less convex" than CES.

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

[31] In their paper the foreign country plays the role of a general-purpose technology.

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

allocative efficiency per the theoretical framework in Section 4.1. 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. *(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.*

Hypothesis 2. *(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 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.*

This hypothesis is tested by the consistency of the observed firm-level responses with the growth in aggregate allocative efficiency as defined in subsection 3.2. Notice that this differs from the ACDR exercise that explores lower output tariffs and the response from both domestic and foreign firms. Although the predictions should not be surprising given the recent literature on non-homothetic demand, this provides a clear direction for my empirical analysis that builds from the firm level up to aggregate industry results. 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. In Section 6, I argue that the shocks are consistent at the micro level with the predicted changes in markups and at the macro level with the implied changes in allocative efficiency. However, I find this only for the cost shock, which I argue is due to very little variation in tariffs during this period. In the next section, I describe the data and important open economy measures for Chile.

5 Data and Background Information

5.1 Data Description

I combine a Chilean firm level panel data 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. Importantly, firms also report the value of inputs that are imported from abroad and what value of their total sales is exported.

Although I do not have firm level data on prices and quantities, the aggregate distortion term can be inferred using aggregate data on growth in real revenue and physical production. The growth of real revenue has an empirical counterpart in the data consistent with the assumptions that input prices are taken as given and prices reflect the marginal utility of a representative consumer. This 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.[33]. For the aggregate price level, the Chilean statistical agency provides 4-digit ISIC industry deflators.[34] Therefore the most disaggregated measure of real income growth available is at the 4-digit ISIC. Furthermore, I will 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 is used to produce an index of production at the 3-digit ISIC level that allows me to track annual growth in physical production by incumbent firms. This index follows a subset of firms with bases in 1989 (for the 1995-2002 data) and 2002 (used for the 2003-2007 data). [35] There is enough data therefore to infer the change in the misallocation distortion as implied by Equation 11.

Other macro and open economy data is taken from a variety of sources. The Central Bank of Chile provides manufacturing GDP, nominal exchange rate and aggregate export and import data. Detailed export and import data at the 4-digit level is provided in the world trade flows database of Feenstra et al. (2005). I compute a real effective exchange rate (REER) as a geometric average of relative prices using trade weights from the BIS[36] and output prices provided by the Penn World Tables (PWT) 8.0.[37] The nominal effective exchange rate (NEER) is a trade weighted average of nominal exchange rates provided

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

[34]These are deflators computed by the INE, which I take as a reasonable approximation of my aggregate price level.

[35]Due to constraints on the number of 3-digit groups and inconsistencies in the classification over time, I aggregate the quantity index to the 2-digit level and conduct the industry analysis at this level.

[36]Data can be found here: http://www.bis.org/statistics/eer/.

[37]I compare these to a REER provided by the IFS database (I do not report the IFS REER).

by the Chilean Central Bank. 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. It provides data from both the World Trade Organization (WTO) and Comtrade. In the main specification I use applied rates reported by Comtrade. To measure input tariffs, which I define below, I use a 3-digit[38] input output matrix provided by the Chilean Central Bank in its National Accounts publications of 1996 and 2003.

5.2 Open Economy Summary Statistics

The time period 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 1 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 from 11% to below 2%.[39] This drop is mostly homogeneous across industries. Given the large liberalization that occurred in the 1970s and 1980s (Pavcnik, 2002), it is hard to know whether this resembles a large entry shock. I find mostly insignificant effects of lower output tariffs on allocative efficiency (and firm markups) in section 6.

[Figure 1 about here.]

Part of the export surge was demand driven as Chile gained from the inflation in commodity prices that was likely due to the increased demand from emerging countries. For Chile this was especially important in the copper industry, which constitutes almost half of its export value. The result was a large terms of trade gain starting in 2003 that I interpret as an exogenous exchange rate appreciation for non-copper industries affected by the cost of imported inputs and/or prices relative to their foreign competitors. In fact the post-2003 period exhibits a large increase in imports, driven especially by intermediate inputs.[40] Figure 2 describes a terms of trade index taken from the WDI (right axis), and the annual log differences in the REER and NEER (described above).Chile experienced an appreciation in 1997, a sustained depreciation from 1999-2003, and a sustained appreciation 2004-2006 led by the terms of trade gain. The real and nominal effective exchange rates

[38] I concord industry descriptions by hand to match my ISIC revision 3 data.

[39] Using the Most Favored Nation (MFN) tariffs instead of the applied rates, rates only decrease to 6%.

[40] Desormeaux et al. (2010) establishes that firms and households import a significant amount of their intermediary inputs. In current work with Felipe Lucero, I use customs data to examine firm level imports in Chile.

mostly move together except that the depreciation in 1999 is much sharper in nominal terms.

[Figure 2 about here.]

Figure 3 plots manufacturing exports and imports as a ratio of total manufacturing value added.[41] For the manufacturing firms that I consider, importing is as, or even more important than the export side.[42] Although there is evidence of both export and import growth, it seems that export earnings are the initial impetus, with the demand for intermediate inputs driving imports.

[Figure 3 about here.]

6 Empirical Analysis

In this section I test the model predictions about reallocation and the aggregate misallocation consequences to connect firm level behavior with aggregate data. I split the section into empirical specification and results. The measure ΔAE_j has already been described above, so in the next subsections I summarize the method to calculate firm level markups and what the regression framework will be. In Section 6.2, I start with suggestive evidence by plotting the time series of markup dispersion and compare it to the time series of aggregate allocative efficiency as described in Section 3.2. Finally, the results will be confirmed using a regression analysis with differential treatment groups to investigate how firm specific reallocation determines allocative efficiency.

6.1 Empirical Specification

6.1.1 Production Function Estimation and Markups

I use the method from DeLoecker and Warzynski (2012) to first 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). I then use the coefficients and cost shares to estimate firm-level markups. The details on production function estimation and translating this to markups is in Appendix E.

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

[42] 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.

Table 1 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%.

[Table 1 about here.]

6.1.2 Regression Specification

In the regression analysis of Subsection 6.2.3, I start at the industry-level and then move on to the firm-level. I create industry level measures of $\Delta\tilde{R}$, ΔQ, and ΔAE as introduced in Section 3.2. Then, I use a framework similar to Pavcnik (2002) and Amiti and Konings (2007), that study, respectively, how output and input tariffs affect firm revenue TFP. I use markups as the outcome variable and extend the framework to also test the impact across the firm distribution. I am interested in testing the results in Section 4 with respect to the distributional effects of aggregate shocks. I show that the distributional effects and aggregate outcomes are consistent with the model.

My data has information on whether a firm is an importer/exporter plus the respective value. I interact this information with macroeconomic shocks that include trade liberalization variables and the terms of trade. The terms of trade shock is interpreted as an exogenous exchange rate appreciation for non-copper manufacturing as I eliminate the copper-based metal industries from the analysis. I abstract from the political economy concerns and interpret lower output tariffs as a competition shock. Information on imports and exports is important because competition and cost shocks affect firms depending on their exposure. The general framework is:

$$Outcome_{ijt} = \alpha_{i/j} + \alpha_t + \beta\tau_{j,t} + \gamma Expos_{ijt} + \psi\tau_{j,t} * Expos_{ijt} + \zeta Z_{ijt} + \zeta_2 Z_{ijt} * \tau_{j,t} + u_{ijt} \tag{13}$$

α_t and $\alpha_{i/j}$ represent time (t) and firm (i)/industry (j) (depending on the level of aggregation) fixed effects respectively. Notice that this specification is able to test the comparative statics predicted above, and furthermore I interact $\tau_{j,t} * Expos_{ijt}$ with firm TFP to examine whether this interaction is more pronounced in more productive firms.

