Markups and Misallocation with Trade and Heterogeneous Firms[*]

Ariel Weinberger
University of Oklahoma

September 2015

Abstract

With non-homothetic preferences, a monopolistic competition equilibrium is inefficient in the way inputs are allocated towards production. This paper quantifies a gains from trade component that is present only when reallocation is properly measured in a setting with heterogeneous firms that charge variable markups. Due to variable markups, reallocations initiated by aggregate shocks impact allocative efficiency depending on the adjustment of the market power distribution. My measurement compares real income growth with the hypothetical case of no misallocation in quantities. Using firm and industry-level data from Chile during a period with large terms of trade gains, I find that cost reductions are associated with losses in allocative efficiency because firms pass-through measured productivity gains into markups. From industry-year variation, there is also 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.

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

1 Introduction

An important conclusion from the last decade of trade theory is that tougher competition raises the average productivity of producing firms. In fact, the big breakthrough of the Melitz (2003) heterogeneous firm model is to add reallocation of market share to the most efficient firms, i.e. selection, as a further aggregate productivity gain. 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 that are identical to the social optimum given the aggregate domestic environment. In that model, the reallocation of market share when using CES is always welfare improving, and the market equilibrium is shown to be allocatively efficient.[1] In a more general setting, the literature on growth and productivity has argued that within-industry production misallocation, or allocative inefficiency, is an important reason for cross-country income differences (Hsieh and Klenow, 2009; Restuccia and Rogerson, 2008).[2] With production misallocation the reallocation implied in the existing trade theory is not properly measured. Motivated by this literature, I incorporate a possible non-optimal market share reallocation to the Melitz model using as a starting point the result of Dhingra and Morrow (2012) (DM) that non-constant markups in a monopolistic competition framework imply a sub-optimal allocation across firms. Given this starting point, I find a sufficient statistic for the distortionary effects of market power on the allocation of production across firms over time in response to changes in competitive pressures and costs. My contribution is to produce a quantitative measure of changes in misallocation using aggregate data, motivate this through market share reallocations due to trade, and find an empirical application where allocative inefficiency plays a significant role in how reallocation impacts real income.

I relate allocative efficiency to the CES feature of constant markups, and investigate an economy where the market equilibrium with heterogeneous firms is not necessarily efficient. When the demand side in the Melitz model is generalized to allow for less restrictive preferences, 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. A high markup is a symptom of under-production (and vice-versa), and therefore I motivate the growth in welfare-relevant resource efficiency at the industry level using observed markup differences between initially high and low markup firms over time.

---

[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.

To allow for non-constant markups I use the variable elasticity (VES) framework with monopolistic competition. Variable markups imply 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. DM characterize qualitative properties of this misallocation and investigate the case where market size increases. In relation to DM, my contribution is to produce a quantitative measure of changes in welfare that is due to solely to the market share adjustment across firms. Further, I include shocks to the input and output markets that motivate time series variation in allocative efficiency.

Mechanically, I capture the difference between growth rates of aggregate real income and physical production. These measures coincide in a constant markup environment, so I link deviations in the growth of real income and physical production to changes in the market power distortion and show that this distortion is present in the welfare decomposition of a representative consumer.[3] This provides a sufficient statistic that captures a change in misallocation that is due exclusively to heterogeneity in market power,[4] and can be calculated with widely available data. In order to connect allocative efficiency to trade shocks, I take the structural specification of changes in allocative efficiency and relate it to firm-level reallocation. I allow for exogenous changes in the competitive environment – which affects firm demand elasticities – and exogenous cost shocks to motivate the underlying factors behind changes in misallocation.

Firm-level markups themselves are governed by the production allocation, and firms make production decisions taking aggregate variables as given. Shocks to the open economy will affect misallocation through their distributional effects on firm-level markups within a sector. As mentioned above, I allow for two effects that can result from globalization. One possibility is that there is tougher competition on domestic firms, and this affects firm-level demand elasticities. A separate possibility is to lower marginal costs for domestic firms through cheaper intermediate inputs. The first shock forces firms to lower their markups and results in a smaller dispersion of markups because the bigger firms reduce their markups relatively more. If a shift in demand elasticities leads initially high-markup firms to lower their prices relatively more, then inputs must be reallocated to these firms as they move down their demand curve. The latter shock allows firms to

---

[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.

[4]With constant markups, growth in quantity is allocated optimally across producers.

charge higher markups due to incomplete pass-through into prices, resulting in larger markup heterogeneity because pass-through is smaller for high-markup firms.

Edmond et al. (2014) (EMX) also quantify misallocation in the context of a trade model and measure the welfare gains due to trade liberalization. Their framework however relies on more restrictive demand by imposing nested CES preferences. Misallocation is due to supply-side frictions, because with oligopolistic competition the producer's markup depends on its sectoral sales share. In contrast to this study, my measure of misallocation in Section 4.2 is based on the change in the covariance of prices and quantities, an interesting statistic that has not been explored in this literature[5]. I also expand on the limited focus of competition on the output side by adding input side effects (DM and EMX concentrate on market size and output tariffs respectively). I derive the statistic with a general form for utility (restricting to additive separability), and maintain the monopolistic competition environment as in Krugman (1979) and Melitz (2003). In relation to the theoretical and empirical studies of trade liberalization based on the monopolistic competition framework, I build on the works that have thus far focused on average productivity and reallocation of market shares to more productive firms. Although that source of gain is still present in this model, variable markups imply that reallocation also depends on how market power allows firms to under-/over-produce.

I investigate empirically changes in aggregate allocative efficiency and its relation to firm level reallocation using both aggregate and firm-level panel data for Chile from 1995-2007, a period that includes both trade liberalization, and large terms of trade gains due to the increase in the price of copper. 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. This allows me to test the predictions of the model in response to reductions in costs of imports and tougher competition. Firms can be categorized as importers of intermediate inputs, exporters of final goods, as well as both or none. The working hypothesis is that importers reduce costs with an appreciation. Exporters and other domestic producers might face stricter competition in this case, as well as when output tariffs are reduced. I focus on the terms of trade gain because of the large magnitude of the appreciation.

Although the distortion I measure is at the industry level, it is the product of aggregating firm-level responses. At the firm level, I show that the terms of trade appreciation raises markups more for importers. The response is largest for firms with initially high

---

[5]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. (2012) relate the monopolistic competition distortion to changes in the revenue shares for markup aggregates.

markups, 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. Using the structural specification of misallocation, I measure changes in resource efficiency across time using aggregated data and show that the reallocation witnessed at the firm level is consistent with allocative efficiency findings at the industry level. The Melitz-type reallocation is captured in the physical production index (which increases in tandem with the appreciation shock), but this misses the movement in real income that is due to allocative efficiency variation.

My main results show 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 6.8 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 1.9 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.

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. (2012)). 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 degree of misallocation because productive firms raise their markups the most. 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 delineates the theoretical framework and Section 4 differentiates between growth in real income in the CES and VES models. Section 5 provides predictions for aggregate movements in misallocation based on two distinct ways that open economy

---

[6]In Section 7 I delineate the reasons for this definition

shocks drive reallocation at the firm level. Section 6 describes the data and Section 7 presents the empirical results. Section 8 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 quantity-misallocation distortion present in this paper that is the result of the interaction of non-homothetic demand and firm heterogeneity. Feenstra and Weinstein (2010) use a Translog expenditure function to measure the pro-competitive plus variety effects from increased global competition. Arkolakis et al. (2012) 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. Dhingra and Morrow (2012) characterize this extra welfare term qualitatively, but do not attempt to give a quantitative interpretation.

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), Holmes et al. (2012) and Edmond et al. (2014) all focus on welfare gains of tougher competition when the distribution of markups plays a key role. de Blas and Russ (2015) and Holmes et al. (2012) generalize the assumptions on the productivity distribution in the model of Bernard et al. (2003) to find implications on firm-level markups and overall welfare. Holmes et al. (2012) derive a welfare decomposition that includes allocative efficiency but holds only for homothetic tastes. Peters (2011) applies a model with head to head Bertrand competition and one top supplier for each differentiated good to relate markups to the productivity difference between the two most productive firms. In Edmond et al. (2014), markups are endogenous to competition and welfare gains from lowering misallocation are due exclusively to the level and dispersion of markups. Finally, misallocation can be attributed to supply-side wedges by adding an additive cost as in Khandelwal et al. (2013). 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 mapping 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.

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 firms are heterogeneous in productivity but markups are constant due to CES preferences. The distortions mean that firms optimally choose non-equal marginal products even though they face identical factor prices. This generates heterogeneous revenue productivities (TFPR) even though in an undistorted world these would be the same for all firms. Misallocation in HK is due to firms with higher production efficiency (TFPQ) being too small as they hire too few inputs due to distortions. A similar measure of allocative inefficiency is derived in Basu and Fernald (2002): some firms are producing too little (much) and choose revenue productivities that are too high (low). 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 aggregate productivity literature, a distortion inflicts a wedge between total revenues and total output, and leads to an inefficient allocation of resources. [7]

This paper fits into the Aggregate Productivity Growth (APG) literature that decomposes APG into growth in average firm productivity and reallocation. I argue that reallocation increases welfare if inputs are reallocated to where they have the highest social valuation in terms of marginal utility. This argument is made in Basu and Fernald (2002), Petrin and Levinsohn (2012) and Basu et al. (2010), where the markup is the gap between marginal revenue productivity of an input and the cost share of that input in the total input cost. If aggregate productivity is linked to the aggregate value added in the economy, then there is an aggregate productivity gain (APG) 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). When production is reallocated to high markup firms, these firms jointly lower their price and increase their production. I separate from the APG literature by applying this theory to open economy shocks that affect firms distinctively and how this aggregates to a distortion at the industry level. Additionally, whereas the above papers tend to regard prices and markups as fixed, I allow for the joint movement of prices and quantities.

---

[7]HK assume constant markups, so it is not possible for the firm's market power to affect misalloca-tion. In section 4.3 I discuss how aggregate productivity in these models relates to a VES economy with monopolistic competition.

Empirically, my results are closest to DeLoecker et al. (2012). Studying the trade liberalization of India, they find large productivity gains for manufacturing firms but also an incomplete pass-through of those gains into consumer prices. Although they do not incorporate these findings into a model with aggregate productivity implications, it is evident a CES model would over-state the gains from trade. This is what I find, that firm-level productivity gains are not necessarily passed through to aggregate real revenue.

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. Their method uses a decomposition of weighted average plant-level productivity from Olley and Pakes (1996). The decomposition of 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 methodology 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 trade liberalization 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   Model: Variable Elasticity and Allocative Efficiency

In this section I describe the Variable Elasticity of Substitution (VES) framework that is fully laid out in Dhingra and Morrow (2012) and Zhelobodko et al. (2012). This sets up an environment in which markup heterogeneity is the driving factor behind allocative inefficiency. Given this starting point, in Section 4 I construct a sufficient statistic for the growth rate of allocative efficiency.

Preferences are general as I do not choose a functional form for utility, but I assume that utility 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.[8] For this reason more productive firms (producing a differentiated good with a lower marginal cost) will have more market power and charge higher markups than their less productive counterparts. Whenever possible I use the notation of Dhingra and Morrow (2012).

I will refer to each "economy" as individual sectors at the 2 digit ISIC level. In each

---

[8]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".

sector there is a measure of differentiated varieties produced by single-product firms that are imperfect substitutes. The VES form is applied for preferences within a sector, where consumers demand differentiated goods: $U(M_e, q) = M_e \int u(q(c))dG(c)$. M_e represents the mass of entering varieties, c is the marginal cost or labor requirement to produce one unit, $q(c)$ represents the individual consumption of a representative consumer of a good indexed by marginal cost c drawn from a distribution $G(c)$[9], and $\int u(q(c))$ is utility from a unit bundle of varieties. In the theory sections I focus on a "representative sector" since all the qualitative results hold across sectors. The empirical section will use sector-year variation to examine the testable predictions.

For each variety there is inverse demand of, $p(q(c)) = \frac{u'(q(c))}{\delta}$, where the shadow price of income is $\delta = M_e \int_0^{c_d} u'(q(c))q(c)dG$. Therefore the relationship between the inverse demand elasticities and markups is:

$$\mu(q) = |\frac{qu''(q)}{u'(q)}| = |dlnp(q)/dlnq| = (p(c) - c)/p(c). \tag{1}$$

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).

The first step to working with this framework is to establish a socially optimal allocation under the general VES preferences and compare this to the market equilibrium. Although the social planner maximizes overall utility given the resource constraint, individual firms will solve a profit maximization problem. Using the optimal price condition above, the market equilibrium is such that each firm maximizes revenues that depend only on the representative utility function since $p(q(c))q(c) \propto u'(q(c))q(c)$. From Dhingra and Morrow (2012) (DM) we can set up the two maximization problems, one solves for the social optimum and the other solves for the market equilibrium:

$$\text{Social:} \max_{q, M_e, c_d} M_e \int_0^{c_d} u(q(c))dG(c) \text{ s.t. } L \geq M_e \left[\int_0^{c_d} (cq(c)L + f) \, dG(c) + f_e \right] \tag{2}$$

$$\text{Market:} \max_{q, M_e, c_d} M_e \int_0^{c_d} u'(q(c))q(c)dG(c) \text{ s.t. } L \geq M_e \left[\int_0^{c_d} (cq(c)L + f) \, dG(c) + f_e \right] \tag{3}$$

where the full allocation consists of equilibrium values for $\{M_e, q(c), c_d\}$. f_e is the sunk entry cost, f is the fixed cost of production, and L is market size.

