Quality Heterogeneity and Misallocation: The Welfare Benefits of Raising your Standards*

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Abstract

Using data from Chile, we find that more restrictive standards are associated with a reallocation of domestic sales from small to large firms, which has allocative efficiency implications. Guided by this evidence, we study the welfare effects of the reallocation brought about by stricter standards in a model with monopolistically competitive, heterogeneous firms, and a general demand system. Restrictive standards have an ambiguous effect on welfare. On the one hand, they improve allocative efficiency because low-quality firms over-produce in the market allocation. This market distortion is driven entirely by the presence of variable markups and exists to varying degrees in both homothetic and non-homothetic frameworks. On the other hand, the imposition of stricter standards forces firms to pay a fixed cost that is welfare reducing. We estimate our model for Chile and find significant heterogeneity in the welfare gains from moving to the optimal standards policy across industries.

Keywords: Allocative Efficiency, Product Standards, Variable Markups, Quality Heterogeneity.

JEL Code: L11, D6, F13.

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1 Introduction

The design of regulations and product standards crucially depends on the tradeoff between legitimate concerns for public health and safety and the higher costs for firms that have to comply with such regulations. Furthermore, regulators balance preferences of local constituents while minimizing the protectionist aspect on foreign firms. In this paper, we argue that a key aspect of the tradeoff has not been considered: the different effects of regulations on firms that are heterogeneous in their quality and capabilities. Regulations are a bigger burden for small, low-quality firms. Indeed, this is the predominant finding of the empirical literature, which this paper confirms: more restrictive regulations force out small firms and reallocate production towards larger firms (Fontagné et al., 2015; Asprilla et al., 2019). We build a framework to study the welfare implication of such a reallocation of production, and quantify the effects of reallocation by calibrating our model using Chilean firm-level data.

We show that the reallocation induced by regulations can reduce the distortions that arise in allocatively inefficient markets, where large firms under-produce due to market power heterogeneity (Dhingra and Morrow, 2019). Previous studies suggest that such distortions can have a large impact on aggregate productivity (Hsieh and Klenow, 2009). In our framework, larger firms produce higher-quality goods; but because the large firms under-produce, the average quality in the market is too low relative to an efficient allocation. By eliminating low-quality firms and increasing the output of larger high-quality firms, regulations can improve welfare through a novel channel.

Optimal standards must also account for negative and unintended effects. Stricter standards can lead to negative welfare effects such as fewer varieties, softer competition, and the use of resources for compliance costs, which can offset the gains in allocative efficiency. Even when a policymakers' objective is to address a positive externality associated with the consumption of high-quality goods, we show that regulations can both reduce misallocation and the externality. Thus, we provide an enhanced framework for policymakers to quantify the optimal level of regulations that are ubiquitous in domestic and trade policy.

Our theoretical framework is motivated by three stylized facts based on panel data on Chilean firms and information from the TRAINS database on sanitary and phythosanitary (SPS) standards. First, we document a positive association between firm size and firm markups. Second, we document that when SPS standards become more pervasive in an industry, small, low-quality firms are forced to exit. Hence, there is a reallocation of production from small, low-quality firms, which have low markups, to large, high-quality firms, which have high markups. This reallocation is driven by changes in the extensive margin, i.e., in the number of surviving firms.

In our third stylized fact, we document that the reallocation towards larger firms is accompanied by a rise in their markups, which suggests possible anti-competitive effects of regulations. However, we find that input measures such as capital intensity, average wages, and material cost per worker, are not affected by regulations. This suggests that changes in SPS standards are not associated with changes in unit costs or quality. These results are in line with the trade literature (references below), which documents that stricter regulations at a destination mainly reduce the number of exporters to said destination, but do not reduce the average export values. The connection to the wider trade literature further motivates our focus on extensive margin channels: regulations from several countries and industries are imposed for a variety of reasons such as addressing externalities and informational frictions, yet allocative implications due to the reallocation they generate have not been acknowledged.

To study the welfare consequences of such a reallocation, we incorporate regulations on product standards into a closed economy model of perfect information, monopolistic competition, and firms that are heterogeneous in quality. We model regulations as a fixed cost that all firms need to pay. Thus, our results can be generalized for all vertical norms and not exclusively product standards.[1] To provide a general framework to analyze allocative inefficiency, we choose the "Generalized Translated Power" (GTP) preferences proposed by Bertoletti and Etro (2018), which nest the most common classes of preferences used in the literature.