The trade liberalization variable (τ_{jt}) can be output tariffs, input tariffs, or terms of trade. The firm- or industry-level indicator of exposure, $Expos_{ijt}$, can take the form of an exporter/importer dummy or a share of exports in total sales/share of imports in inputs. Following Ekholm et al. (2012), a "Net Exposure" variable is described below. The main variable of interest is the interaction of the trade variable with the firm/industry indicator. Therefore the framework is a difference-in-difference approach with the import/export

dummy or net exposure continuous variable as the treatment group. Lastly, Z_{ijt} includes other firm/industry characteristics.[43] Importantly, I add the interaction of Z_{ijt} with the trade liberalization variable to control for heterogeneous effects of trade shocks across firms (i.e. κ_i). The outcome variable is the log markup ($ln(\frac{1}{1-\mu_{ijt}(\delta_{jt},\tau_{jt},c_{it})})$) at the firm-level. At the industry-level, the outcome variable has j, t subscripts and is constructed consistent with Section 3.2.

6.2 Results

Before moving to the regression results, I provide suggestive evidence of the contemporaneous correlation of markup dispersion and allocative inefficiency.

6.2.1 Markup Moments

The majority of the literature on variable markups has focused on average markups due to a "pro-competitive" effect (Feenstra and Weinstein, 2010). That focus does not include possible allocative inefficiencies, so here I show the evolution of the dispersion of markups.[44]

I use the standard deviation of log markups as my measure, though the results (in terms of dispersion) would be qualitatively similar using the Pareto shape parameter.[45] In addition to using the material input markup wedge, I also use the labor coefficient-cost share wedge though I omit results here for brevity. In Figure 4 the dispersion is calculated within each 2-digit sector and averaged (excluding basic metals) to exhibit the manufacturing inudstry as a whole, where the weights are defined by sector value added. The increase in dispersion in the 2003-2006 period is concurrent with the large exchange rate appreciation. This is consistent with a story where part of the terms of trade gain is passed on by firms into markups, and so we should see a drop in allocative efficiency as a results of a cost shock. This is in fact confirmed below and I show that it is driven by industries that rely on intermediate input imports.[46]

[43] These include: industry Herfindahl index, index of "import competition", firm TFP, firm size, a dummy for whether a foreign entity owns more than 10% of the firm, capital intensity, and the Rauch classification of differentiation in the industry.

[44] I drop the top and bottom 1% of firms (sorted by markups) in each year-sector and also the Basic Metal industry which would drive the results if it were included. It does not seem to matter how much I eliminate in terms of outliers. I have also dropped up to the top and bottom 3% of firms without a change in qualitative results.

[45] I calculate the Pareto parameter using the procedure outlined in Head et al. (2014). These results are available upon request.

[46] As a note, the results are very similar if I disregard industry classification and conduct the analysis

[Figure 4 about here.]

6.2.2 Aggregate Allocative Efficiency

In this section I use the measure of misallocation from Equation 11 applied at the industry level, aggregating to the 2-digit level.Figure 5 shows real revenue growth and physical production growth at the aggregate manufacturing level.[47] Appendix D discusses the construction of these measures. 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 (base years are 1995 and 2002). 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.[48]

The aggregate data implies that reallocation pre-2003 induced better allocative efficiency. Without sustained growth in quantity produced, the value of production grew in almost every year. This trend was reversed after the terms of trade shock. Now the evidence points towards a reallocation that is lowering allocative efficiency. The regression results will illuminate the mechanisms underlying these aggregate measures.

[Figure 5 about here.]

I stress that growth in allocative efficiency does play an important role in the overall real revenue and therefore should not be ignored in studies of reallocation. In the context of the Chilean economy, I can run the following though 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 (as in the CES model) versus using the growth rate that allows for changes in the covariance of prices and quantities. 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

on manufacturing as a whole. This relieves some concern about the reallocation across industries that is ignored in this analysis.

[47] 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, reiterating the fact that there is very little across sector reallocation.

[48] Also, notice that by assuming a Pareto distribution in the theory, it eliminates movements in the cutoff cost, so I do not focus on entry.

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).[49] These two separate sub-periods provide evidence that growth in allocative efficiency can provide either an amplification or dampening effect on welfare depending on whether the economy is becoming more or less resource efficient.

Using the full sample of firms for revenue growth reduces the role for misallocation but the signs remain the same (revenue growth follows quantity growth a little more closely, but allocative efficiency still amplifies real income growth in the first sub-period and dampens it in the second).[50] To check the importance of entry, Figure 6 shows the number of firms that entered and exited from 1996-2006. Except for 1996 and 2006, they tend to move together so that net entry is not large. Both measures are about 60 on average (to put that into context, the census lists approximately 5000 firms per year), although the effect of entry is a little larger during the terms of trade shock. In terms of the size of these firms, the value added of new enterers is on average 5.8% of the economy, reaching a peak of 13% in 2003 and 10% in 2005.

[Figure 6 about here.]

The next section investigates trade shocks that are mechanisms for these aggregate outcomes. I will go beyond the contemporaneous correlation evidence to difference-in-difference regressions that compare the effect of a shock across industries/firms differentiated by their exposure. In response to the terms of trade appreciation, I expect the production of industries that rely on imported intermediates to increase relative to non-importers, but for their allocative efficiency to decrease. In response to trade liberalization, industries that export a greater portion of their output, or face import competition on output sold domestically, should instead face tougher competition and raise allocative efficiency. I find strong evidence for the former prediction, but only weak evidence for the latter, which most likely reflects the magnitude of the appreciation relative to the reduction in output tariffs.

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

[50] The regression results in the next subsection are also run with both samples, though the results in that case are very similar to each other quantitatively as well.

6.2.3 Regression Results

The reported interaction coefficients contain the following firm/industry treatments. $Importer*(Exp = 0)$ is an indicator for firms that import a positive amount of inputs and do not export any output (similar interpretation for $Exporter*(Imp = 0)$). At the industry level, I take the average of the firm dummies. As a separate strategy, I calculate the share of imports in total material inputs, the "Imported Share," and exports relative to total sales, the "Exported Share." Then as in Ekholm et al. (2012), I combine these to create a "Net Exposure" variable which is the difference between export share and import share for a firm. They model firm revenues and costs to take 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. The competitive pressure a firm faces in response to a real exchange rate shock therefore depends on its net exposure.[51] I *fix* these shares to a base period so that a change in the firm-level exposure won't drive the result. The specific derivations used in Ekholm et al. (2012) are provided in Appendix F.