There is a sector-specific zero profit condition such that expected profits net of sunk costs are zero: $\int \pi(c)dG = f_e$. In the language of Dixit and Stiglitz (1977), the social optimum is a "constrained optimum" since firms need to be compensated for the chance

---

[9] $c \in (0, c_d]$, where c_d is the highest possible cost with positive demand.

of losing the entry cost and not producing. Even when the entry, productivity cutoff and quantity allocation are such that social welfare is maximized, this will not be the perfectly competitive limit as prices will be greater than average costs. Below I show that the markup at the constrained optimum is the same for all firms.

Under the social problem, the social planner sets a quantity such that $u'(q^{opt}(c)) = \lambda c$ for all firms indexed by c, their marginal cost. λ is the Lagrange multiplier in the social problem and is a sector aggregate that represents the shadow value of resources. At these quantity allocations, if firms set prices as a constant of the marginal utility, then $p(q^{opt}(c)) = \frac{\lambda}{\delta} c$. Then, under the socially optimal allocation all firms set prices as a constant over marginal cost. The markup for all firms is the difference between λ and δ, or the difference between the maximum welfare per capita and the maximum real aggregate revenue per capita given representative consumers' utility function.

Then, under VES demand, the following is true:

Proposition 1. *A social planner guarantees a constrained optimum by setting all quantities such that the marginal utility for every good, and hence the price-cost ratio, is constant across firms. This means that the dispersion of prices and marginal utilities is always equal to the dispersion in costs within a sector. The benchmark for allocative efficiency is a degenerate dispersion of markups. A positive markup dispersion across firms is evidence of misallocated resources.*

In the market equilibrium, firms charge variable markups. Following the first order conditions of Equation 3, 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 $((p-c)/c)$. Given that $p = u'(q(c))/\delta$:

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

Under VES 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.[10] 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 prices and marginal utilities are a function of a constant over marginal cost and the market allocation mirrors a constrained optimum.

---

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

4 Quantifying Allocative Inefficiency

Dhingra and Morrow show that the VES model 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 welfare due to reallocation in the VES model relative to the commonly used CES framework. I use the definition of real revenue to compare the CES allocation with the allocation that results from VES utility, with the restriction that the demand functions are such that the demand elasticity decreases with sales.[11] I decompose real revenue into physical production and a covariance term that includes firm markups and input expenditures. Part of the welfare loss in the market equilibrium is therefore represented by the dispersion in markups. Intuitively, a dispersion in markups distorts the quantity allocation of the producing firms and lowers aggregate real revenue.

My analysis will be less general than DM in that I eliminate one of the three allocation choices. The available firm-level data is not equipped to measure consumer variety gains, and using a general framework that does not assume a functional form for $u(q(c))$ means there is no obvious way to correct welfare for variety gains.[12] Therefore M_e will be taken as given in all equilibria and I examine the conditional distribution given a set of producers.

I start by decomposing welfare when utility is homothetic, where welfare is proportional to revenue. I then generalize preferences to the VES form, where the welfare consequences of reallocation are different from the Melitz-Chaney model because market share is not necessarily allocated efficiently, creating an extra distortion term. The rest of the section focuses on how to measure changes in the distortion caused by misallocation. Since revenue is proportional to welfare only when preferences are homothetic, in Subsection 4.2 I conduct the following thought experiment: what is actual growth in real revenue relative to CES case? Therefore for my main measure of interest, I quantify the reallocation-induced welfare growth that is not captured by the Melitz-Chaney framework with homothetic preferences and Pareto distributed productivity. In Subsection 4.4 I incorporate the change in allocative efficiency into the total change in utility in response to reallocation of production. This decomposition of the (separable) components of welfare change establishes that the Melitz-Chaney framework does not capture all the possible welfare changes.

---

[11]This standard assumption in the trade literature assures that more productive firms charge higher markups.

[12]In the homothetic case for example this is done using the Ideal Price Index that measures cost of living.

4.1 Utility with CES

To start I explore the social allocation where 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:

$$U = M_e L \int u(q)dG \propto M_e L \int_0^{c_d} u'(q(c))q(c)dG(c)$$

$$\propto \lambda M_e L \int_0^{c_d} \frac{1}{1-\mu(q(c))} cq(c)dG(c)$$

$$\propto \lambda \Big(\int_0^{c_d} \frac{1}{1-\mu(q(c))} dG(c) \Big) \big(L - M_e G(c_d)f - M_e f_e \big) \tag{5}$$

where the last line uses the budget constraint 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. As shown in Dhingra and Morrow (2012), the market allocation maximizes utility when $\frac{p(c)}{c} = \frac{1}{1-\mu(q(c))}$ is constant.

When the sub-utility is not homothetic, the market allocation price/cost ratio is a function of productivity: $p(c)/c = \frac{1}{1-\mu(q^{mkt}(c))}$, where $\mu(q^{mkt}(c))$ is the inverse demand elasticity the firm faces. Utility and aggregate revenue diverge, $Cov(\frac{1}{1-\mu(q(c))}, cq(c)) \neq 0$, and the market allocation no longer maximizes utility. In Appendix A, I show that changes in utility arises with the reallocation of inputs to higher price firms as in Basu and Fernald (2002). In order to get a measure of misallocation in the data, I compare growth in real revenue in the socially optimal and market allocation. By following the joint movement of prices and quantities, real revenue can differ from average productivity. For example, cost advantages are not passed through completely to prices so that some firms under-produce and others over-produce, which distorts total revenue relative to the CES benchmark. Notice that this framework is consistent with the results of Edmond et al. (2014) and Arkolakis et al. (2012), who both find that it is the *joint distribution* of markups and production that matters.[13]

4.2 VES and Market Power Distortions: Quantifying Misallocation using Real Revenue

The following quantification is the focus of this paper and will produce the aggregate measure used in the empirical section. Let aggregate revenue, $R = M_e L \int_0^{c_d} p(q(c))q(c)dG(c)$.

---

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

I will work with the conditional distribution of $g(c)$ on $(0, c_d]$, defined as follows:

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

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, $Q \equiv LM \int_0^{c_d} q(c)h_d(c)dc$.[14] $q(c)$ stands for the consumption of an individual variety by a representative consumer. I will decompose aggregate revenue in terms of mean and variances using the covariance: $\text{Cov}(p, q) = \int_0^{c_d}(p(q(c)) - \tilde{p})(q(c) - \tilde{q})h_d(c)dc$, with $\tilde{p}$ and $\tilde{q}$ the average price and average quantity respectively.[15] I use that to examine real revenue by dividing both by the average price:

$$R = ML \left[\int_0^{c_d} p(q(c))h_d(c)dc \int_0^{c_d} q(c)h_d(c)dc \right] + ML\left[\text{Cov}(p, q)\right] \tag{7}$$

$$\frac{R}{P} = ML \int_0^{c_d} q(c)h_d(c)dc + ML\left[\text{Cov}(p, q) / \int_0^{c_d} p(q(c))h_d(c)dc\right] \tag{8}$$

I denote $\frac{R}{P}$, real revenue, with $\tilde{R}$. The last term, as will be shown shortly, is a residual that will capture allocative efficiency since it represents the deviation of real revenue from physical production. Equation 8 can be further expanded substituting for $\tilde{R}$ and Q, and then taking logs to get growth rates:

$$\frac{\tilde{R}}{Q} = 1 + \frac{\text{Cov}(p, q)}{\int_0^{c_d} p(q(c))h_d(c)dc \int_0^{c_d} q(c)h_d(c)dc}$$

$$\Delta ln\left(\frac{\tilde{R}}{Q}\right) \approx \Delta\left(\frac{\text{Cov}(p, q)}{\int_0^{c_d} p(q(c))h_d(c)dc \int_0^{c_d} q(c)h_d(c)dc}\right) \tag{9}$$

The last line uses the approximation that $ln(1 + x) \approx x$. The way I will identify changes in allocative efficiency is by establishing that Equation 9 is zero in the case of allocative efficiency. Therefore, I can use the observable left hand side to measure whether the market equilibrium is getting closer or farther from efficiency.

To get an intuitive interpretation, I define the terms in Equation 9 with respect to the allocation variables. There are two changes to the allocation over time: inputs/production are reallocated as firms change their production quantity (vector of q(c)); and the cutoff cost (c_d) changes given the new competitive environment. The former effect will not affect

---

[14] $M = M_e G(c_d)$ is the measure of firms that produce.

[15] $\tilde{p} = \int_0^{c_d} p(q(c))h_d(c)dc$; $\tilde{q} = \int_0^{c_d} q(c)h_d(c)dc$.

the covariance term when utility is CES: the distribution of prices is equal to the distribution of marginal costs in that case, so reallocating quantity will have no affect on the distribution of prices. However if the cutoff cost changes, this impacts the distribution depending on the assumed distributional properties. Therefore I relate the general VES model to the Melitz-Chaney framework as a benchmark, where $G(c)$ is Pareto. In the Pareto case truncation does not affect the shape of the distribution. This does not hold, for example, in the log-normal[16].

In Appendix B I take the case of CES preferences and Pareto distribution of costs and show that the terms in Equation 9 are zero, which establishes the following Lemma:

Lemma 1. *The RHS of Equation 9 is equal to zero when i) the distribution of prices stays unchanged and ii) a change in the cutoff cost does not affect the shape of the price and/or quantity distribution. The conditions that $u(q(c))$ is CES and $G(c)$ is Pareto fit the two requirements and, as shown in Appendix B, $\Delta ln(\frac{\tilde{R}}{Q}) = 0$ in the allocative efficiency case.*

I interpret my measure as the difference in the growth of real revenue relative to the case where reallocation is restricted to the Melitz-Chaney framework. The difference in growth rates is due entirely to the growth rate in allocative efficiency that is set to zero in that framework. The measure in (9) provides a sufficient statistic for the necessary correction in the real revenue effects on welfare due to reallocation that is not captured in Melitz-Chaney. Given that the market power distortion exists only in the non-efficient market equilibrium, I label the change in the covariance term as ΔAE, with the interpretation that it tracks movements in real revenue that can only occur when misallocation is present:

$$\Delta(AE) = \Delta ln \left(\frac{\tilde{R}}{Q} \right) \tag{10}$$

With allocative efficiency, changes in real revenue are captured completely by the growth in an index of physical production (which includes reallocation). Change in real revenue not captured in physical production is therefore due to changes in allocative efficiency. Although I do not have firm level data on prices and quantities, the 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

---

[16]From Head (2011): the truncated log-normal has an expected value: $E[x|x > x_0] = e^{(\mu+0.5\sigma^2)} \frac{1-\Phi(z_0-\sigma)}{1-\Phi(z_0)}$ with $z_0 = \frac{ln(x_0)-\mu}{\sigma}$. That last ratio in the expected value is the effect of the truncation. Eeckhout (2004) shows that log-normal is the right approximation to a distribution where the tails look Pareto but the shape parameter is sensitive to the choice of a minimum truncation point.

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) and Petrin and Levinsohn (2012) defined by total growth in (deflated) value added within an industry, and corrected for the growth in primary inputs.[17]. For the aggregate price level, the Chilean statistical agency provides 4-digit ISIC industry deflators. 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. There is enough data therefore to infer the change in the misallocation distortion as implied by Equation 10 and I detail the use of this data in the empirical sections below. For a further decomposition of the price-quantity covariance into markups and inputs that relates to Basu and Fernald (2002), see Appendix C.

4.3 Discussion

The above decomposition identifies the role of the markup distribution in the market equilibrium with variable markups. The misallocation distortion that I measure in this paper differs from Hsieh and Klenow (2009) by breaking the linkage between physical productivity and welfare[18]. Reallocation raises revenue and welfare not necessarily by re-allocating production to more productive firms, but raising the production of firms with a high social benefit relative to their labor requirements (which is the markup in my model). As in Hsieh and Klenow (2009), misallocation depends on firm-level distortions (firm heterogeneity is necessary) taking economy aggregates as given, although the distortion is due to non-homothetic demand instead of supply side wedges.

An important question regarding the quantification of distortions is where resources should be reallocated to improve social efficiency. This is an unsettled topic in the literature. Channeling the theory of Olley and Pakes (1996) and Melitz (2003), Pavcnik (2002) (and more recently Bartelsman et al. (2013)) focused on the covariance of market share and productivity to summarize allocative inefficiency (higher covariance implies better

---

[17]By the national revenue accounting identity, I use that the sum of value added is equal to the sum of final demand in an industry.

[18]The focus on average firm productivity in the previous literature makes sense in a CES world where the covariance term above is constant. Changes in the real revenue would be tracked by the change in aggregate weighted firm-level productivity as in Pavcnik (2002). This is not the case in (7) as an increase in quantity is not necessarily associated with more production value.

allocative efficiency/aggregate productivity). However Petrin and Levinsohn (2012) argue that this is not a correct measure of welfare gains due to reallocation as firms with higher productivity are not necessarily those that will have the highest social return from extra inputs. If firms minimize costs then the markup is the gap between the value of the marginal product and the marginal cost (or the factor price). Reallocating inputs from a firm with a lower than average markup to a firm with higher than average markup moves the economy closer to equalizing the marginal rates of transformation.