The sign of the welfare change in response to stricter standards is ambiguous as it depends on the strength of countervailing effects. The positive effect is due to an improvement in the market's allocative efficiency: due to the markup distribution, high-quality firms under-produce and low-quality firms over-produce, relative to an efficient allocation. The reallocation from low- to high-quality firms, which we label the *composition effect* of the standard, moves the allocation closer to the efficient one. The standard has also three negative effects on welfare, which limit the optimal level of restrictiveness. First, there is a reduction in product variety due to firm exit. Second, and connected to the first, the exit of firms can generate *anti-competitive* effects, whereby surviving high-quality firms increase their markups in response to lower competition. Third, the payment of the fixed cost reallocates workers from output-producing activities to compliance activities, which is welfare reducing. Our general demand system, with a parsimonious parameterization, accommodates different degrees of anti-competitive effects, and the model shows that if these

[1] Vertical norms are easily characterized as being more or less stringent, such as limits on car emissions or on residue levels of pesticides. As a specific example, the U.S. requires prosciutto to be dry cured for two years. One can view this as the imposition of a fixed compliance cost that will drive out potential producers. We ignore horizontal norms, which arise when the local firms' differentiated good is adopted as a norm, as electric plugs (Baldwin et al., 2000).

are sufficiently low, then the standard improves welfare. Absent the endogenous distortion that arises due to variable markups, the positive composition effect never dominates.

There are three assumptions to clarify from the outset. First, the closed economy framework allows us to clearly decompose effects on domestic firms, which we believe maintains a manageable scope for this paper.[2] Second, motivated by Kugler and Verhoogen (2012), we link the size heterogeneity of firms to exogenous quality draws.[3] Finally, the baseline analysis abstracts from consumption externalities that might drive the implementation of regulations we explore in the data. The latter assumption allows us to highlight the novel part of the paper, the allocative efficiency consequences of regulations. However, we verify that our theoretical results hold in an important extension in which we include a positive externality from consuming high-quality goods. We find that the regulation improves allocative efficiency and the externality at the same time under the most plausible scenario.

We leverage our model to estimate the restrictiveness of regulations in the Chilean manufacturing sector, as well as across individual industries. Our goal is to quantify the welfare implications of implementing counterfactual regulatory policies. We note that, although a standard allows for an intuitive theoretical mechanism through which low-quality firms exit, in reality there can be numerous policies that generate the same distributional effect on production. We find a significant presence of such policies across Chilean industries, for example, in 2000, the presence of regulations reduced the survival probability of a firm by 40%.

The estimated regulations are different from the optimal value implied by our model, so we compute the welfare gains associated with setting the standards to their optimal value. As the extent of anti-competitive effects is crucial in determining possible welfare changes, we calibrate the parameter that governs such effects by estimating the elasticity of prices with respect to size and to income with Chilean export transactions. In our baseline specification, welfare gains from moving to the optimal regulations are in the range of 0.1-0.3%. The estimation also highlights the heterogeneity across sectors within manufacturing: metal, furniture, machinery, chemical, apparel, and media sectors have estimated restrictiveness that is about 25% or less of the optimal regulations, while the motor vehicle/transport sector has a restrictiveness significantly larger than optimal. The welfare-improving impacts of regulations are sensitive to anti-competitive effects and are larger when regulations are

[2]Standards are crucial in trade policy, so we introduce trade separately in a companion paper (Macedoni and Weinberger, 2020). We confirm that the results in this paper hold, and in fact the optimal restrictiveness of regulations declines with lower trade barriers. Notice however that standards are imposed on *all firms in the domestic economy*, so trade is not necessary as a rationale for standards.

[3]In a model extension in the appendix, we link firm quality to exogenous productivity draws and allow the variable costs of production to be related to quality.

imposed without requiring wasteful compliance costs. If the regulations also target additional negative externalities, the welfare gains could be larger.