Making the distinction of import/export exposure is important because open economy shocks will affect importers and exporters differently. In Section 4 the comparative statics depend on the nature of the shock: a shock to the input side (for a given level of competition) or a shock on the output side (for a given cost shifter). Therefore the characteristic of a firm determines its predicted response to globalization and cost shocks that happen simultaneously. As the net exposure becomes more negative this identifies a firm that imports a larger share of its imports than its export share of sales. This type of firm is most likely insulated from competitive pressure as it is likely to reduce costs without necessarily competing in the global market. Similarly, a firm has positive exposure if exporting is more important than its' importing. For this same reason the dummy variables identify firms that only import/export and not those that do both[52]. Tables 2-3 are at the industry level and the exposure/import/export characteristic is an average of firms in the industry. Tables 4- 5 show firm-level markup responses to changes in the terms of trade (TOT) and output tariffs (interacted with the exposure of the firm). Additionally, I interact these with firm productivity to get at the distributional responses that are necessary for

[51] Since equal import and export shares don't necessarily cancel each other out, I also run all regressions with import and export shares as separate regressors.

[52] Firms that are both importers and exporters tend to look more like exporters.

the reallocation results in Section 4.

The regressions include all the individual terms that are part of the interactions and the Z_{ijt} characteristics covered above, though I omit some from the results for brevity. In the firm level regressions I use year and firm fixed effects. The variation is within firms and across years as I am attempting to identify the firm level response to shocks in annual aggregate variables. At the industry level I use sector and year fixed effects. Finally, notice that I use the terms of trade in a place where the real effective exchange rate (REER) could have a similar interpretation. The motivation behind the currency exposure variable of Ekholm et al. (2012) relies on the real exchange rate, but the terms of trade is very highly correlated to it in the data (0.65). I choose the terms of trade because the annual data is easily accessible from the *World Development Indicators*. The REER, as described in Figure 2, relies on a combination of sources/methodologies because output prices are from the PWT and trade share weights are computed by the BIS. The same regressions using the REER instead of terms of trade resulted in identical conclusions.

Industry Level Results In Section 3.2 I described the aggregate measures that are a result of reallocation across existing producers. I turn now to the industry-level analysis, of which the main measure of interest is the growth rate of allocative efficiency. The variation consists of comparing sectors (at 2-digit ISIC aggregate) who import the highest percentage of their inputs with sectors that are more open to competition (export more and compete with imports). I also replace exporters with a measure of "Openness", the sum of exports and imports of final goods into an industry divided by total industry sales. Lower output tariffs affect the industries that import final goods and therefore compete with domestic firms, so I expect these industries to face fiercer competition.

The main outcome variable of interest is the implied growth rate in misallocation, ΔAE, from Equation 11 (the residual from $\Delta ln(\tilde{R}) - \Delta ln(Q)$). I add $\Delta ln(Q)$ as an outcome and, for robustness, also: $\Delta Cov(markup, inputs)$ (shown in Appendix B to be one of the components of the allocative efficiency variable). The interaction terms include sector characteristics — Herfindahl index (HHI), fraction of firms that are multinational (MNC), and average employment (EMP) — interacted with the growth rate in terms of trade and output tariffs. The regressions use value added weights for sectors, which gives an empirical counterpart to β_j in Section 3.1. In using variation across sectors and years, I am of course measuring only within-industry misallocation. However, the similarity in my weighted average of industry allocative efficiency measure with an aggregate measure that pools together all industries is evidence that intersector reallocation was not an important part of changes in manufacturing allocative efficiency. As in 6.2.2, I eliminate firms that do not produce for 6 consecutive years. In results that do not eliminate these en-

tering firms, the regression results are very similar both qualitatively and quantitatively.

In Table 2, the main result is that when the TOT increases, industries with a larger fraction of importers (that are not exporters) suffer in terms of allocative efficiency (third row of Column (1)). There is no evidence that either the terms of trade or output tariffs have an effect on allocative efficiency in "open" sectors. Unsurprisingly, both importers and exporters have higher physical production ($\Delta ln(Q)$) at higher terms of trade (Column 2). The last column uses the markup-input expenditure covariance as a measure of misallocation in place of ΔAE[53]. Intuitively, the reallocation increases efficiency if inputs are transferred to the high markup firms to raise their production. The results with respect to the terms of trade are similar to Column (1) (though not significant) which is reassuring that the growth rate in allocating efficiency is properly estimated. [54]

I repeat this analysis using export and import shares, as well as net exposure, in Table 3. The shares are the average firm share at the sectoral level. The first column illustrates 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. Conversely, industries exposed to global competitive pressures have positive growth rates in allocative efficiency. One way to interpret this coefficient is to compare industries with different extreme values of net exposure. For example, an industry with firms that import all of their inputs but do not export will have a net exposure of -1. Net exposure of 0 means the ratio of exports to sales is equal to the ratio of imports to total inputs (or it could signify no import or exports). Therefore the coefficient in the third row of Column (1) is interpreted as an industry with net exposure of 0 having allocative efficiency growth than is 4.24 percentage points larger than the industry with net exposure of -1 in response to a 1% increase in the growth of the terms of trade. As expected, the importing industries become more misallocated with terms of trade gains. Positive exposure industries also become more efficient when output tariffs decrease, an indicator of tougher competition. An interpretation of the coefficient in the fourth row is that an industry with net exposure of 1 (all sales are exported without importing inputs) has a growth rate of allocative efficiency that is 1.14 percentage points more than the reference industry with net exposure of 0 in response to a 1% decrease in the growth rate of output tariffs.[55] Column (2) decomposes exposure into the export and import shares. It is the

[53] A higher covariance increases AE according to Equation 19 in Appendix B.

[54] The preceding results can be re-done by replacing the Terms of Trade with the the REER or NEER. These two variables contain very similar information. The regression results are very similar, and the interpretations the same, when replacing the TOT for either of these.

[55] Another way to interpret the magnitude of these results is to create a binary variable for "exposure." Given the sector averages, I define an industry as negatively exposed ($NegativeExposure = 1$) if the aver-

larger import share that drives reductions in misallocation in response to TOT shocks. At lower output tariffs, a larger exported share does not seem to increase allocative efficiency as might be expected. Once again the signs are consistent when replacing the allocation efficiency measure with the covariance of markups and input expenditure in Columns (4) and (5).

Column (3) examines the effect on physical production. It is the negatively exposed industries that increase their production after increases in the TOT. I find that exposed industries raise quantity with reduction in output tariffs, though their revenue productivity is lower. Notice that in Table 2 I found that "open" industries were also raising their quantity production in response to the terms of trade gains. Therefore it seems that there was a widespread increase in physical production but that industries differed in their allocative efficiency of this production.

In summary, in response to appreciations in the terms of trade, industries that have a higher share of importers relative to exporters become more misallocated. To a lesser extent, there is some evidence that more import competition raises allocative efficiency in industries with relatively more exporters.

[Table 2 about here.]

[Table 3 about here.]

Firm Level Results The firm level regressions mostly affirm the predicted reallocation effects of Section 4 and are consistent with the industry results above. To start, I establish that the assumption that more productive firms also have higher markups — shown in other papers, such as DeLoecker and Warzynski (2012) — holds for this data as well. The first column of Table 4 regresses firm markups on firm characteristics: TFP, employment, and capital intensity (capital divided by revenue). The expected results emerge, that higher markups are correlated with both higher TFP and more employment.