I make a similar argument: reallocating inputs towards more productive firms is only optimal to the point where their marginal rates of transformation would be equalized. In the VES model, "over/under-producing" is a result of market power and pass-through. In a constant markup model there is full pass-through so more productive firms pass on their lower costs to prices by increasing their quantity until the markup is the same as less productive firms. Due to incomplete pass-through, some of the cost advantages are passed through to markups instead, which is why low cost firms have higher markups. To do this, the low-cost firms reduce their production, and so produce less than under the optimal allocation. High cost firms choose low markups by producing more than is optimal. 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 $\frac{p}{p'} = \frac{c}{c'}$.

4.4 Total Welfare Decomposition

Equation 10 captures the change in misallocation (in real income terms) within a given measure of heterogeneous firms. However this does not capture the full implications of allocative inefficiency on welfare. It has been known since Dixit and Stiglitz (1977), summarized in Vives (2001), and expanded in Mrazova and Neary (2013a) that an inefficiency still exists with homogeneous firms due to a distortion in the number of available varieties.[19][20] I will now decompose the full welfare expression in my model to express clearly how I ignore this part of misallocation. Starting from $U(M_e, q) = M_e L \int u(q(c)) dG(c)$, 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 (2012), the (utility-weighted) average elasticity of utility is $\bar{\epsilon} = \frac{\int \epsilon(q) u(q)}{\int u(q)}$. Using this definition, total utility is now $U(M_e, q) = \frac{1}{\bar{\epsilon}} M_e L \int u'(q(c)) q(c) dG(c) dc$. Then, with δ as the marginal utility of in-

---

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

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

come, $u'(q(c)) = \delta p(q)$. I follow the same steps as subsection 4.2 to decompose revenue within the welfare function:

$$U = ML\frac{\delta}{\bar{\epsilon}} \int p(q)q(c)h_d(c)dc$$

$$= ML\frac{\delta}{\bar{\epsilon}}\left[\frac{PQ}{ML}\right]\left[\frac{\tilde{R}}{Q}\right]$$

$$\Delta ln(U) = \Delta ln(\delta) + \Delta ln(1 - \bar{\epsilon}) + \Delta ln(P) + \Delta ln(Q) + \Delta ln(AE) \tag{11}$$

Related to the result in Equation 5, the second and last terms in Equation 11 are zero with CES preferences. The last term, my measure of allocative efficiency, is zero by Lemma 1 with CES preferences if the distribution of costs is Pareto. The second term is a part of allocative efficiency that I do not capture, and is zero when the sub-utility function is CES.[21] Vives (2001) refers to $(1 - \epsilon(q))$ as "the proportion of social benefits not captured by revenues when introducing a new variety." A marginal entrant would lower the per-capita quantity sold by each incumbent firm, and therefore move $\epsilon(q)$ depending on the functional form of $u(q)$: for example in the linear demand case without the non-separable term, $(1 - \epsilon(q))' > 0$, so the extra entry lowers the social benefits of the incumbent firms (the "business stealing" effect), while concurrently raising variety and welfare through higher revenues. Under the CES benchmark allocation these two effects cancel each other out.

The first term is the Lagrange multiplier of the budget constraint.[22] In Equation 11, $\Delta ln(\delta)$ is equal to the negative of $\Delta ln(P)$ in the CES demand case by Proposition 1. Therefore in that case we are left with $\Delta ln(U) = \Delta ln(Q)$[23], which explains why the literature has thus far concentrated on quantifying TFP gains. With VES preferences, there are extra terms that need to be accounted for to measure welfare gains. In Appendix D I show the ACDR gains from trade decomposition as a comparison. That decomposition includes a distortion that is only present in the non-homothetic case. However, due to their assumption of Pareto distribution in productivities, the distortion is constant. The focus of this paper is on the growth rates of this distortion: the last term in Equation 11. The next section details the separate competition and cost shocks that I study, in contrast to the model with output tariffs of ACDR.

---

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

[22]In ACDR, its inverse represents the choke price. In fact, in their demand system, they show that the percentage change in the choke price is equal to the percentage change in prices for homothetic preferences (though they ignore the CES case).

[23]Q is defined as $LM \int_0^{c_d} q(c)f(c)dc$. With heterogeneous firms, Q can rise due to selection.

5 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. I assumed that there exists an equilibrium allocation at each point in time in which firms make decisions given the aggregate environment. Next I will investigate how changes in the aggregate environment affect the reallocation of production and the implications for allocative efficiency. The strategy is to fit into a reduced-form approach aggregate shocks that affect the equilibrium allocation. Changes in the domestic environment can affect firms through either i) their residual demand curve or ii) their marginal cost.

Changes in the residual demand curve can be due to tougher competition (or conversely, being more insulated from competition) through a larger market size. This changes the slope of the residual demand curve and leads firms to adjust prices (and quantities) for a given cost. In standard trade models with CES preferences, competition leads to a standard selection effect that increases welfare through a higher average productivity. Aside from the competition effect, trade policy and other global shocks affect the marginal costs of firms. This type of trade gain has gotten a lot more attention in the recent literature on imported intermediate goods and technology adoption. Higher terms of trade, lower inputs tariffs, or better access to intermediate goods markets, lower the costs of production for domestic firms. When this effect has been investigated and combined with CES consumer preferences, cost decreases are fully passed on to prices.

However, with VES preferences, allocative efficiency comes into play though imperfect pass-through. Take for example an increase in market size. Demand elasticities increase for all firms by a constant, lowering prices and increasing quantity. There is the standard competition effect: the lowest productivity firms get selected out (this will raise average productivity). Additionally with VES, competition affects firms' demand curves heterogeneously because demand elasticies are a function of sales. I show in Section 5.1 that this reallocates production from less to more productive firms because more productive firms lower their markup relatively more. Marginal cost shocks affect the production distribution in the opposite way. Not all of the marginal cost decrease is passed through to a pure aggregate productivity gain for the economy as some of that is eaten up by the pass-through into markups. More productive firms are able to increase their markup relatively more, resulting in relatively more production going to the less efficient firms, or a real income-reducing reallocation.

A reduced-form approach allows for a more general framework than just integrating output tariffs into the model. Focusing exclusively on output tariffs can confound the

tougher competition and lower costs, so that the two channels above can cancel each other out. 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 competition.

5.1 Global Shocks and Markups

I analyze competition shocks that can change the slope of firms' residual demand curves as well as shifts in the marginal cost distribution of domestic producers that are possible through increased trade and cheaper inputs. The average productivity/selection responses from these two shocks have been studied extensively in the canonical trade model. However the impact on the markup distribution has not yet been explored. Allowing for production to increase with either type of shock, I differentiate between shocks that also increase allocative efficiency (I call these *pro-resource reallocation*) and those that dampen welfare gains by reducing allocative efficiency (*anti-resource reallocation*). I adopt a method introduced by Mrazova and Neary (2013b) to compare the distributional changes at the new equilibria and determine whether a shock is pro- vs anti-resource allocation.

The main measure of interest is the growth rate of misallocation, and the following analysis will allow me to explain the growth rate through reallocation. The goal is to infer reallocations' effect on the misallocation distortion through the response of the markup distribution to an aggregate shock. First, an import competition shock (without taking trade costs into consideration) occurs with a shift in the number of firms (M_e) or the market size (L). Intuitively, this shifts the demand elasticities that firms face. In a two country model with trade costs (as in Melitz and Ottaviano (2008)), changes in demand elasticities can also be a result of lower import tariffs which allow for more foreign entry. However that case would also have to take into account lower costs of importing inputs.[24] Second, I allow for lower costs of production/efficiency improvements for domestic firms that can result from cheaper inputs. In contrast to import competition, this shock is identified by movements in a firm's supply curve.

Both scenarios above will shift firm markups as each shock affects the pricing decision of the firm. In the globalization scenario, larger market size/tougher entry imply an increase in the marginal utility of income ($\frac{\partial \delta}{\partial L} > 0$). Since $p(c) = \frac{u'(q(c))}{\delta}$, prices shift for all

---

[24]DeLoecker and Goldberg (2013) actually differentiate between shocks to the residual demand curve and shocks to the marginal cost curve as responses to output and input tariffs changes respectively.

firms by a constant proportion.[25] Let $p_i(\delta', c_i)$ represent the price decision of firm i after a globalization shock.

To examine the second case, I introduce imported inputs as a source of production with a constant labor requirement. To give the firm marginal cost more structure, let the cost using only domestic inputs be expressed as a labor requirement to produce one unit: $c_i(\varphi_i) = \frac{a}{\varphi_i}$, with a a constant, and φ_i the firm's draw from a productivity distribution. With trade, firms can also import inputs at a labor requirement of $\frac{a(\tau-1)}{\varphi_i}$ with $\tau > 1$. The total marginal cost of production is then $c_i(\tau, \varphi_i) = \frac{a\tau}{\varphi_i}$, where τ is a scalar in the marginal cost curve that represents the cost of importing inputs. A shock that lowers the cost of imported inputs scales down $a\tau$. This allows for a productivity shock that lowers production cost and allows firms to increase markups with incomplete pass-through. The impetus for this mechanism can be a terms of trade gain (of course a terms of trade loss would just imply an increase in τ), or lower input tariffs.[26]

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

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

Markups are a function of one firm primitive and two aggregate variables that identify the domestic environment. There is a continuum of firms endowed with productivity φ_i, leaving changes in allocation equilibria (vector $q_i(c(\tau, \varphi_i))$ and c_d) due solely to movements in δ and $a\tau$. Although changes in either aggregate acts as a constant shifter to the demand or supply curve, the firm-level response is of course heterogeneous because markups are a function of sales.

Next, I show how a pro-resource reallocation shock is the result of an increase in δ (i.e. globalization), and an anti-resource reallocation shock results from a decease in $a\tau$ (i.e. firms see a reduction in costs). Both events can of course occur simultaneously, but which effect dominates will depend on the exposure of the industry. In the empirical tests, I compare across industry exposure in a differences-in-differences type approach that leverages exposure to the output versus input market.

To relate the pro- and anti-resource 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 $\frac{\partial m_i^2(\delta, \tau, \varphi_i)}{\partial \tau \partial \varphi_i}$. The first comparative static is

---

[25]Marginal utility of income and market size/entry are aggregates and taken as given at the firm-level.

[26]$0 < \frac{\partial q}{\partial c}\frac{c}{q} < -1$, so that a reduction in marginal costs will increase the equilibrium individual consumption of each variety and increase its markup.

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? If $\frac{\partial m_i^2(\delta, \tau, \varphi_i)}{\partial \tau \partial \varphi_i} > 0$, markup differences across low versus high productivity firms get smaller at higher τ. This follows the method of Mrazova and Neary (2013b), who use the second derivative to establish super/sub-modularity. Details are provided in Appendix E.

Going back to Equation 12, $\frac{\partial m_i(\delta, \tau, \varphi_i)}{\partial \tau} < 0$, or markups decrease with τ. By differentiating this with respect to firm-specific productivity, we get the differential effects of a change in τ for firms with different marginal costs. With CES preferences, it can be shown that $\frac{\partial m_i^2(\lambda, \tau, \varphi_i)}{\partial \tau \partial \varphi_i} = 0$.[27] With the assumption of decreasing demand elasticity made in Section 3, it can be shown that $\frac{\partial m_i^2(\lambda, \tau, \varphi_i)}{\partial \tau \partial \varphi_i} > 0$.[28] Therefore at lower τ's, there is a *bigger* markup difference between a low cost and a high cost firm. Intuitively, an environment where τ is smaller and λ is unchanged is characterized by larger markup differences between low and high cost firms. This means that lowering τ (firms being able to charge higher markups) is more beneficial for *low-cost* firms as they can increase their markup relatively more by passing through less of their cost decreases to prices. In reallocation terms, among existing firms inputs are reallocated relatively to initially low markup firms for this result to hold.

This setup makes the simplifying assumption that importing requires a constant labor requirement but I should point out some alternative frameworks.[29] 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. The anti-resource reallocation result should only be exacerbated if it is the most productive firms that get the cost decreases.

In a Krugman (1979) globalization episode where the market size (indexed by L) expands, $\frac{\partial q_i}{\partial L}\frac{L}{q_i} < -1$ (equilibrium consumption of each variety decreases), and demand

---

[27]See Appendix E for the derivation.

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

[29]An example of a setup where τ is the same for all firms is Acemoglu et al. (2012). In that case the foreign country plays the role of a general-purpose technology.

elasticities increase. The same result occurs when entry intensifies (M_e increases) and the probability of surviving to produce decreases. With markups a positive function of individual consumption, this is equivalent to a decrease in the firm-level markup for all varieties. Using the same super/sub-modularity argument as above, tougher competition not only lowers the average markup but also leads the lower cost firms to decrease their markup more than high cost firms.[30] This can be shown using $p_i(\delta', c_i(\tau, \varphi_i)) = \frac{\delta' \eta(c_i)}{\delta' \eta(c_i) - 1} c_i(\tau, \varphi_i)$ where $\eta(c_i)$ is the original demand elasticity faced by a firm with marginal cost c_i (before the globalization shock). δ' is an aggregate that shifts demand elasticities for all firms with $\delta' > 1$ when L or M_e increase, and $c_i = \frac{a\tau}{\varphi_i}$ is constant for each firm since there is no shock in τ. Then $\frac{\partial p_i(\delta, c_i(\tau, \varphi_i))}{\partial \delta'} < 0$: an upward shift in demand elasticities lowers prices for all firms. Furthermore as shown in Appendix E, $\frac{\partial p_i^2(\delta, c_i(\tau, \varphi_i))}{\partial \delta' \partial c_i} < 0$. Again, this relies on the assumption that demand elasticities decrease with sales (in the CES case $\frac{\partial p_i^2(\delta, c_i(\tau, \varphi_i))}{\partial \delta' \partial c_i} = 0$). The price difference between a low and high-cost firm gets *smaller* with bigger upward shifts in demand elasticities – markups differences tighten – and the reallocation implication is that higher markup firms increase production relatively more as they move down their demand curve.