Relationship with the Literature. The trade literature has highlighted that economic integration can reduce the misallocation across firms that are heterogeneous in their productivity. International trade forces the exit of low-productivity firms and, thus, aggregate productivity increases (Melitz, 2003), which can improve allocative efficiency in the presence of variable market power (Edmond et al., 2015; Dhingra and Morrow, 2019).[4] This paper shows that a similar reallocation can be achieved with domestic policies that force the exit of low-quality firms.[5] Under a plausible set of conditions – governed by the demand faced by firms – regulatory measures can raise welfare through an increase in allocative efficiency. Relative to Dhingra and Morrow (2019) and Bertoletti and Etro (2018), we extend optimality results to a framework with quality differentiation.

In the same vein, our paper relates to the macro and industrial organization studies on the effect of size-dependent policies on welfare. These studies find that government policies that protect small firms and hinder the size of large firms have large distortionary implications (Guner et al., 2008; Garicano et al., 2016). Interestingly, product standards have the opposite effect: by making selection tougher and reallocating production to high-quality firms, distortions are *reduced*.

In a related paper, Edmond et al. (2018) propose a comprehensive analysis of the effects of various policies on misallocation and welfare, in a general dynamic model. Aside from quantifying misallocation within the context of different policies, an important difference with their paper is in the preferences used. While the authors rely on Kimball's preferences, which are homothetic, our model uses a general demand system that nests homothetic preferences as a special case. We show theoretically and quantitatively that, under homothetic preferences, standards generate the smallest welfare gains, because they generate the largest anti-competitive effect. Our quantitative exercise yields a parameter for the anti-competitive effect that is far from that implied by homothetic preferences.

An important contribution of this paper is to provide a rationale for product standards that has not been explored in the previous literature. Quality standards or regulations could be raised to address negative externalities, such as environmental externalities (Parenti and Vannoorengberghe, 2019; Mei, 2020), informational asymmetries (Disdier et al., 2020;

[4]Quantitative evidence of misallocation has been highlighted in Basu and Fernald (2002), Restuccia and Rogerson (2008), Hsieh and Klenow (2009), Behrens et al. (2020), and Weinberger (2020), among others. Relatedly, Costinot et al. (2020) lament the dearth of analysis for optimal trade policies when firms are heterogeneous.

[5]Furthermore, our results generalize to a framework in which firm quality depends on the underlying distribution of productivity.

Macedoni, 2021), or other market imperfections (Baldwin et al., 2000; Atkeson et al., 2014). Standards could also be used as murky protectionism (Baldwin and Evenett, 2009), as studied by Fischer and Serra (2000) in the context of an international duopoly. This paper is the first to explore the role of inefficient markets due to variable markups, a perspective ignored in the previous literature that mostly relied on perfect competition (Parenti and Vannoorengberghe, 2019) or monopolistic competition with constant markups (Gaigné and Larue, 2016; Mei, 2020; Disdier et al., 2020). Standards can both achieve a reduction of negative externalities associated with low-quality goods and, as a further benefit, reduce misallocation.

Our introduction of a minimum quality standard into the model resembles Gaigné and Larue (2016), who also consider the effects of a minimum quality level allowed in the market. In their model, firms upgrade quality at a cost. Thus, standards force some low-quality firms to upgrade their quality in order to survive in the market. Local welfare improvements of regulations are possible "starting from a low standard", but since their result relies on CES preferences and constant markups, the market allocation is always efficient. Instead, in our paper, standards are preferred to a laissez-faire allocation.

This paper is organized as follows. Section 2 presents the stylized facts that motivate our model. Section 3 describes out theoretical framework and discusses the welfare effects of quality standards. Section 4 shows the results from estimating the model. Section 5 concludes.

2 Motivational Evidence

The theoretical framework in Section 3 introduces regulations on product characteristics as a fixed cost, which selects out of the market the smallest firms. In a setting with variable markups, the extensive margin response generates changes in allocative efficiency. In this section, we provide three stylized facts that motivate this setting with firm-level. First, we confirm the heterogeneity in market power and that this correlates with firm characteristics such as size and quality indicators. Second, more regulations force out relatively small, low-quality firms. Third, more regulations raise sales and markup heterogeneity in the industry, but leave unchanged input expenditures.