The rest of Table 4 investigates the responses to aggregate shocks using firms defined as "import but do not export" and "export but do not import". Importing firms are affected the most by TOT changes. For example, importers who are not exporters have higher markups at larger values of TOT (appreciations). Column (2) shows that a 10 percent increase in the terms of trade increases markups by 0.29 percent more for importers who do not export relative to the rest of firms. This is not the case for exporters. The

age net exposure is less than -0.1 (this was the median exposure across industries). The results are available upon request but not shown in the Table since they tell the same story.

regressions include firm employment and an indicator of whether the firm is a multinational, plus their interaction with the terms of trade as, to control for the fact that cost shocks are not necessarily common across firms.[56] In the next column I run the same specification using lagged import tariffs instead of the terms of trade, but find mostly zeroes. This is probably due to the fact that tariff reductions were small and homogeneous across industries.[57]

The next step is to show that the distributional effects follow the predictions in Section 4. I have found evidence thus far for the first order comparative static predictions, especially for cost reductions raising markups. In Column (4) and (5) of Table 4 I examine whether the findings vary across the distribution of firms. For the cost shocks to indeed reduce allocative efficiency, the incomplete pass-through results should be stronger for the more productive firms. To test this I add an interaction of TFP with the original interaction of the terms of trade with importer/exporter dummies. The "TFP*TOT*IMP" interaction in column (4) shows that the importer-TOT interaction is stronger for higher values of TFP, although the coefficient is not significant. This is evidence that there is a real revenue-reducing reallocation (not captured with constant markups) due to an incomplete pass-through effect of cost shocks to importers that is stronger for more productive (and bigger) firms. These results will become even stronger using the net exposure variable below. Again, the results with the output tariff as the policy variable (column (5)) are close to 0.

Table 5 uses import/export shares, as well as the net exposure, instead of dummies. I once again control for firm size and its interaction with the terms of trade, and measure the distributional effects in the last two columns. The case of cheaper inputs is consistent with a cost shifter, and in this case I expect firms with negative exposure to be the ones affected. The negative coefficient on the interaction between terms of trade and net exposure in the first column means that a higher terms of trade (TOT) increases markups for firms that have negative exposure (input importers) relative to firms with no exposure. From the coefficient in the second row of column (1), there is no interaction effect of tariffs with the exposure measure. In the second column I decompose net exposure into the export and import shares in that measure. The trade elasticity of imports and exports are not necessarily equal which could complicate the interpretation of the net exposure vari-

[56] Cost and competition shocks could affect firms differentially depending on their size and for that reason I interact these with the terms of trade. I referred to the firm specific effects as κ_i in the theory.

[57] As a note, I also constructed input tariffs as in Amiti and Konings (2007) using output tariffs and a three-digit input-output (IO) matrix provided by the Chilean Central Bank. The results are consistent with the theory (input tariffs as a cost shock), however since input tariffs are so highly correlated with output tariffs (0.99) I am skeptical of the usefulness of this measure for Chile and do not report the results.

able. However, using only import share or export share is also problematic because a firm can be intensive in both. This is why I prefer the net variable that allows either imports or exports to dominate. In column (2), the interaction coefficients are of the correct sign and significant for the import share. Firms with higher import share raise markups more after terms of trade increase. The results using net exposure are therefore confirmed by its separation into import and export share, and I use this variable for the distributional effects in the last two columns.

The penultimate column of Table 5 investigates the reallocation results. I once again control for firm characteristics, namely capital intensity, employment, and multinational indicator, and their interaction with the policy variable to control for heterogeneous responses across different types of firms. The result in column (3) is consistent with the prediction that the incomplete pass-through of cost shocks to markups is larger in more productive firms. It shows that for a given exposure to competition, terms of trade appreciations have a statistically significant bigger effect for firms that have higher productivity. Although the t-statistic is only around -1.92, together with the results in the previous table, there is a consistent and robust finding of the differential markup responses.

Finally, in the last column of Table 5 I use another interaction term to confirm the distributional results. In this case I eliminate the TFP variable which might be problematic to use with the markup since they are estimated jointly in the production function estimation.[58] To differentiate firms, I create a dummy for firms in the 75th percentile of the markup distribution in 1995 and interact it with the terms of trade and exposure characteristic.[59] Again, there is evidence that of the firms that raise markups due to a terms of trade shock (those with high import share), it is the initially high markup firms that do so that most. This interaction is significant at the 5% level. According to the theory, this is a reallocation that reduces industry real revenue and should show up in the aggregate results.

The results at the firm level confirm the observed changes in allocative efficiency. The results are strongest for the terms of trade appreciation. Markups increase for importers and the effect is larger for the initially high-markup firms. Although importing industries have relatively higher production, this is dampened by their relatively larger decrease in allocative efficiency.

[58] I have checked however that the regressions that do not necessitate the TFP measure (e.g. terms of trade-importer interactions) are robust to controlling for TFP. Columns (2) and (3) in Table 4, and columns (1) and (2) in Table 5 are run without controlling for TFP, but are robust to its inclusion. However for the distributional effects so far I have used TFP in the distribution interactions.

[59] I include only the interaction of interest in the reported results.

[Table 4 about here.]

[Table 5 about here.]

7 Conclusion

This study examines how misallocation fits into demand systems with preferences that are 'additively separable but not necessarily CES. The distortion that keeps the market economy away from productive efficiency is the heterogeneity in market power, and I show this effect can be important using the case of Chile. I compute the growth in misallocation that is consistent with the co-movement of prices and quantities. I then turn to open economy shocks as potential factors for changes in this market power distortion. I use a reduced form approach that allows trade liberalization and terms of trade shocks to have separate and simultaneous effects on firm markups and the relative markup differences across firms.

The main variation during the examined period is that Chile experiences a large demand shock for its commodities that raises its terms of trade and produces large gains in revenue. Markup dispersion decreases until 2003, but increases significantly after the terms of trade gain for Chile. 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 homothetic preferences results in a mismeasurement of how reallocation impacts revenue growth. In Chile's case, the growth in revenue is significantly impacted by reallocation of production across existing firms.