5.2 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 allocative efficiency per the theoretical framework in Section 5.1. With the assumptions on demand, reallocation of production can be inferred from the observed markup response and this is allows for the channel that links the shocks to aggregate misallocation.

Hypothesis 1. *A "favorable" cost shock is anti - resource reallocation as it reallocates inputs to initially low markup firms. Increased import competition is pro - resource reallocation as quantity production is shifted relatively to highly-valued products.*

This hypothesis is tested by the consistency of the observed firm-level responses with the growth in aggregate allocative efficiency as defined in subsection 4.2. In the following empirical analysis 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.

---

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

In Section 7, 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. In the next section, I describe the data and important open economy measures for Chile.

6 Data and Background Information

6.1 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. The percentage of firms that export and the fraction that import are both consistently around 20% throughout the data span.

From Section 4, there are three aggregate measures that I use in Equation 10: revenue, prices, and quantity. The growth in real income (revenue over prices) can be computed by aggregating deflated value added of all firms within an industry[31]. Value added is at the firm level, and the ENIA provides sales and input deflators at the 4-digit ISIC level. Therefore the most disaggregated measure of real income growth available is at the 4-digit ISIC. For physical production, I use an index provided by the INE at the 3-digit level. However due to constraints on the number of 3-digit groups, I aggregate the quantity index to the 2-digit level and conduct the industry analysis at this level. This index follows a subset of firms with bases in 1989 (for the 1995-2002 data) and 2002 (used for the 2003-2007 data).

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

---

[31]See Appendix F.

rate (REER) as a geometric average of relative prices using trade weights from the BIS[32] and output prices provided by the Penn World Tables (PWT) 8.0.[33] The nominal effective exchange rate (NEER) is a trade weighted average of nominal exchange rates provided 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[34] input output matrix provided by the Chilean Central Bank in its National Accounts publications of 1996 and 2003.

6.2 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)). Although Chile has been a WTO member since 1995, in the period under analysis it underwent several important trade liberalization episodes. The decrease in average tariffs and signings of various trade agreement were concurrent with an increase in the share of exports to manufacturing GDP. Part of this 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, which was later followed by a large increase in imports, driven especially by intermediate inputs.[35]

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 decreased from 11% to below 2%.[36] This drop is mostly homogeneous across industries.

[Figure 1 about here.]

Aside from the average tariffs above, the many trade agreements signed by Chile are anecdotal evidence of its trade liberalization. Appendix G lists these agreements.

---

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

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

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

[35]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.

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

Apart from trade reform, Chile also experienced a large shock to its exchange rate during this period. 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). The terms of trade increases starting in 2003, which coincides with the incline in import and export values at about the same time (next paragraph). I expect the exchange rate to play a role in my analysis as Chile goes through sustained depreciations and appreciations during my data span. 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 mostly move together except that the depreciation in 1999 is much sharper in nominal terms.

[Figure 2 about here.]

[Figure 3 about here.]

Since my data spans firms in the manufacturing sector, I investigate how manufacturing specifically is affected by liberalization and subsequent terms of trade gains. Although the Mining industry is not included in my data, the Basic Metal industry is significantly affected by the price of copper, so I drop it from my analysis below.[37] Figure 3 plots manufacturing exports and imports as a ratio of total manufacturing value added. Exports and imports are gross flows from Feenstra et al. (2005) (so they can be greater than total manufacturing value added). I sum flows only for manufacturing industries (ISIC industries 15-37 after I concord with ISIC rev.3). I also report manufacturing exports/imports excluding the Basic Metal industry. Manufacturing exports as a ratio of manufacturing GDP rises sharply starting in 1999, though imports do not rise until 2004. Exports climb before the terms of trade gain, evidence of a push towards exports and help from the depreciation of the Peso, while imports seem to react to the terms of trade gain through the higher purchasing power. This pattern still holds after eliminating the Basic Metal industry, though there is a big drop-off in exports/GDP. For the manufacturing firms that I consider, importing is as, or even more important than the export side.[38] 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.

---

[37]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.

[38]Imports are not affected by excluding Basic Metals.

7 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 specification and results, with the former defining measures that I summarize in the results.

The misallocation distortion that I estimate in this paper occurs because the allocation of production is not based only on firm level productivity but also firm level market power. Market power is positively related to productivity, allowing more productive firms to under-produce in order to increase profits through a high markup. A way to gauge the evolution of this distortion in the data is to measure the markup estimates directly. In the next subsections I summarize the method to calculate firm level markups and then show suggestive evidence by concentrating on the aggregate average and dispersion of markups. This can be compared to the time series of aggregate allocative efficiency as described in Section 4.2. Later, I turn to a regression analysis with differential treatment groups to investigate how pro- and anti- resource reallocation effects determine allocative efficiency.

7.1 Empirical Specification

7.1.1 Production Function Estimation and Markups

I have defined allocative efficiency as a degenerate markup distribution. I now investigate to what extent we see markup dispersion in Chile, and how this compares across industries and years. I use the method from DeLoecker and Warzynski (2012) to first calculate production function coefficients ala Ackerberg et al. (2006) (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 to estimate firm-level markups. The details on production function estimation and translating this to markups is in Appendix H.

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.]

7.1.2 Regression Specification

In the regression analysis of Subsection 7.2.4, I start at the firm-level with a framework similar to Pavcnik (2002) and Amiti and Konings (2007), that study, respectively, how output and input tariffs affect firm revenue TFP. I am interested in testing the results in Section 5 with respect to the distributional effects of aggregate shocks. I then aggregate to the industry level to use my measures of $\Delta \tilde{R}$, ΔQ, and ΔAE as introduced in Section 4. 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:

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

α_t and $\alpha_{i/j}$ represent time (t) and firm (i)/industry (j) (depending on the level of aggregation) fixed effects respectively. There is a trade liberalization variable (τ_{jt}) that can be output tariffs, input tariffs, or terms of trade, plus a firm- or industry-level indicator of exposure, $Expos_{ijt}$. This indicator 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 variable as the treatment group. Lastly, Z_{ijt} includes other firm/industry characteristics.[39] The outcome variable is the log markup ($ln(\frac{1}{1-\mu_{ijt}(\delta_{jt},\tau_{jt},c_{it})})$) at the firm-level[40]. At the industry-level, the outcome variable would has j,t subscripts and follow the measures in Section 4.2.

---

[39]These include: industry Herfindahl index, index of "import competition", 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.

[40]I also report revenue TFP.

7.2 Results

This section starts with suggestive evidence in summarizing the distribution of firm level markups. The last subsection details the results of the regression framework outlined in Section 7.1.2.

7.2.1 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). Here I show the evolution of both the average and dispersion of markups.[41] Figure 4 plots the mean markup computed by sector and reports a sectoral value added-weighted average. The figure shows that there is a reduction in the mean markup at the beginning of the period but that it rises starting in 1997.

[Figure 4 about here.]

Next I turn to the markup distribution, which is the new contribution to the reallocation analysis relative to the rest of the gains from trade literature in the monopolistic competition framework. 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.[42] In addition to using the material input markup wedge, I also use the labor coefficient-cost share wedge as a separate measure. Figure 5 takes all firms in a given sector, with the markup dispersion calculated annually excluding the Basic Metal industry, and averaged, where the weights are defined by sector value added. This is therefore an economy-wide measure of markup dispersion using only the dispersion within sectors. The increase in dispersion is consistent with the story in Section 5[43]. The dispersion gets smaller through 2002, and then spikes up in 2003. The FTAs signed by Chile starting in the mid-1990s and the rise in trade are compatible with a globalization episode that reduces markup dispersion. The spike in markup dispersion coincides with the terms of

---

[41]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.

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

[43]This is consistent with the theory in Section 5, where anti-resource allocation shocks that raise markups for all firms also lead to higher dispersion due to the shape of the markup function.

trade shock and large increase in the value of imports.[44] If firms are responding heteroge-
neously to increases in productivity in a way that increases dispersion in market power,
misallocation could be a source of *dampening* the positive welfare effects that arise from
an increase in the value of Chile's production.

[Figure 5 about here.]

7.2.2 Markup Dispersion versus Productivity Dispersion

A useful comparison is to look at the markup dispersion versus productivity dispersion.
In Hsieh and Klenow (2009), markups are constant and misallocation is given by the dis-
persion in revenue productivity. I find that the results above would not hold if revenue
productivity dispersion were used as an indicator for changes in allocative efficiency. For
example, I compare the markup distribution versus the TFP distribution in 1995 and 2005,
since this is where the biggest difference should be seen. Figure 6 shows the distribution
of log markups on the left in 1995 and 2005. The right panel is the distribution of revenue
TFP across all firms in 1995 and 2005. In the markup distribution we can see that the fat-
ness of the distribution is larger in 2005 as expected given the markup dispersion results
above. However this is not evident in the TFP distribution: it has definitely shifted to the
right but with no noticeable change in the dispersion.[45]

[Figure 6 about here.]

7.2.3 Aggregate Allocative Efficiency

In this section I use the measure of misallocation from Equation 10 applied at the industry
level, aggregating to the 2-digit level.[46]

Figure 7 shows real revenue growth and physical production growth at the aggregate
manufacturing level.[47] Appendix F discusses the calculation of real revenue growth. The
analysis is complicated by the fact that the physical production index does not necessarily
include all producing firms because it is based on a survey that chooses representative

---

[44]The pattern is similar whether I use labor or materials to calculate the markup.

[45]This result still holds if I use only firms that are active throughout the whole time span and ignore new
firms after 1995.

[46]Quantity data is available at 3-digit, but due to some inconsistencies in appending pre- and post-2002
data, I aggregate up to two digits.

[47]Each is calculated at the 2-digit sector level and I aggregate to the manufacturing level using value
added shares by sector. I eliminate sector 27 (basic metals) since this industry represents more than half of
total value added after 2004.

28

firms in the base year (in my sample, the 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, when I calculate growth rates for real revenue, I produce a measure that only includes firms that are in the database for 7 years or longer. This is the measure I use, though I also compare results when the census of firms are included in the revenue measure.

As with the economy as a whole, manufacturing production slows down between 1998-2002 and picks up starting in 2004. Real revenue growth is mostly higher than production up until 2003 and then is lower in 2004, 2006 and 2007. 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 7 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 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).[48] 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.

The counter-factual above is measured using only a subset of firms that are in the dataset for at least 7 years to try to be as consistent as possible with the way the physical production index is calculated. Using the full sample of firms for revenue growth reduces

---

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

the role for misallocation but the signs remain the same (revenue growth follows quantity growth a little more closely, but allocative efficiency still amplifies welfare growth in the first sub-period and dampens it in the second).[49]

The next section will investigate trade shocks that are mechanisms for these aggregate outcomes. I will go beyond the contemporaneous correlation evidence to regression results. I expect industries that rely on imported intermediates to benefit more in terms of measured productivity and cost-advantages. An increase in industry productivity would present itself through more physical production, but not necessarily the income component. Industries that export a greater portion of their output, or face import competition on output sold domestically, should instead face tougher competition and this would induce pro-resource reallocation behavior.

7.2.4 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 and 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.[50] I provide the specific derivations used in Ekholm et al. (2012) in Appendix I.

Making the distinction of import/export exposure is important because open economy shocks will affect importers and exporters differently. In Section 5 the comparative statics depend on the nature of the shock: a shock to the input side (for a given level of

---

[49]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.

[50]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.

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[51]. Tables 2- 4 show firm-level markup and revenue TFP responses to changes in the terms of trade (TOT) and output/input tariffs (interacted with the exposure of the firm). Table 5 tests whether the markup responses are different across the distribution in order to make a claim about reallocation. Finally Tables 7 and 6 are at the industry level and the exposure/import/export characteristic is an average of firms in the industry.

The regressions include all the individual terms that are part of the interactions and the Z_{ijt} characteristics covered above, but for the most part I omit them from the results and report the interaction results in the following tables. 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 or nominal effective exchange rates (REER and NEER) 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 or NEER instead of terms of trade resulted in identical conclusions. I point out the one case where the REER yielded slightly different results in the discussion below.

In Table 2 the firm characteristics are "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 (1) shows that a 10 percent increase in the terms of trade increases markups by 0.37 percent more for importers who do not export relative to the rest of firms. This is not the case for exporters. The second column adds revenue TFP as an

---

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

explanatory variable to control for the fact that the measured markup can be confounded with productivity in the production function estimation. However, even controlling for TFP leaves the markup results mostly unchanged. In the last column, revenue TFP is the outcome variable so that we can compare the markup responses with TFP. In this case, a lower tariff raises TFP of exporters and a higher terms of trade raises the markups of importers.