2.1 Data and Summary Statistics

2.1.1 Chilean Firm Data: Firm Size, Quality Indicators, and Market Power

The Chilean data is a census of a panel of firms with more than 10 employees from 1995 to 2007, provided by Encuesta Nacional Industrial Annual (ENIA) and collected by

the National Institute of Statistics (INE). Each firm is classified with a 4-digit ISIC industry code. There are approximately 5,000 firm level observations per year and firms are tracked across time with a unique ID number. The census includes balance sheet data such as sales, factor expenditure, etc. In the robustness analysis, we extend our specification to customs data which includes the universe of firms that sell to Chile from a small set of countries.[6]

The specification that establishes an extensive margin response to regulations considers a panel of firms such that only firms alive in 1995 are included, and compares relative survival rates across these firms. To examine survival, the panel is expanded so that every firm is present in each of the years (creating a balanced panel). A firm is given a survival dummy equal to 0 if it was not present in the original data. This "fill-in procedure" – present in Fontagné et al. (2015) and Fernandes et al. (2019) – allows us to interpret firms in the first year as the "potential" producers. We also examine how sales and other outcomes of the largest firms change relative to the smallest firms, in this case conditioning for survivors.[7]

To investigate the welfare effects of product standards, our theory differentiates firms based on the quality of the product they produce. The key limitation data-wise, as faced by previous literature, is the lack of an explicit measure of quality. We will rely on firm domestic sales as well as three observable input measures – capital intensity, average wages, and material costs (intermediate inputs) per worker – as proxies to infer quality. Each characteristic arguably correlates with output quality, given the relationship of output quality with input quality (Fan et al., 2018). These have been used in previous studies; for example, (Hallak and Sivadasan, 2013) use the same quality proxies for Chile, although they complement them with Indian product-level data that also allows use of ISO 9000 certification and input/output prices.[8] Table 5 in the appendix establishes that all input quality proxies are strongly correlated with size. It is important to note that connecting the empirical results to the theory does not hinge on the ability of our proxies to capture quality uniquely. As in Kugler and Verhoogen (2012), in our model there is a direct mapping from quality to sales heterogeneity.[9] Therefore, we believe that an agnostic interpretation of the empirical analy-

[6]In the Chilean data, we cannot capture single vs. multi-product firms which is a concern since the regulations are on products and not on firms. However, the main results are robust to using customs data, which is at the firm-product-level. Our theoretical results can be extended to include multi-product firms that produce varieties of different quality. We argue that our theoretical results are not affected since, in the presence of a Pareto distribution of the underlying firm characteristics, aggregate variables depend only on the extensive margin of firms (Macedoni and Xu, 2020).

[7]For specifications with sales as the outcome, we also conduct robustness tests with a balanced sample, allocating zero sales to exiters, and also allowing for entry.

[8]We find a positive correlation between price and size in customs data (Appendix Table 15), which suggests that larger firms sell higher-quality goods. In a previous working paper version, we replicate our results with Indian product-level data using ISO 9000 certification (a known proxy of quality) and product unit values as quality indicators.

[9]These relationships are also consistent with Hottman et al. (2016), which find that product "appeal" is

sis, where reallocation across firms can be interpreted as either being across firm quality or firm size, is consistent with the theoretical model.[10]

As in the majority of studies on market power, we do not observe markups directly but apply the method proposed by De Loecker and Warzynski (2012) (DLW) to infer them with production data. This method assumes standard cost minimization of flexible inputs and is not tied to a particular demand system (see De Loecker (2021) for the defense and shortcomings to the approach). It relies on the textbook result that only in the presence of perfect competition are the revenue and cost shares of an input equal to each other. Therefore, the approach sets the markup as a wedge between the revenue share of a variable factor of production and its cost share. The cost share is observed in the data given that we have revenue and expenditures of variable inputs. Observing the revenue share entails estimating a firm-level production function by sector with the approach of Ackerberg et al. (2015). That estimation yields an output elasticity of materials (a flexible input) equal to its revenue share given cost minimization. The ratio of this elasticity to the cost share is interpreted as the price-cost markup (see Appendix 6.1.2 for details – Tables 6 and 7 report production function results by sector and summary statistics for the rest of firm measures). To minimize the effect of outliers, since the estimation produces some large markups that might be due to the mismeasurement of material costs, we conduct two corrections. First, we report the Lerner index, equal to $1 - \frac{1}{markup}$, which maintains the ranking of price-cost margins across firms but ranges from 0 to 1.[11] Second, we winsorize markups at the 2.5% level (the literature tends to do this at anywhere between 0.5 and 5%).