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 (2010). 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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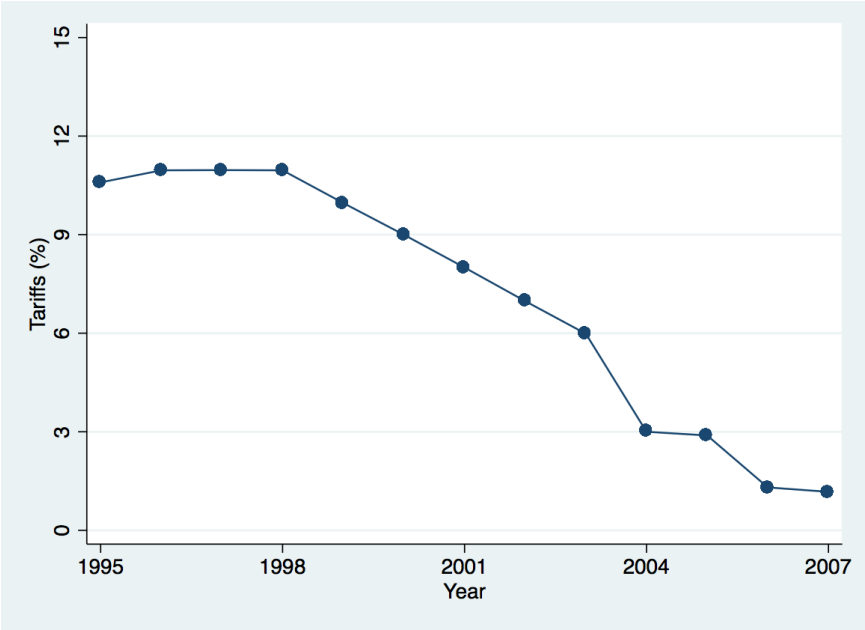
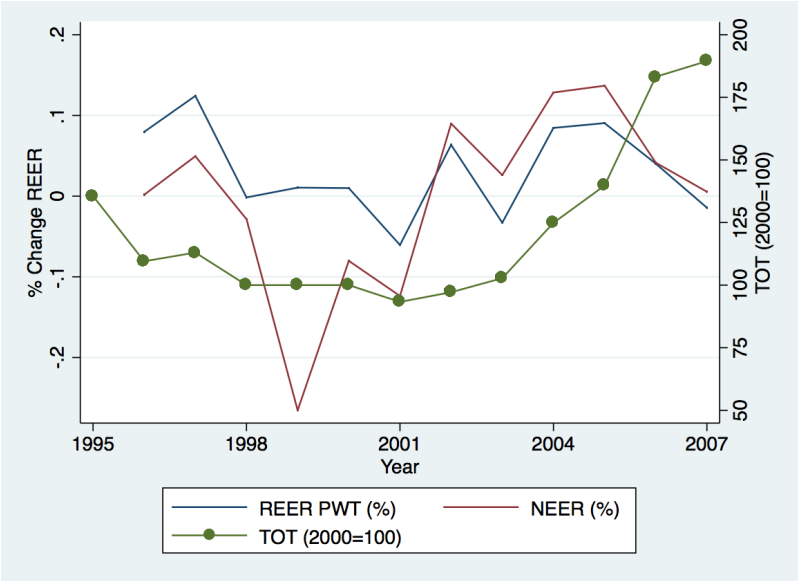
Figure 1: Average Applied Tariffs 1995-2007



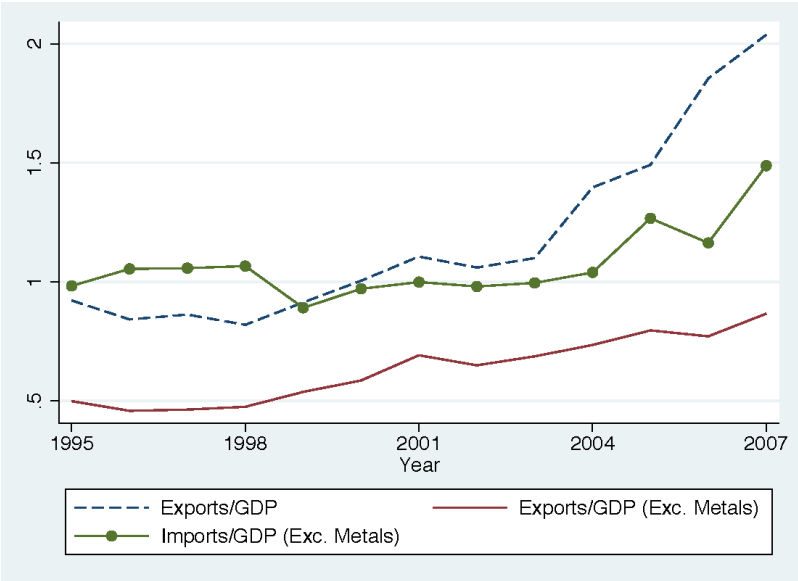
Source: Comtrade Database, downloaded from World Integrated Trade Solution (WITS). Bilateral tariffs are aggregated to 4-digit level using an unweighted average of 6-digit tariff lines, and then weighted by trade shares to get an average applied tariff rate across all trade partners.

Figure 2: Terms of Trade (2000=100) and Real Effective Exchange Rate (% change), 1995-2007



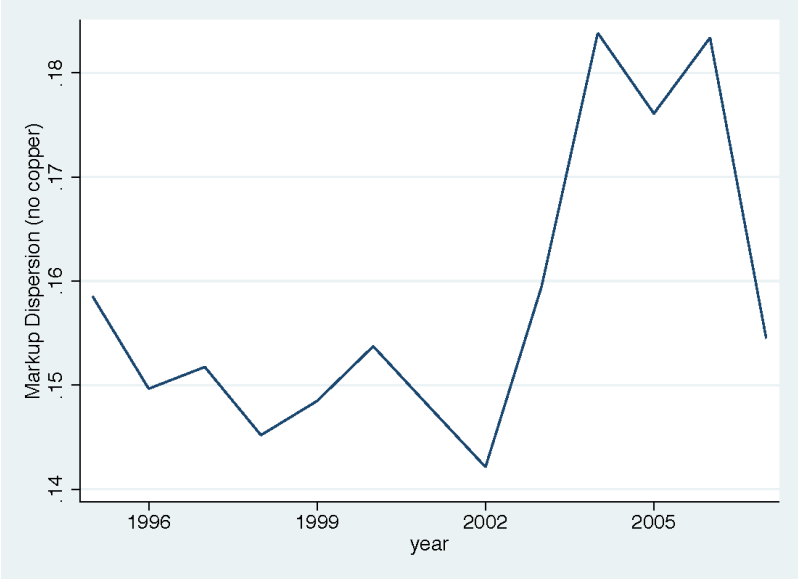
Sources: WDI Indicators, PWT 8.0, BIS, Chilean Central Bank. TOT is an index from WDI. I calculate REER PWT using Penn World Tables to calculate Chile's production price index relative to its top trade partners and take a geometric average using trade shares (from BIS) as weights. I report the annual % change. Nominal effective exchange rate is annual % change, downloaded from Chilean Central Bank (with same weights as REER).

Figure 3: 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.

Figure 4: Markup Dispersion: Average across sectors

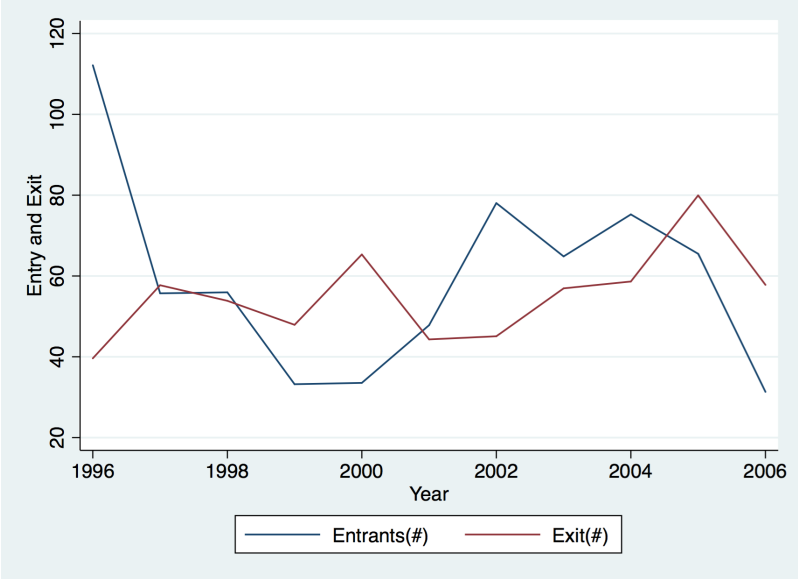


Markup dispersion calculated for each sector by estimating the shape parameter of a log-normal distribution using maximum likelihood. I take the economy-wide average by weighting each sector by its value added share. I eliminate firms in the bottom and top 1% of the markup distribution.