Table 3 uses import/export shares, as well as the net exposure (Columns (1) and (3)), instead of dummies. 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. The coefficient in the second row of Column (1) is consistent with lower tariffs raising markups for firms exposed to final goods trade. The signs are the same for TFP though not significant. In Columns (2) and (4) 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 variable. In the markup column, a higher import share drives the markup responses to the terms of trade. For TFP the coefficients on net exposure are insignificant but significant when we focus only on the export share of sales. It is consistent with tariff reductions affecting those firms competing in the global market for final goods.

[Table 2 about here.]

[Table 3 about here.]

I also construct input tariffs using output tariffs and a three-digit input-output (IO) matrix provided by the Chilean Central Bank. The availability of IO matrices in this period is limited to 1996 and 2003, so I assume the intermediate input shares of each industry are constant throughout 1995-2001 and 2002-2007. Input tariffs are constructed as in Amiti and Konings (2007): a weighted average of output tariffs, with the weights based on the cost shares of each input used in the industry at the 3-digit level.[52] Most tariff reductions are manufacturing-wide, so that input tariffs are almost identical to output tariffs (the correlation between the two is .99). For this reason I report the results using input tariffs but am skeptical of the usefulness of this measure in Chile.

---

[52]There are 74 products in the matrix, which I concord to the 3-digit ISIC level manually using product descriptions. This is slightly more disaggregate than the 2-digit IO table available from the STAN Database.

Table 4 identifies firms through export and import shares to test the differential effects of output and input tariffs. From the first column, there is evidence that lower input tariffs lead to higher markups for negatively exposed firms. This is expected if a lower input tariff acts as a cost reducer in the same way as terms of trade gains. In Column (2), by decomposing the net exposure, there is evidence that lower input tariffs raise markups for importers and lower output tariffs reduce markups for exporters. Overall importing firms gain from lower input tariffs but not lower output tariffs as predicted by the model. However because of the many insignificant results, I will concentrate on just terms of trade and output tariffs at the industry level.

[Table 4 about here.]

The next step is to show that the distributional effects follow the predictions in Section 5. I have found evidence thus far for the first order comparative static predictions, especially for cost reductions raising markups. I now examine the extent to which these findings are spread across the distribution of firms. The results of two separate strategies are expressed in Table 5. The first two columns interact the "TOT*Net Exposure" and "OutputTariff*Net Exposure" interactions with an indicator of whether a firm is in the top 30% of the markup distribution in a base year. I use 1995 and 2002 as base years. Column (1) shows that for a given exposure to competition, terms of trade appreciations have a bigger effect for firms that have larger markups initially (in the Top 30%). The coefficient in the second row is significant at the 10% level and is clearly larger for top firms compared to the first row. In the second pair of columns, I multiply the interaction of interest with the firm markup in the base year. Again, having a higher base markup leads to clearly larger effects in response to terms of trade shocks.[53] The coefficients are very small with respect to output tariffs, which suggests that lower tariffs either did not exert a strong competition effect or the drop in tariffs is too small.

This is the one case where substituting the REER for TOT yields slightly different results. In that case I did not find that top firms increased their markups more than the rest. However if I restrict the sample to after 2000, then I do find the result that the REER impacted the markups of top firms by more. This suggests, as expected, that my results are driven by the sustained appreciation during the copper boom of 2004-2006, while the small real appreciation in the mid-nineties (when the terms of trade is mostly constant) did not generate any observable the anti-resource reallocation.

---

[53]In a quantile regression, it is firms in the 60th-75th percentile that are the largest winners in terms of markup increases.

The firm level regressions mostly affirm the predicted reallocation effects of Section 5. In Section 4 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 method is similar to the firm-level analysis in that I compare sectors (at 2-digit ISIC aggregate) who import the highest percentage of their inputs with sectors that are more open (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 10 (the residual from $\Delta ln(\tilde{R}) - \Delta ln(Q)$). I add $\Delta ln(Q)$ as an outcome, as well as $\Delta Cov(markup, inputs)$, which is shown in Appendix C to be one of the components of the allocative efficiency variable. The interaction terms include the same sector characteristics as before, interacted with the growth rate in terms of trade and output tariffs. One concern is that the ΔAE variable is created using a physical quantity measure that does not cover the census of manufacturing firms. The Chilean statistical agency uses a fixed subset of firms for this measure, which means that firms who do not produce for at least 6 years in a row are most likely not present in the measurement.[54] To account for this, I eliminate firms that do not produce for 6 consecutive years to measure the outcome variables. In results that do not eliminate these entering firms, the regression results are very similar both qualitatively and quantitatively.

In Table 6, 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. In Column (1) there is evidence also that acceleration in the growth of TOT increases allocative efficiency in "open" industries. Lower output tariffs have no allocative efficiency effects in open industries, as reflected in the last row of Column (1). Unsurprisingly, both importers and exporters have higher physical production ($\Delta ln(Q)$) at higher terms of trade (Column(4)). The last column uses the markup-input expenditure covariance as a measure of misallocation in place of ΔAE[55]. Intuitively, the reallocation is pro-resource efficient if inputs are transferred to the high markup firms to raise their production. The

---

[54]The physical quantity index is computed 1989-2002 with a base in 1989 and 2002-2007 with a base in 2002.

[55]A higher covariance increases AE according to Equation 22 in Appendix C.

results with respect to the terms of trade are similar to column (1) which is reassuring that the growth rate in allocating efficiency is properly estimated. [56]

As with the firm regressions, I repeat this analysis using export and import shares in Table 7. The shares are now the average firm share at the sectoral level. The first column illustrates that industries exposed to global competitive pressures have positive growth rates in allocative efficiency in response to an increase in the growth rate of the TOT. 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 first row of Column (1) is interpreted as an industry with net exposure of 0 having allocative efficiency growth than is 6.8 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 second 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 1.88 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. Column (2) decomposes exposure into the export and import shares. It is the larger import share that drives reductions in misallocation in response to TOT shocks, though a larger exported share does not seem to increase allocative efficiency with lower output tariffs. 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).

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 average net exposure is less than -0.1[57]. The results are available upon request but not shown in the Table for brevity. An industry labeled as negatively exposed to globalization has a growth in allocative efficiency 0.63 percentage points lower in response to a 1 percentage point increase in the growth rate of the TOT. This is statistically significant, and given that the average annual allocative efficiency

growth is 1.1%, is important economically as well.

Staying on Table 7, 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 6 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 production but that industries differed in their allocative efficiency of this production. In summary, the results at the industry level confirm the observed firm reallocation. 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 6 about here.]

[Table 7 about here.]

8   Conclusion

This study examines how misallocation fits into demand systems with preferences that are "less convex" than 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. By having a benchmark of allocative efficiency, I can back out 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 even if they both lead to average productivity gains. The shocks can be summarized by industry aggregates that act impact firm-level pricing decisions.

Chile experiences an increase in openness and 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. I find evidence that the increase in markup dispersion is due to firms acting heterogeneously in response to cost reductions, and this means that allocative efficiency can be a significant factor in terms of overall welfare gains/losses. 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 real income growth relative to physical production growth can be smaller/larger than what is implied by CES models because reallocation is now properly measured. In Chile's case the growth in real income 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 import composition. 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.

References

Acemoglu, D., Carvalho, V. M., Ozdaglar, A., Salehi, A. T., 2012. The network origins of aggregate fluctuations. Econometrica 80 (5), 1977–2016.

Ackerberg, D., Caves, K., Frazer, G., Dec. 2006. Structural identification of production functions. MPRA Paper 38349, University Library of Munich, Germany.
URL http://ideas.repec.org/p/pra/mprapa/38349.html

Amiti, M., Itskhoki, O., Konings, J., 2012. Importers, exporters, and exchange rate disconnect. Working paper research, National Bank of Belgium.
URL http://ideas.repec.org/p/nbb/reswpp/201212-238.html

Amiti, M., Konings, J., 2007. Trade liberalization, intermediate inputs, and productivity: Evidence from indonesia. American Economic Review 97 (5), 1611–1638.

Arkolakis, C., Costinot, A., Donaldson, D., Rodriguez-Clare, A., June 2012. The elusive pro-competitive effects of trade. Working paper, MIT.

Atkeson, A., Burstein, A., 2008. Pricing-to-market, trade costs and international relative prices. American Economic Review 98 (5), 1998–2031.

Bartelsman, E., Haltiwanger, J., Scarpetta, S., 2013. Cross-country differences in productivity: the role of allocation and selection. American Economic Review 103 (1), 305–334.

Basu, S., Fernald, J., 2002. Aggregate productivity and aggregate technology. European Economic Review 46, 963–991.

Basu, S., Pascali, L., Schintarelli, F., Serven, L., 2010. Productivity, welfare and reallocation: Theory and firm-level evidence. NBER working paper 15579.

Bernard, A., Eaton, J., Jensen, B., Kortum, S., 2003. Plants and productivity in international trade. American Economic Review 93, 1268–1290.

Berthelon, M., 2011. Chilean export performance: The role of intensive and extensive margins. Working Paper Series 615, Banco Central de Chile.

Chamberlin, E., 1933. The Theory of Monopolistic Competition. Cambridge: Harvard University Press.

de Blas, B., Russ, K. N., 2015. Understanding markups in the open economy. American Economic Journal: Macroeconomics 7 (2), 157–80.

DeLoecker, J., Goldberg, P. K., Aug. 2013. Firm performance in a global market. NBER Working Papers 19308, National Bureau of Economic Research, Inc.
URL http://ideas.repec.org/p/nbr/nberwo/19308.html

DeLoecker, J., Goldberg, P. K., Khandelwal, A. K., Pavcnik, N., Mar. 2012. Prices, markups and trade reform. NBER Working Papers 17925, National Bureau of Economic Research, Inc.
URL http://ideas.repec.org/p/nbr/nberwo/17925.html

DeLoecker, J., Warzynski, F., 2012. Markups and firm-level export status. American Economic Review 102 (6), 2437–2471.

Desormeaux, J., Garca, P., Soto, C., Autumn 2010. Terms of trade, commodity prices and inflation dynamics in chile. In: for International Settlements, B. (Ed.), Monetary policy and the measurement of inflation: prices, wages and expectations. Vol. 49 of BIS Papers chapters. Bank for International Settlements, pp. 115–128.

Dhingra, S., Morrow, J., 2012. Monopolistic competition and optimum product diversity under firm heterogeneity. Working Paper.

Dixit, A. K., Stiglitz, J. E., June 1977. Monopolistic competition and optimum product diversity. American Economic Review 67 (3), 297–308.

Edmond, C., Midrigan, V., Xu, D., 2014. Competition, markups and the gains from international trade. American Economic Review forthcoming.

Eeckhout, J., December 2004. Gibrat's law for (all) cities. American Economic Review 94 (5), 1429–1451.

Ekholm, K., Moxnes, A., Ulltveit-Moe, K., 2012. Manufacturing Restructuring and the Role of Real Exchange Rate Shocks. Journal of International Economics 86, 101–117.

Feenstra, R., Kee, H. L., 2008. Export variety and country productivity: Estimating the monopolistic competition model with endogenous productivity. Journal of International Economics 74 (2), 500–518.

Feenstra, R. C., 2014. Restoring the Product Variety and Pro-competitive Gains from Trade with Heterogeneous Firms and Bounded Productivity. NBER Working Papers 19833, National Bureau of Economic Research, Inc.
URL `http://ideas.repec.org/p/nbr/nberwo/19833.html`

Feenstra, R. C., Lipsey, R. E., Deng, H., Ma, A. C., Mo, H., January 2005. World trade flows: 1962-2000. Working Paper 11040, National Bureau of Economic Research.
URL `http://www.nber.org/papers/w11040`

Feenstra, R. C., Weinstein, D. E., Feb. 2010. Globalization, markups, and the u.s. price level. NBER Working Papers 15749, National Bureau of Economic Research, Inc.
URL `http://ideas.repec.org/p/nbr/nberwo/15749.html`

Goldberg, P. K., Khandelwal, A. K., Pavcnik, N., Topalova, P., November 2010. Imported intermediate inputs and domestic product growth: Evidence from india. The Quarterly Journal of Economics 125 (4), 1727–1767.

Gopinath, G., Neiman, B., 2012. Trade adjustment and productivity in large crises. Working Paper.

Head, K., 2011. Skewed and extreme: Useful distributions for economic heterogeneity. Working paper series, University of British Columbia.

Head, K., Mayer, T., Thoenig, M., Feb. 2014. Welfare and Trade Without Pareto. Sciences po economics discussion papers, Sciences Po Departement of Economics.
URL `http://ideas.repec.org/p/spo/wpecon/infohdl2441-f6h8764enu2lskk9p2m9j4i07.html`

Holmes, T. J., Hsu, W.-T., Lee, S., March 2012. Allocative efficiency, markups, and the welfare gains from trade. Working paper, University of Minnesota.
URL `http://www.econ.umn.edu/~holmes/papers/alloc_eff_trade.pdf`

Hsieh, C.-T., Klenow, P., 2009. Misallocation and manufacturing tfp in china and india. Quarterly Journal of Economics 124 (4), 1403–1448.

Kasahara, H., Lapham, B., 2013. Productivity and the decision to import and export: Theory and evidence. Journal of International Economics 89 (2), 297–316.

Kasahara, H., Rodrigue, J., 2008. Does the use of imported intermediates increase productivity? plant-level evidence. Journal of Development Economics 87 (1), 106–118.

Khandelwal, A. K., Schott, P. K., Wei, S.-J., October 2013. Trade Liberalization and Embedded Institutional Reform: Evidence from Chinese Exporters. American Economic Review 103 (6), 2169–95.

Krugman, P. R., 1979. Increasing returns, monopolistic competition, and international trade. Journal of International Economics 9 (4), 469–479.

Levinsohn, J., Petrin, A., 2003. Estimating production functions using inputs to control for unobservables. Review of Economics Studies 70 (2), 317–342.

Melitz, M., 2003. The impact of trade on intra-industry reallocations and aggregate industry productivity. Econometrica 71 (6), 1695–1725.

Melitz, M., Ottaviano, G., 2008. Market size, trade and productivity. Review of Economic Studies 75, 295–316.

Mrazova, M., Neary, P. J., Dec. 2013a. Not So Demanding: Preference Structure, Firm Behavior, and Welfare. Economics Series Working Papers 691, University of Oxford, Department of Economics.

Mrazova, M., Neary, P. J., January 2013b. Selection effects with heterogeneous firms. Working paper.

Olley, G., Pakes, A., 1996. The dynamics of productivity in the telecommunications equipment industry. Econometrica 64 (6), 1263–1298.

Pavcnik, N., 2002. Trade liberalization, exit and productivity improvements: Evidence from chilean plants. Review of Economic Studies 69, 245–276.

Peters, M., 2011. Heterogeneous markups and endogenous misallocation. Working Paper.

Petrin, A., Levinsohn, J., 2012. Measure aggregate productivity growth using plant-level evidence. The RAND Journal of Economics 43 (4), 705–725.

Restuccia, D., Rogerson, R., 2008. Policy Distortions and Aggregate Productivity with Heterogeneous Plants. Review of Economic Dynamics 11 (4), 707–720.

Vives, X., 2001. Oligopoly Pricing: Old Ideas and New Tools. Vol. 1 of MIT Press Books. The MIT Press.

Zhelobodko, E., Kokovin, S., Parenti, M., Thisse, J., 2012. Monopolistic Competition: Beyond the Constant Elasticity of Substitution. Econometrica 80 (6), 2765–2784.
URL http://ideas.repec.org/a/ecm/emetrp/v80y2012i6p2765-2784.html

Appendices

A Relationship to Basu and Fernald (2002)

To relate changes in the markup distribution to welfare, I derive an expression straight from the utility function following Basu and Fernald (2002). I take the total derivative of

the utility function with the assumption that each year the economy is at a new equilibrium of production.

$$U(q(c), M_e) = M_e L \int_c u(q(c)) dG(c)$$

$$dU = M_e L \int_c u'(q(c))(\Delta q) dG(c) = \delta M_e L \int_c p(q(c))(\Delta q) dG(c) \quad (14)$$

(Δq) is the total production change for a firm. The second line is the total derivative of utility function $U(q(c), \bar{M}_e)$ (fixed entry) with a shock to the production of surviving firms, and substitutes prices for marginal utility ($u'(q(c)) = \delta p(q(c))$).

Then rewrite Equation 14 in terms of means and variances:

$$dU = \delta M_e L \Big[\int_c p(q(c)) dG(c) \int_c (\Delta q) dG(c) + \delta M_e L \text{Cov}(p(q(c)), (\Delta q)) \Big] \quad (15)$$

To see how the markups contribute to the distortion I show the relationship between changes in utility and markups under general preferences, again assuming the economy is hit with a shock that affects the allocation of production. I work with the absolute markup, consistent with the measure from the data, which corresponds with the previous notation as: $\frac{p(q(c))}{c} = \frac{1}{1-\mu(q(c))}$.

$$dU = M_e L \int_c u'(q(c))(\Delta q) dG(c) = \delta M_e L \int_c \frac{p(q(c))}{c} c(\Delta q) dG(c)$$

$$= \delta M_e L \int_c \frac{1}{1 - \mu(q(c))} c(\Delta q) dG(c)$$

$$= \delta M_e L \Big[\int_c \frac{1}{1 - \mu(q(c))} dG(c) \int_c c(\Delta q) dG(c) + \text{Cov}\Big(\frac{1}{1 - \mu(q(c))}, c(\Delta q)\Big) \Big] \quad (16)$$

In this case the conditions for the covariance term are obvious since it must be constant if $u(q(c))$ is CES.

Lemma 2. *The last term in Equation 16 is constant when the markup distribution is degenerate. The sufficient condition is that $u(q(c))$ is CES.*

From Equation 16, the change in utility depends not only growth in production, but also to changes in the covariance of the markup and input expenditure. In the CES case, the covariance term is zero because cost heterogeneity is optimally passed through to prices so that markups are constant. In the VES case with the assumption of decreasing demand elasticity, the covariance term is negative and the distribution of markups affects

41

utility. Shocks to the production allocation can raise utility depending on whether more production goes towards the high markup firms. In the process, their markup decreases as they move down their demand curve and increase production.

Equation 16 provides no term that can be taken to the data and interpreted as allocative efficiency. This analysis also relies on prices taken as given and does not consider the co-movement of prices and quantities as I do in Section 4.2.

B   Price-Quantity Covariance

This appendix establishes the result of Lemma 1 that Equation 9 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: $\text{Cov}(p,q) = \int_0^{c_d}(p(q(c)) - \tilde{p})(q(c) - \tilde{q})h_d(c)dc$,[58] and the RHS of Equation 9, $\Delta\left(\frac{\text{Cov}(p,q)}{\int_0^{c_d} p(q(c))h_d(c)dc \int_0^{c_d} q(c)h_d(c)dc}\right)$. Using the definition of the covariance above, this reduces to

$$\Delta\left(\frac{\int_0^{c_d} p(q(c))q(c)h_d(c)dc}{\int_0^{c_d} p(q(c))h_d(c)dc \int_0^{c_d} q(c)h_d(c)dc} - 1\right) \tag{17}$$

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 17 and reduce the numerator and denominator separately:

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

$$= \left(\frac{R}{\tilde{P}}\right)\left(\frac{1}{1-\mu}\right)^{1-\sigma}\left(\frac{\theta}{\theta-\sigma+1}\right)c_d^{1-\sigma} \tag{18}$$

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

$$= \frac{1}{1-\mu}\frac{\theta}{\theta+1}c_d \tag{19}$$

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

$$= \left(\frac{R}{\tilde{P}}\right)\left(\frac{1}{1-\mu}\right)^{-\sigma}\left(\frac{\theta}{\theta-\sigma}\right)c_d^{-\sigma} \tag{20}$$

---

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

Next, combining the three above terms into Equation 17:

$$\Delta \left(\frac{\int_0^{c_d} p(q(c))q(c)h_d(c)dc}{\int_0^{c_d} p(q(c))h_d(c)dc \int_0^{c_d} q(c)h_d(c)dc} - 1 \right) = \Delta \left(\frac{(\theta+1)(\theta-\sigma)}{\theta(\theta-\sigma+1)} \right) \tag{21}$$

where the term inside the parenthesis on the RHS is constant. Therefore, under the case of CES sub utility and Pareto $G(c)$, the terms in Equation 9 are zero.

C   Growth in Real Income, Quantities, Productivities and Markups

Equation 10 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 provide a comparison to the Basu and Fernald (2002) decomposition in Appendix A. 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 $P = \int_0^{c_d} p(q(c))f(c)dc$ and $\frac{p}{c} = (\frac{1}{1-\mu(c)})$:

$$R = LM \left[\int_0^{c_d} \frac{p(q(c))}{c} cq(c)f(c)dc \right]$$

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

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

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

$$\frac{\tilde{R}}{Q} = 1 + \frac{LM}{PQ} \left[\text{Cov}(\frac{1}{1-\mu(c)}, cq) + \int_0^{c_d} cq(c)f(c)dc \left[\text{Cov}(p, \frac{1}{c}) \right] \right] - \frac{LM}{Q} \left[\text{Cov}(cq, \frac{1}{c}) \right]$$

$$\Delta ln \left(\frac{\tilde{R}}{Q} \right) = \Delta \left[\frac{LM}{PQ} \left[\text{Cov}(\frac{1}{1-\mu(c)}, cq) + \int_0^{c_d} cq(c)f(c)dc \left[\text{Cov}(p, \frac{1}{c}) \right] \right] - \frac{LM}{Q} \left[\text{Cov}(cq, \frac{1}{c}) \right] \right] \tag{22}$$

To identify misallocation from Equation 10 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 10, the price-quantity co-variance 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).

C.1 Misallocation and Markup Dispersion

Given Equation 22, I can show how markup dispersion drives the market power distortion. This is evident from the definition of the correlation:

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

(23)

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.

D Comparison to ACDR

The allocative efficiency distortion that I measure in this paper can be linked to the distortion that separates non-homothetic demand with the homothetic Translog case in ACDR, though the distortion in that paper is constant due to the unbounded Pareto productivity distribution assumption. They measure the change in total expenditure necessary to keep a constant utility level in response to a shock in variable trade costs. The main welfare decomposition in that paper can be decomposed as follows, with welfare growth interpreted as the inverse of the following growth in expenditure ($d\ln e_j$):

$$d\ln e_j = \underbrace{(1-\rho)\sum_i \lambda_{ij} d\ln(w_i\tau_{ij})}_{\text{Total selection effect}} + \underbrace{\rho\sum_i \lambda_{ij} d\ln(w_i\tau_{ij})}_{\text{(Price+Variety effect of competition)}} + \underbrace{\rho\frac{\beta-1}{1-\beta+\theta}\sum_i \lambda_{ij} d\ln(w_i\tau_{ij})}_{\text{(Distortion)}}$$

(24)

ρ stands for the weighted average markup elasticity with respect to marginal cost (or one minus the price-cost pass through elasticity), β represents the difference between the total

price elasticity and cross-price elasticity (equal to 0 in the VES because preferences are separable), and θ is the parameter that governs the dispersion of productivity assuming the distribution is Pareto.

The first term is a selection effect that represents the higher quantity that can be produced because the selected firms have a higher average productivity. As is known from tax incidence in monopolistic competition, the welfare gains from higher quantity are scaled by the price pass-through. The second term is the "pro-competitive" price and variety effects measured by Feenstra and Weinstein (2010). They show that competition leads to an overall increase in variety and lower average costs when competition with free entry increases scale.

The last term comes into effect only when $\beta < 1$, or when preferences are non-homothetic. In this case there is a reallocation of demand shares towards low-markup firms in response to lower trade costs, increasing expenditure. In the VES case, $\beta = 0$ and the magnitude of the distortion effects in response to a trade cost shock depends on the weighted average of markup elasticities and degree of firm heterogeneity. This is the distortion present in my model which features variable markups and firm heterogeneity with non-homothetic demand. I can identify this distortion with aggregate data because it is the only part of aggregate real income that does not track aggregate quantity[59]. In response to lower production costs, the distortion I find is similar to ACDR in that there is a relative reallocation of production towards initially low-markup firms. However I also show that a competition shock actually lowers this distortion. In that case the reallocation that happens due to selection is reinforced by the fact that high-markup firms increase their production more than low-markup firms.

E   Super/Sub Modularity

To recount the first order comparative static, I start with $m_i(\delta, \tau, \varphi_i) = \frac{p_i(a\tau/\varphi_i)}{a\tau/\varphi_i}$. Let $a = 1$, then: $\frac{\partial m_i(\delta, \tau, \varphi_i)}{\partial \tau} = -\frac{p_i \varphi_i}{\tau^2} < 0$.

I now turn to the reallocation effects. In general, the function $m_i(\delta, \tau, \varphi_i)$ is supermodular in τ and φ_i (for a given δ) if:

$$\Delta_{\varphi_i} m_i(\delta, \tau_1, \varphi_i) \leq \Delta_{\varphi_i} m_i(\delta, \tau_2, \varphi_i) \text{ when } \tau_1 \geq \tau_2 \tag{25}$$

$$\text{where } \Delta_{\varphi_i} m_i(\delta, \tau, \varphi_i) = m_1(\delta, \tau, \varphi_1) - m_2(\delta, \tau, \varphi_2) \text{ for } \varphi_1 \geq \varphi_2 \tag{26}$$

---

[59]Though again, I capture the growth rate of this distortion which is constant in the ACDR model.

Notice $\Delta_{\varphi_i} m_i(\delta, \tau, \varphi_i)$ is always positive. 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.

I borrow some notation from Mrazova and Neary (2013b). Notably, I go back to indexing firms by their cost draw, c (equivalent to $1/\varphi$), drop the firm subscript, and write $m(\delta, \tau, \varphi) = \frac{p}{\tau c}$. This is to be consistent with the way they differentiate across firms by the marginal cost. I also use the following notation and results:

1. $p(q(c)) = p$

2. $\epsilon = -\frac{p}{q(c)p'}$ (elasticity of demand)

3. $\rho = -\frac{(q(c))p''}{p'}$ (convexity of demand)

4. $\frac{dq}{dc}c = \frac{\tau c}{2p' + q(c)p''}$ (from the curvature of the marginal revenue curve)

5. $2p' + q(c)p'' = -\frac{p}{q(c)\epsilon^2}\left(\epsilon - 1 - q(c)\epsilon_q\right) > 0$. This is positive only when demand function is "log-concave," because in this case ϵ_q ($\frac{\partial \epsilon(q(c))}{\partial q(c)}$) is negative (elasticity of demand decreases with sales).