Figure 5: 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.

Figure 6: Entry and Exit (number of firms)



Entry is defined as a fim not in the census in the previous year. Exit is the number of firms not in the census, that were in the census the previous years. Both measures are total number of firms in manufacturing. For context, there are about 5,000 firms in each year of the census.

Table 1: Factor Coefficients and Markups by 2-digit ISIC Sectors

				(1)		
	Obs	θ_L	θ_K	θ_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.

Table 2: Industry Level: Change in Aggregate Outcomes by Share of Importing Firms (using only incumbent firms)

	Δ AE	Δ Q	Δ Cov(markup,inputs)
	(1)	(2)	(3)
D.ln(TOT)	1.801		
	(2.261)		
D.Output Tariff	0.038	-0.060*	-0.043
	(0.029)	(0.032)	(0.036)
Δ TOT*Importer (Industry Share)	-6.248*	2.470**	-2.898
	(3.228)	(0.967)	(2.011)
Δ TOT*Openness	0.073	0.101*	-0.193
	(0.160)	(0.055)	(0.170)
Δ OutputTariff*Openness	0.010	0.024	-0.001
	(0.014)	(0.022)	(0.012)
HHI	2.253***	-0.161	1.035**
	(0.491)	(0.206)	(0.408)
MNC	-1.506	1.195***	-0.436
	(0.913)	(0.341)	(0.563)
Δ TOT*MNC	-2.458	-0.670	-3.388**
	(1.851)	(0.526)	(1.451)
EMP	-0.068	0.029	-0.228
	(0.131)	(0.090)	(0.194)
Δ TOT*EMP	-0.317	0.279	0.227
	(0.448)	(0.174)	(0.289)
Avg Outcome	0.011	0.034	0.006
Fixed Effects	Year,Sector	Year,Sector	Year,Sector
R^2	0.268	0.363	0.097
N	192	192	204

Dependent variables are ΔAE, ΔQ, and Δ Cov(markup,inputs). These are all at the 2-digit ISIC level. The first two are one year growth rates with their definitions in the text. For the covariance I use first differences. ΔTOT, $\Delta OutputTariff$ and $\Delta InputTariff$ are all one year growth rates. I use the fraction of firms in an industry where (Imp*Exp=0)=1 as "Importer (Industry Share)". "Openness" is the sum of exports and imports of final goods into an industry divided by total industry sales. Standard errors are clustered at the 2-digit industry level. I drop the basic metal industry (ISIC 27).

Table 3: Industry Level: Change in Aggregate Outcomes by Average Industry Exposure (using only incumbent firms)

	Δ AE		Δ Q	Δ Cov(markup,inputs)	
	(1)	(2)	(3)	(4)	(5)
D.ln(TOT)	1.293				
	(2.439)				
D.Output Tariff	-0.030	-0.104	0.014	-0.040	-0.052
	(0.031)	(0.065)	(0.032)	(0.042)	(0.066)
Δ TOT*Net Exposure	4.244*		-1.808**	2.694	
	(2.412)		(0.723)	(2.191)	
Δ OutputTariff*Net Exposure	-1.144		-0.391***	0.016	
	(0.912)		(0.073)	(0.144)	
HHI	2.200***	1.846**	-0.142	1.001	0.967
	(0.631)	(0.820)	(0.220)	(0.651)	(0.666)
MNC	-1.322	0.141	1.098**	-0.590	-0.333
	(1.121)	(1.249)	(0.385)	(0.912)	(0.891)
Δ TOT*MNC	-0.913	-3.283**	-0.565	-2.946	-2.925
	(2.378)	(1.138)	(0.409)	(2.257)	(2.110)
EMP	-0.041	-0.468*	0.030	-0.267	-0.284
	(0.144)	(0.247)	(0.121)	(0.264)	(0.293)
Δ TOT*EMP	-0.313	0.329	0.289	0.267	0.277
	(0.529)	(0.713)	(0.191)	(0.395)	(0.397)
Δ TOT*Imported Share		-6.749*			-2.363
		(3.790)			(3.272)
Δ TOT*Exported Share		4.842			4.391
		(8.627)			(8.873)
Δ OutputTariff*Exported Share		0.671			-0.363
		(0.472)			(1.464)
Avg Outcome	0.011	0.011	0.034	0.006	0.006
Fixed Effects	Year,Sector	Year,Sector	Year,Sector	Year,Sector	Year,Sector
R^2	0.264	0.375	0.352	0.094	0.095
N	192	192	192	204	204

Dependent variables are ΔAE, ΔQ, and Δ Cov(markup,inputs). These are all at the 2-digit ISIC level. The first two are one year growth rates with their definitions in the text. For the covariance I use first differences. ΔTOT, $\Delta OutputTariff$ and $\Delta InputTariff$ are all one year growth rates. Net Exposure is defined as (Export Sales/Total Sales)-(Imported Inputs/Total material input costs). The prior two components are "Exported Share" and "Imported Share." These shares are fixed to their values in 1995 or 2002. Standard errors are clustered at the 2-digit industry level. I drop the basic metal industry (ISIC 27).

Table 4: Firm Level: Differential Effect on Markups by Importer/Exporter

	Mark-up				
	(1)	(2)	(3)	(4)	(5)
TFP	0.028***			-0.081***	0.044***
	(0.001)			(0.021)	(0.006)
EMP	0.009**	0.041**	-0.015**	0.050***	-0.001
	(0.004)	(0.020)	(0.007)	(0.019)	(0.006)
K/Y	0.001	0.000	0.000	0.001	0.001
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
MNC		0.155**	-0.047**	0.195**	-0.051**
		(0.079)	(0.023)	(0.077)	(0.022)
TOT*IMP*(Exp=0)		0.029**		0.010	
		(0.013)		(0.012)	
TOT*EXP*(Imp=0)		0.012		0.007	
		(0.012)		(0.012)	
OutputTariff*IMP*(EXP=0)			-0.007		0.003
			(0.008)		(0.007)
OutputTariff*EXP*(IMP=0)			-0.007		-0.007
			(0.007)		(0.008)
TFP*TOT*IMP*(EXP=0)				0.017	
				(0.016)	
TFP*TOT*EXP*(IMP=0)				-0.011	
				(0.011)	
TFP*TARIFF*IMP*(EXP=0)					-0.013
					(0.010)
TFP*TARIFF*EXP*(IMP=0)					0.004
					(0.006)
Fixed Effects	Year,Firm	Year,Firm	Year,Firm	Year,Firm	Year,Firm
R^2	0.763	0.757	0.768	0.764	0.776
N	56491	58629	48482	56491	46787

Dependent variable is log markup measured using the procedure outlined in DeLoecker and Warzynski (2012) (DLW). TFP measurement also follows DLW. Terms of trade and output tariffs also in logs. Imp*(Exp=0) signifies importers who do not export (and vice-versa for Exp*(Imp=0)). The following controls are used: capital intensity, a dummy if the firm is a multinational and its interaction with TOT, firm employment and its interaction with TOT, plus year and firm fixed effects. Standard errors are clustered at the firm level. I drop the basic metal industry (ISIC 27).