6. $\frac{d\epsilon}{dc} = \epsilon_q \frac{dq}{dc}$ (this is $\eta'(c)$ when $\eta(c)$ is the demand elasticity as in the text).

7. $\tau c = \frac{\epsilon - 1}{\epsilon} p$

I measure reallocation by looking at how the changes in τ leads to differential effects depending on firm marginal cost (which determines sales).

$$
\begin{aligned}
\frac{\partial m(\delta, \tau, \varphi)^2}{\partial \tau \partial c} &= -\frac{1}{\tau^2 c^2}\left(p'\frac{dx}{dc}c - p\right) \\
&= \frac{1}{\tau^2 c^2}\left(p - p'\left(\frac{\tau c}{2p' + q(c)p''}\right)\right) = \frac{1}{\tau^2 c^2}\left(p - p'\left(\frac{\frac{\epsilon-1}{\epsilon}p}{-\frac{p}{q(c)\epsilon^2}(\epsilon - 1 - q(c)\epsilon_q)}\right)\right) \\
&= \frac{1}{\tau^2 c^2}\left(p - p'\left(\frac{-\epsilon(\epsilon - 1)q(c)}{\epsilon - 1 - q(c)\epsilon_q}\right)\right) = \frac{1}{\tau^2 c^2}\left(p + \frac{p'q(c)\epsilon(\epsilon - 1)}{(\epsilon - 1 - q(c)\epsilon_q)}\right) \\
&= \frac{1}{\tau^2 c^2}\frac{p(\epsilon - 1 - q(c)\epsilon_q) + p'q(c)\epsilon(\epsilon - 1)}{\epsilon - 1 - q(c)\epsilon_q} = \frac{1}{\tau^2 c^2}\frac{p(\epsilon - 1 - q(c)\epsilon_q) - p(\epsilon - 1)}{\epsilon - 1 - q(c)\epsilon_q} \\
&= \frac{1}{\tau^2 c^2}\frac{-pq(c)\epsilon_q}{\epsilon - 1 - q(c)\epsilon_q} > 0 \qquad (27)
\end{aligned}
$$

In the last line, it is ϵ_q (or $\epsilon'(q(c))$) that is dependent on the curvature of demand. If $u(q(c))$ is CES, then $\epsilon'(q(c)) = 0$. With elasticity of demand decreasing with sales, $\epsilon'(q(c)) < 0$ and we get the final result that $\frac{\partial m(\delta, \tau, \varphi)^2}{\partial \tau \partial c} > 0$.

In the globalization case, there is a shift in demand elasticities that is due to $\frac{\partial \delta}{\partial L} > 0$. This affects the price decision since we know that prices can be written with the firm demand elasticity governing the markup: $p(\delta', c(\tau, \varphi)) = \frac{\delta'\eta(c)}{\delta'\eta(c)-1}c(\tau, \varphi)$ where $\eta(c)$ is the demand elasticity faced by a firm with marginal cost c, δ' is an aggregate that shifts demand elasticities for all firms with $\delta' > 1$ when L or M_e increase, and $c = \frac{a\tau}{\varphi}$ is constant for each firm since there is no shock in τ. I follow the same steps as for τ above but change notation to denote demand elasticities ($\eta(c)$ in the text) again with ϵ as in Mrazova and Neary (2013b):

$$\frac{\partial p(\delta', c(\tau, \varphi))}{\partial \delta'} = \frac{-\epsilon}{(\delta'\epsilon - 1)^2} < 0 \tag{28}$$

Then for the reallocation effects I measure how this shock to the demand elasticity affects firms with different marginal costs:

$$\frac{\partial p(\delta, c(\tau, \varphi))^2}{\partial \delta' \partial c} = \frac{-\frac{d\epsilon}{dc}(\delta'\epsilon - 1)^2 + 2\epsilon(\delta'\epsilon - 1)\delta'\frac{d\epsilon}{dc}}{(\delta'\epsilon - 1)^4}$$

$$= \frac{-\epsilon_q\left(-\frac{p}{q(c)\epsilon^2}(\epsilon - 1 - q(c)\epsilon_q)(\delta'\epsilon - 1)\right) + 2\epsilon\delta'\epsilon_q\left(-\frac{p}{q(c)\epsilon^2}(\epsilon - 1 - q(c)\epsilon_q)\right)}{(\delta'\epsilon - 1)^3}$$

$$= \frac{1}{(\delta'\epsilon - 1)^3}\left[\frac{\epsilon_q p}{q(c)\epsilon^2}(\epsilon - 1 - q(c)\epsilon_q)(3\delta'\epsilon - 1)\right] < 0 \tag{29}$$

where, again, $\epsilon_q < 0$. Therefore prices are sub-modular in δ' and c, which leads to the conclusion that a shock with $\delta' > 1$ leads to all firms lowering prices and lower cost firms decreasing them relatively more than high-cost firms. Therefore inputs are reallocated to the more productive firms as they must produce relatively more to move down their demand curve.

F   Data and Variable Definitions

Here I describe my measure of the left hand side of Equation 8, 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.

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: $\sum_i P_i Y_i = \sum_i VA_i = \sum_i P_i Q_i - \sum_i \sum_j P_{ij} X_{ji}$.

G   Trade Agreements

Below is a list of all the trade agreements signed by Chile:

- $1990's$: Trade agreements with Canada (1996), Mexico(1998), and Central America.

- 1996: Association agreement with the Mercosur countries

- 2002: Agreements with the European Union and South Korea

- Free Trade Agreement (FTA) with the United States starting 2004. Completely free bilateral trade does not begin until 2016, but tariffs decreased immediately.

- In 2003 Chile unilaterally lowered its across-the-board import tariff to 6% for all countries with which it does not have a trade agreement.

- FTA with China signed in late 2005.

H   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.[60] 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

---

[60]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.

provided by the Chilean Statistics Institution (INE). Notice that this Translog production specification allows for heterogeneous firm level output coefficients.[61] 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.[62][63] 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.[64]

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 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:

$$\frac{1}{1-\mu_{it}} = m_{it} = \frac{\theta_{it}^x}{\alpha_{it}^x} \tag{30}$$

I   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

---

[61]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.

[62]For a full account of the 2-step procedure see Olley and Pakes (1996), Levinsohn and Petrin (2003), or Ackerberg et al. (2006).

[63]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.

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

$REER_i = p_i/(Ep_i^*)$. Ekholm et al. (2012) consider a small change in the $REER_i$ holding output constant:

$$\frac{\partial r_i}{\partial REER_i} \frac{REER_i}{r_i} = -\frac{ep_i^* q_i^*}{r_i}. \tag{31}$$

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[65]:

$$\frac{\partial C_i}{\partial REER_i} \frac{REER_i}{C_i} = -\frac{E c_i^* v_i^*}{C_i}. \tag{32}$$

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 shown to be:

$$\frac{\partial \pi_i}{\partial REER_i} \frac{REER_i}{\pi_i} = -\frac{E p_i^* q_i^*}{r_i} - \frac{\frac{E p_i^* q_i^*}{r_i} - \frac{E c_i^* v_i^*}{C_i}}{\pi_i/r_i}. \tag{33}$$

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.

---

[65]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.

**Figure 1:** Average Applied Tariffs 1995-2007
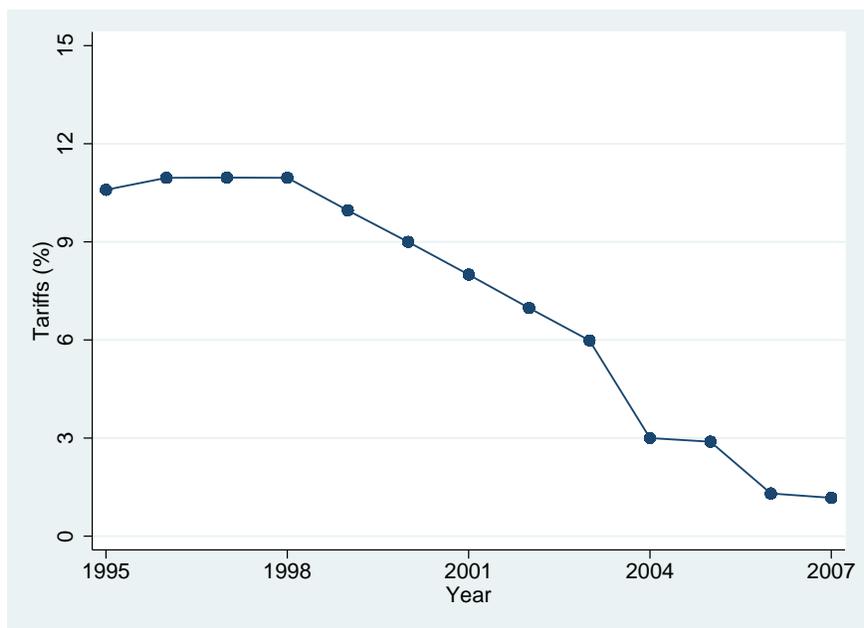
Source: Comtrade Database, downloaded from World Integrated Trade Solution (WITS). Bilateral tariffs are aggregated to 4-digit level using an unweighted average of 6-digit tariff lines, and then weighted by trade shares to get an average applied tariff rate across all trade partners.

Figure 2: Terms of Trade (2000=100) and Real Effective Exchange Rate (% change), 1995-2007
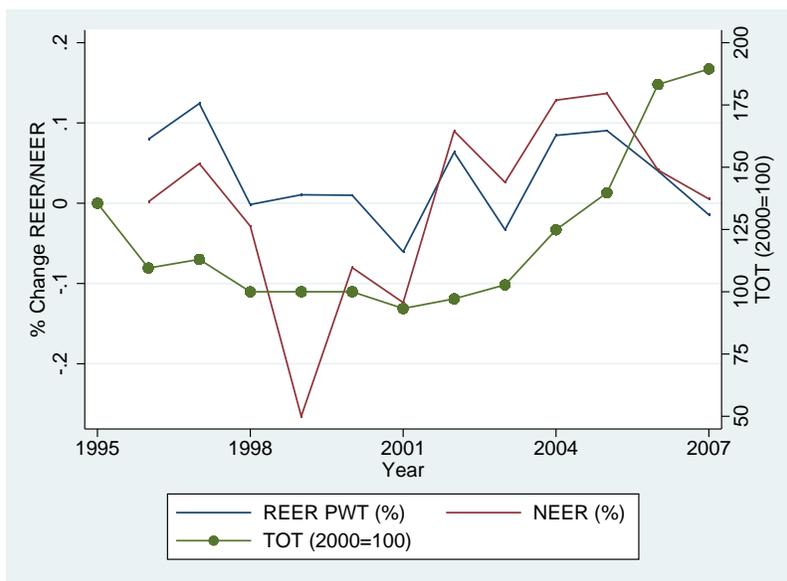
*Sources: WDI Indicators, PWT 8.0, BIS, Chilean Central Bank. TOT is an index from WDI. I calculate REER PWT using Penn World Tables to calculate Chile's production price index relative to its top trade partners and take a geometric average using trade shares (from BIS) as weights. I report the annual % 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
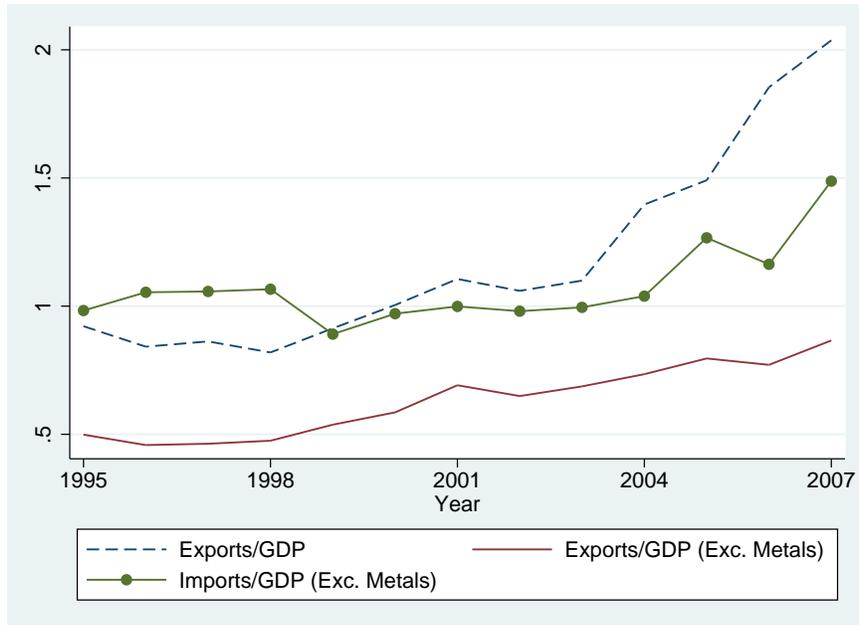
Figure 4: Average Market Markup
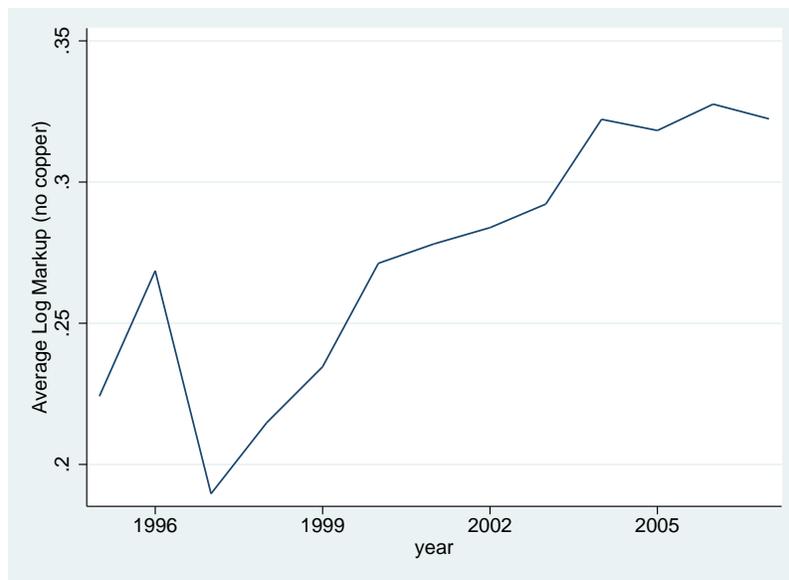
Mean calculated for each sector assuming a log normal distribution. Economy-wide average taken by weighting each sector by its value added share. I eliminate firms in the bottom and top 1% of the markup distribution.