Table 5: Firm Level: Differential Effect on Markup by Degree of Exposure to Competition

	Mark-up			
	(1)	(2)	(3)	(4)
TOT*Net Exposure	-0.044**		-0.012	-0.005
	(0.021)		(0.023)	(0.024)
OutputTariff*Net Exposure	-0.008		-0.001	
	(0.013)		(0.015)	
TOT*Imported Share		0.078***		
		(0.030)		
TOT*Exported Share		0.011		
		(0.030)		
OutputTariff*Imported Share		0.034*		
		(0.017)		
OutputTariff*Exported Share		0.032*		
		(0.020)		
TFP*TOT*Exposure			-0.036*	
			(0.019)	
TFP*TARIFF*Exposure			-0.011	
			(0.010)	
TOT*Exposure*Top 25%				-0.072**
				(0.036)
K/Y	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
MNC	0.210**	0.203**	0.258***	-0.000
	(0.094)	(0.098)	(0.091)	(0.009)
EMP	0.009	0.006	0.028	-0.009**
	(0.022)	(0.024)	(0.021)	(0.005)
Fixed Effects	Year,Firm	Year,Firm	Year,Firm	Year,Firm
R^2	0.764	0.764	0.773	0.741
N	41053	41053	39632	38672

Dependent variable is log markup measured using the procedure outlined in DeLoecker and Warzynski (2012) (DLW). TFP measurement also follows DLW. Terms of trade and output tariffs also in logs. Net Exposure is defined as (Export Sales/Total Sales)-(Imported Inputs/Total material input costs). The prior two components are "Exported Share" and "Imported Share." All shares are fixed to a 1995 or 2002 value. Column (2) characterizes firms by import and export share, while the rest of the specifications are done with net exposure. The following controls are used: capital intensity, a dummy if the firm is a multinational and its interaction with TOT, firm employment and its interaction with TOT, plus year and firm fixed effects. The last two columns contain triple interactions but I omit the underlying controls (e.g. TFP, TFP-TOT interaction, etc.) from the table for brevity. "Top 25%" is a dummy equal to one if a firm is in the top quarter of the markup distribution in 1995. Standard errors are clustered at the firm level. I drop the basic metal industry (ISIC 27).

Appendices

A Price-Quantity Covariance

This appendix establishes the result that Equation 10 is zero in the case when the sub utility function is CES and the added assumption of Pareto distribution of marginal costs. I use the definition of the covariance: $\text{Cov}(p,q) = \int_0^{c_d}(p(q(c))-\tilde{p})(q(c)-\tilde{q})h_d(c)dc$,[60] and the RHS of Equation 10, $\Delta\left(\frac{\text{Cov}(p,q)}{\int_0^{c_d} p(q(c))h_d(c)dc \int_0^{c_d} q(c)h_d(c)dc}\right)$. Using the definition of the covariance above, this reduces to

$$\Delta\left(\frac{\int_0^{c_d} p(q(c))q(c)h_d(c)dc}{\int_0^{c_d} p(q(c))h_d(c)dc \int_0^{c_d} q(c)h_d(c)dc} - 1\right) \tag{14}$$

When preferences are CES, $p(c) = \frac{1}{1-\mu}c$ with μ 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, $h_d(c)dc = \frac{g(c)}{G(c_d)} = \theta c^{\theta-1}c_d^{-\theta}$. Thus I can input all this information into Equation 14 and reduce the numerator and denominator separately:

$$\begin{aligned}
\int_0^{c_d} p(q(c))q(c)h_d(c)dc &= \left(\frac{R}{\tilde{P}}\right)\frac{1}{1-\mu}\left(\frac{1}{1-\mu}\right)^{-\sigma}\int_0^{c_d} cc^{-\sigma}\theta c^{\theta-1}c_d^{-\theta}dc \\
&= \left(\frac{R}{\tilde{P}}\right)\left(\frac{1}{1-\mu}\right)^{1-\sigma}\left(\frac{\theta}{\theta-\sigma+1}\right)c_d^{1-\sigma} && (15)\\
\int_0^{c_d} p(q(c))h_d(c)dc &= \frac{1}{1-\mu}\int_0^{c_d} c\theta c^{\theta-1}c_d^{-\theta}dc \\
&= \frac{1}{1-\mu}\frac{\theta}{\theta+1}c_d && (16)\\
\int_0^{c_d} q(c)h_d(c)dc &= \left(\frac{R}{\tilde{P}}\right)\left(\frac{1}{1-\mu}\right)^{-\sigma}\int_0^{c_d} c^{-\sigma}\theta c^{\theta-1}c_d^{-\theta} \\
&= \left(\frac{R}{\tilde{P}}\right)\left(\frac{1}{1-\mu}\right)^{-\sigma}\left(\frac{\theta}{\theta-\sigma}\right)c_d^{-\sigma} && (17)
\end{aligned}$$

Next, combining the three above terms into Equation 14:

$$\Delta\left(\frac{\int_0^{c_d} p(q(c))q(c)h_d(c)dc}{\int_0^{c_d} p(q(c))h_d(c)dc \int_0^{c_d} q(c)h_d(c)dc} - 1\right) = \Delta\left(\frac{(\theta+1)(\theta-\sigma)}{\theta(\theta-\sigma+1)}\right) \tag{18}$$

where the term inside the parenthesis on the RHS is constant. Therefore, under the case

[60] Notice this also relies on productivity being unbounded above. This matters: see Feenstra (2014).

of CES sub utility and Pareto $G(c)$, the terms in Equation 10 are zero.

B Growth in Real Income, Quantities, Productivities and Markups

Equation 11 uses the aggregate price-quantity covariance because this is what will be picked up by the difference between real income and physical production growth. However the decomposition can be expanded further. To do so, I go back to revenue and decompose prices further to bring in markups, and then get the expression for real income (again using $P = \int_0^{c_d} p(q(c))h_d(c)dc$ and $\frac{p}{c} = (\frac{1}{1-\mu(c)})$:

$$R = NL\left[\int_0^{c_d} \frac{p(q(c))}{c} cq(c)h_d(c)dc\right]$$
$$\frac{R}{P} = NL\int_0^{c_d} cq(c)h_d(c)dc \int_0^{c_d} \frac{1}{c}h_d(c)dc + \frac{NL}{P}\int_0^{c_d} cq(c)h_d(c)dc\left[\text{Cov}(p, \frac{1}{c})\right] + \frac{NL}{P}\left[\text{Cov}(\frac{1}{1-\mu(c)}, cq)\right]$$

I can separate out aggregate quantity from the first term on the right hand side. Since $Q = NL\int_0^{c_d} q(c)h_d(c)dc$, then $NL\int_0^{c_d} cq(c)h_d(c)dc \int_0^{c_d} \frac{1}{c}h_d(c)dc = Q - NL\text{Cov}(\frac{1}{c}, cq)$. I substitute this into the last equation and then once again come up with an equation for $\frac{\tilde{R}}{Q}$:

$$\frac{R}{P} = Q - NL\left[\text{Cov}(\frac{1}{c}, cq)\right] + \frac{NL}{P}\int_0^{c_d} cq(c)h_d(c)dc\left[\text{Cov}(p, \frac{1}{c})\right] + \frac{NL}{P}\left[\text{Cov}(\frac{1}{1-\mu(c)}, cq)\right]$$
$$\frac{\tilde{R}}{Q} = 1 + \frac{NL}{PQ}\left[\text{Cov}(\frac{1}{1-\mu(c)}, cq) + \int_0^{c_d} cq(c)h_d(c)dc\left[\text{Cov}(p, \frac{1}{c})\right]\right] - \frac{NL}{Q}\left[\text{Cov}(cq, \frac{1}{c})\right]$$
$$\Delta ln\left(\frac{\tilde{R}}{Q}\right) = \Delta\left[\frac{NL}{PQ}\left[\text{Cov}(\frac{1}{1-\mu(c)}, cq) + \int_0^{c_d} cq(c)h_d(c)dc\left[\text{Cov}(p, \frac{1}{c})\right]\right] - \frac{NL}{Q}\left[\text{Cov}(cq, \frac{1}{c})\right]\right] \tag{19}$$

To identify misallocation from Equation 11 it is the first difference of this term that must be zero. Again, if the distribution is immune to truncation then the first difference must be zero if $u(q(c))$ is homothetic. Comparing to Equation 11, the price-quantity covariance is decomposed to separate out productivity ($\frac{1}{c}$), markups ($\frac{1}{1-\mu}$), total input cost (cq) and prices. Again it is important to notice that an increase in allocative efficiency occurs when there is a reallocation to high markup firms, in this case $\Delta\text{Cov}(\frac{1}{1-\mu(c)}, cq) > 0$ (of course using only this term would omit the simultaneous changes in the other two terms on the right hand side).

B.1 Misallocation and Markup Dispersion

Given Equation 19, I can show how markup dispersion drives the market power distortion. This is evident from the definition of the correlation:

$$\text{Cov}\left(\frac{1}{1-\mu(q(c))}, cq(c)\right) = \text{corr}\left[\frac{1}{1-\mu(q(c))}, cq(c)\right]\sqrt{\int_0^{c_d}\left(\frac{1}{1-\mu(q(c))}\right)^2}\sqrt{\int_0^{c_d}(cq(c))^2} \tag{20}$$

The second term on the right hand side is the standard deviation of the markup distribution. Empirically, both the correlation term and the markup dispersion are important in driving the covariance.

C Super/Sub Modularity

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

$$\Delta_{\varphi_i} m_i(\delta, \tau_1, \varphi_i) \leq \Delta_{\varphi_i} m_i(\delta, \tau_2, \varphi_i) \text{ when } \tau_1 \geq \tau_2 \tag{21}$$
$$\text{where } \Delta_{\varphi_i} m_i(\delta, \tau, \varphi_i) = m_1(\delta, \tau, \varphi_1) - m_2(\delta, \tau, \varphi_2) \text{ for } \varphi_1 \geq \varphi_2$$

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 τ. 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 main text, I will examine two unique example of the VES utility system of Dhingra and Morrow (2015). 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 cases, where each of these elasticities can increase or decrease with quantity. My paper 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 an example of each case of the elasticity of utility, which is sufficient to show that the results are general for the whole VES class I use in this paper. Although alternative 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) social markup changes with quantity; and ii) demand

elasticities changes with quantity.

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

$$u(q) = (q + \alpha)^{\rho}\,, \tag{22}$$

where $\alpha > 0$. In order to get an analytical solution I follow Simonovska (2015) and take the special case for ρ 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 $\mu(q) < 1$.

We follow the model in Section 4 such that the 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:

$$q = (\delta\tau c)^{-1/2} - 1, \text{ where } c \in \left(0, \frac{1}{\delta\tau}\right) \tag{23}$$

$$m = \frac{p}{\tau c} = \frac{u'(q)}{\delta\tau c} = (\delta\tau c)^{-1/2}\,, \tag{24}$$

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 (2015) and is also used in Cavallari and Etro (2017):

$$u(q) = aq^{\rho} + bq^{\alpha}, \tag{25}$$

where $\rho \neq \alpha$, $a < 0$ [61], 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:

$$q = \sqrt{\frac{\delta\tau c - b}{9a}}, \text{ where } c \in \left(0, \frac{b}{\delta\tau}\right) \tag{26}$$

$$m = \frac{p}{\tau c} = \frac{1}{3} + \frac{2}{3}\left(\frac{b}{\delta\tau c}\right) \tag{27}$$

[61] Cavallari and Etro (2017) allow $a < (>) 0$

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 $\frac{\partial m(\delta,\tau,\varphi)^2}{\partial \delta \partial c} > 0$.

D Data and Variable Definitions

Here I describe my measure of the left hand side of Equation 9, which I label $\tilde{R}$. It is 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: $\sum_i P_i Y_i = \sum_i VA_i = \sum_i P_i Q_i - \sum_i \sum_j P_{ij} X_{ji}$.

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.

E Production Function and Markup Estimation

The production function must follow the following functional form:

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

β is the vector of output coefficients, ω_{it} is a firm's (i) productivity at time t, ϵ_{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.[62] 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.[63] 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.[64][65] 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.[66]

I estimate firm level markups from the gap (or "wedge") between the output elasticity of materials (θ_{it}^x) and the cost share of materials (α_{it}^x) in total costs. The only assumption

[62] 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.

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

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

[65] 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.

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

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:

$$\frac{1}{1-\mu_{it}} = m_{it} = \frac{\theta_{it}^x}{\alpha_{it}^x} \tag{28}$$

F Net Exposure Variable

In this Appendix I describe the identification assumption used by Ekholm et al. (2012) to relate the firm level "net currency exposure" to firm level outcomes.

Taking into consideration both domestic and export sales, the optimal revenue of a firm i is $r_i = p_i q_i + E p_i^* q_i^*$, where p_i and p_i^* are prices in local currency set at home and abroad, q_i and q_i^* are sold quantities at home and abroad, and E is the nominal exchange rate (domestic currency per unit of foreign currency). Then the real exchange rate is $REER_i = p_i/(Ep_i^*)$. Ekholm et al. (2012) consider a small change in the $REER_i$ holding output constant:

$$\frac{\partial r_i}{\partial REER_i}\frac{REER_i}{r_i} = -\frac{ep_i^* q_i^*}{r_i}. \tag{29}$$

Notice that this elasticity is equal to the firm export share.

Then, they define a firms' costs as $C_i = c_i v_i + E c_i^* v_i^*$, where c_i and c_i^* are prices of domestic and imported inputs, and v_i and v_i^* are quantities of domestic and imported inputs. Then again consider a small change in the real exchange rate holding inputs constant[67]:

$$\frac{\partial C_i}{\partial REER_i}\frac{REER_i}{C_i} = -\frac{Ec_i^* v_i^*}{C_i}. \tag{30}$$

This elasticity is equal to the share of inputs in total costs.

Finally, this allows for a relationship between the profits and the net effect of the export share and import share in inputs. The elasticity of profits with respect to the REER is

[67] I ignore the differences between the REER measured by output prices and the REER measure by input prices since I don't have these separately in the data anyways.

shown to be:

$$\frac{\partial \pi_i}{\partial REER_i} \frac{REER_i}{\pi_i} = -\frac{Ep_i^* q_i^*}{r_i} - \frac{\frac{Ep_i^* q_i^*}{r_i} - \frac{Ec_i^* v_i^*}{C_i}}{\pi_i / r_i}. \tag{31}$$

In my empirical analysis I am interested in how the currency shock affects firm level markups and industry level allocative efficiency. Since markups are directly relative to profits, I make the same identification assumption as Ekholm et al. (2012) that a positive net currency exposure increases the competitive pressure on firms when there is an appreciation shock, while a negative net exposure reduces the competitive pressure.