Figure 5: Markup Dispersion: Average across sectors
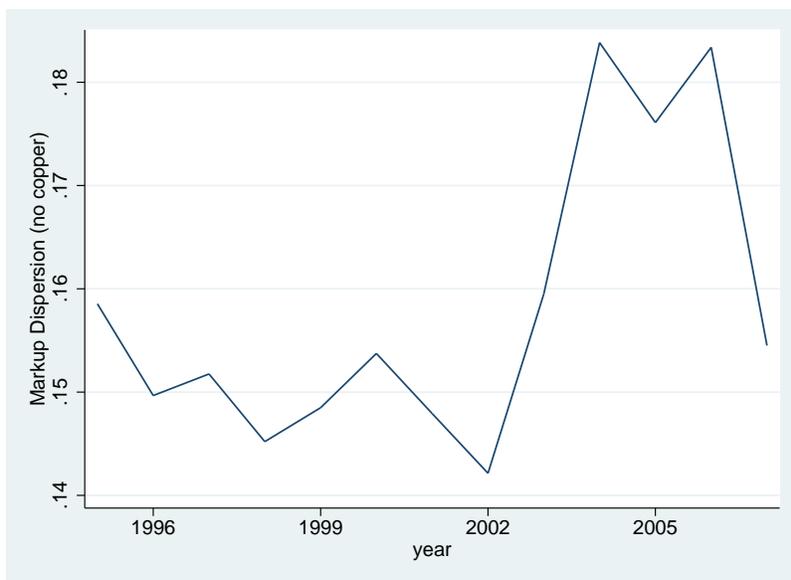
Markup dispersion calculated for each sector by estimating the shape parameter of a log-normal distribution using maximum likelihood. I take the economy-wide average by weighting each sector by its value added share. I eliminate firms in the bottom and top 1% of the markup distribution.

Figure 6: Markup Distribution versus TFP Distribution

(a) Markup Distribution: 1995 versus 2005   **(b)** TFP Distribution: 1995 versus 2005
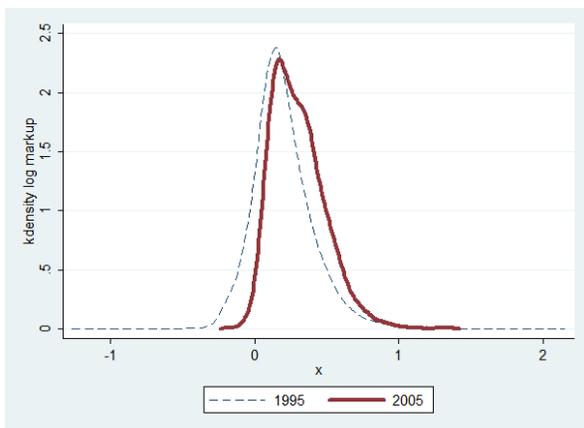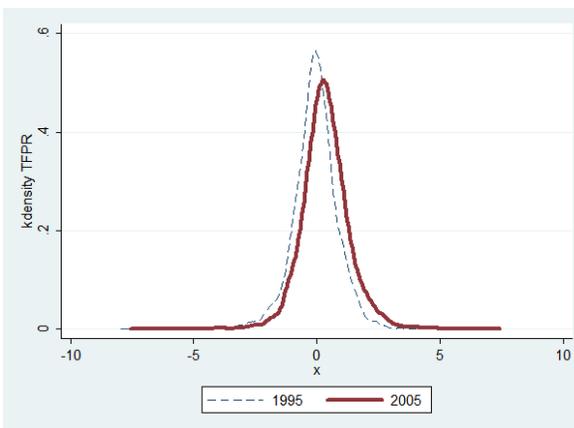
Figure 7: Real Income Growth versus Physical Production
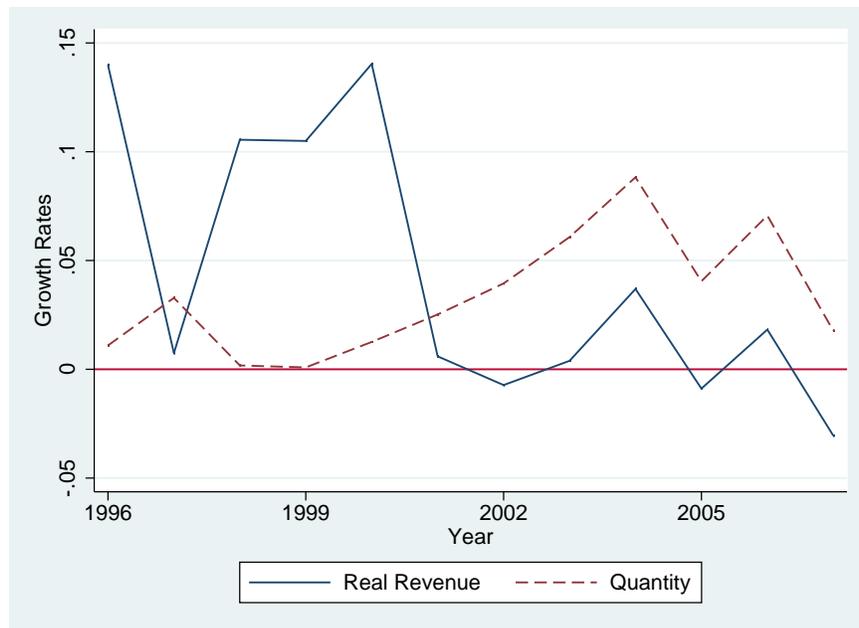
Real revenue is the growth in the sum of deflated value added (minus primary input growth) at the 2-digit ISIC level. Economy-wide average taken by weighting each 2-digit group by its value added share. Quantity growth is taken from the physical manufacturing index provided by the ENIA at the 2-digit ISIC level with same weighting scheme.

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. (2006) 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: Firm Level: Differential Effect on Markups by Importer/Exporter

	Mark-up		TFP
	(1)	(2)	(3)
TOT*IMP*Exp=0	0.037**	0.034**	0.094
	(0.014)	(0.014)	(0.072)
TOT*EXP*Imp=0	0.004	0.004	-0.047
	(0.013)	(0.013)	(0.089)
OutputTariff*IMP*EXP=0	0.002	0.002	-0.008
	(0.002)	(0.002)	(0.009)
OutputTariff*EXP*IMP=0	-0.000	-0.000	-0.021*
	(0.002)	(0.002)	(0.011)
TFP		0.029***	
		(0.002)	
Fixed Effects	Year,Firm	Year,Firm	Year,Firm
R^2	0.161	0.182	0.040
N	47757	46253	46994

Dependent variables are log markup and log revenue TFP measured using the procedure outlined in DeLoecker and Warzynski (2012). 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 but omitted in the table output: Herfindahl Index at 4-digit industry level, a dummy if the firm is a multinational, capital intensity, plus year and firm fixed effects. Standard errors are clustered at the firm level. I drop the basic metal industry (ISIC 27).

Table 3: Firm Level: Differential Effect on Markup by Degree of Exposure to Competition

	Mark-up		TFP	
	(1)	(2)	(3)	(4)
TOT*Net Exposure	-0.084***		-0.150	
	(0.024)		(0.122)	
OutputTariff*Net Exposure	-0.025**		-0.034	
	(0.012)		(0.060)	
TOT*Imported Share		0.096***		0.150
		(0.036)		(0.145)
TOT*Exported Share		-0.020		-0.913***
		(0.029)		(0.204)
OutputTariff*Imported Share		0.029**		0.035
		(0.011)		(0.048)
OutputTariff*Exported Share		0.015		-0.319***
		(0.012)		(0.073)
Fixed Effects	Year,Firm	Year,Firm	Year,Firm	Year,Firm
R^2	0.164	0.170	0.033	0.035
N	47751	47752	46802	46803

Dependent variables are log markup and log revenue TFP. 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." The following controls are used but omitted in the table output: Terms of trade and output tarrifs, Herfindahl Index at 4-digit industry level, a dummy if the firm is a multinational, plus year and firm fixed effects. Standard errors are clustered at the firm level. I drop the basic metal industry (ISIC 27).

Table 4: Firm Level: Input/Output Tariffs on Degree of Exposure to Competition

	Mark-up		TFP	
	(1)	(2)	(3)	(4)
InputTariff*Net Exposure	0.056		-0.004	
	(0.042)		(0.225)	
OutputTariff*Net Exposure	-0.063		0.006	
	(0.045)		(0.241)	
InputTariff*Imported Share		-0.151**		-0.324
		(0.068)		(0.234)
OutputTariff*Imported Share		0.192**		0.368
		(0.078)		(0.261)
InputTariff*Exported Share		-0.033		-0.087
		(0.070)		(0.347)
OutputTariff*Exported Share		0.051		0.107
		(0.066)		(0.342)
Fixed Effects	Year,Firm	Year,Firm	Year,Firm	Year,Firm
R^2	0.169	0.175	0.048	0.112
N	44864	44864	44072	42503

Dependent variables are log revenue TFP and log markup. Input tariffs are constructed as in Amiti and Konings (2007): a weighted average of output tariffs, with the weights based on the cost shares of each input used in the industry at the 2-digit level. Input and output tariffs 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." The following controls are used but omitted in the table output: Herfindahl Index at 4-digit industry level, a dummy if the firm is a multinational, capital intensity, 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 Markups: Distributional Effects using Initial Markup

	Top 30%		Base Year Markup	
	(Markup)	(Markup)	(Markup)	(Markup)
TOT*Net Exposure	-0.018		0.027	
	(0.016)		(0.042)	
TOT*Exposure*Top 30%	-0.064*			
	(0.038)			
OutputTariff*Net Exposure		0.009		0.003
		(0.008)		(0.009)
OutputTariff*Exposure*Top 30%		0.001		
		(0.004)		
TOT*Exposure*Base Markup			-0.173	
			(0.126)	
OutputTariff*Exposure*Base Markup				0.002
				(0.007)
Fixed Effects	Year,Firm	Year,Firm	Year,Firm	Year,Firm
R^2	0.156	0.175	0.210	0.236
N	54339	44492	40689	35088

Dependent variable is log markup. Net Exposure is defined as (Export Sales/Total Sales)-(Imported Inputs/Total material input costs). The Top 30% dummy is constructed using firms who are in the data in 1995 and/or 2002. I rank firms in these two years and set the dummy equal to 1 if a firm is in the top 30% of markups in the base year. "Base year markup" is the markup measured in 1995 for 1995-2001 and 2002 for 2002-2007. Standard errors are clustered at the firm level. I drop the basic metal industry (ISIC 27).

Table 6: 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)	0.015		
	(0.185)		
D.Output Tariff	0.017	-0.041	-0.019
	(0.021)	(0.039)	(0.044)
Δ TOT*Importer (Industry Share)	-7.365**	1.771	-4.173*
	(2.846)	(1.146)	(2.027)
Δ TOT*Openness	0.201	0.092	-0.068
	(0.160)	(0.058)	(0.173)
Δ OutputTariff*Openness	0.006	0.026	-0.005
	(0.013)	(0.023)	(0.013)
Avg Outcome	0.011	0.034	0.006
Fixed Effects	Year,Sector	Year,Sector	Year,Sector
R^2	0.235	0.315	0.083
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 7: 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)	-0.325				
	(0.224)				
D.Output Tariff	-0.038**	-0.029	0.009	0.003	-0.061
	(0.015)	(0.089)	(0.032)	(0.041)	(0.095)
Δ TOT*Net Exposure	6.792**		-1.971**	2.496	
	(2.413)		(0.870)	(1.586)	
Δ OutputTariff*Net Exposure	-1.876*		-0.413***	-0.075	
	(0.939)		(0.103)	(0.134)	
Δ TOT*Imported Share		-7.294**			-4.921*
		(3.092)			(2.754)
Δ TOT*Exported Share		3.085			-0.372
		(6.571)			(6.254)
Δ OutputTariff*Exported Share		0.623			-0.004
		(0.489)			(1.198)
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	0.294	0.344	0.350	0.083	0.104
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." Standard errors are clustered at the 2-digit industry level. I drop the basic metal industry (ISIC 27).