There is clear markup variability: the median Lerner index is 0.20 (1.25 markup), market power at the 90th percentile is twice as large, and the standard deviation is equal to 0.17. As we will rely on the positive association between sales and markups, we further examine their joint distribution by sorting firms in 1995 by their domestic sales. The Lerner index of the top 5% of firms is on average 0.295 (corresponding to a 1.42 markup), compared to 0.24 (or 1.32 markup) for firms around the 90th percentile and 0.157 (1.19 markup) for those in the middle of the *sales* distribution.[12] Firms in the 75th percentile have a Lerner index of 0.20 (1.25 markup), compared to 0.15 (1.17 markup) for those in the 25th percentile.

Table 1 examines the relationship between market power and our indicators of quality and firm size. We report the coefficient of a regression of the Lerner index on log domestic

the most important component of sales heterogeneity.

[10]We have extended the model to the case where firms are heterogeneous in productivity, and the same welfare-improving reallocation is possible, which alleviates the concern that the input measures might be proxies for productivity.

[11]This is a common measure of market power – see Elzinga and Mills (2011).

[12]We sort firms into 20 bins (for each sector) and take the average markup within the bin.

sales and the input quality measures with sector-year fixed effects to capture *across firm* variation. The results are summarized in our first stylized fact:

Stylized Fact 1. *There is evidence of market power heterogeneity across firms within sectors, and that market power largely increases with size and the input measures of quality.*

As reported in the first two columns, we find a positive relationship of the Lerner index with capital intensity and average wages – we do not report materials because of the mechanical relationship in estimating markups from the material cost share. There is also a strong relationship with log sales (last column), which is important because a feature of the model will be that markups increase with firm size.

Table 1: Relationship Between Market Power, Input Measures, and Sales

	Lerner Index		
	(K/L)	(W/L)	(Sales)
Input Measure	0.012***	0.027***	
	(0.001)	(0.002)	
Log Domestic Sales			0.007***
			(0.001)
Fixed Effects	Sector-Year	Sector-Year	Sector-Year
R^2	0.474	0.468	0.463
# Observations	38785	38785	38785

In this table, we report results of a regression of the Lerner index (constructed from the price-cost margin) on measures of quality as well as on firm size. Column headers in parenthesis represent the logged continuous measure used as the explanatory variable. These are log capital per worker, log wages per worker, and log sales. We do not include materials as their cost share is used to construct markups (the outcome in this regression). Markups are winsorized at the 2.5% level. In all cases we control for sector (ISIC 2 digit)-year interacted fixed effects. Standard errors (in parenthesis) are clustered at the firm level, which is the variation exploited. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Evidence for markup heterogeneity and its association with size is present in various studies. In the trade literature, Berman et al. (2012), Amiti et al. (2014), Auer and Schoenle (2016), De Loecker et al. (2016), Asprilla et al. (2019), and Weinberger (2020) have established that larger and more productive importers and exporters have a lower exchange rate pass-through and therefore a larger adjustment in their markups. De Loecker et al. (2016) also reports that output and markups are positively correlated in India, DLW find a positive correlation with export status (which likely correlates with size) in Slovenia, and Burstein et al. (2020) establish the relationship between market share and markups within sectors in France. The recent work of Autor et al. (2020) on how "superstar" firms contribute to the rise in aggregate markups also supports the salience of this relationship, and the authors confirm that larger firms have higher markups in the US.

2.1.2 Detailed Database of Non-Tariff Measures

Given the heterogeneity presented above, we study the implications of imposing product standards. In order to map regulations to the data, we make use of the prevalence of technical measures. These are *domestic* regulations that the WTO interprets as possible barriers to market access. With the secular decline in import tariffs, trade economists have pointed towards technical measures as an increasingly relevant subject in trade agreements (Maskus et al., 2000; Baldwin et al., 2000). These provide us with a useful measure of regulatory standards across industries, as such standards are imposed by governments to restrict access to both domestic and foreign firms. For example, when Chile imposes a "zero-tolerance" regulation regarding salmonella, it must be applied with equal stringency to domestic and imported poultry products. We view it as reasonable to interpret the salmonella regulation as a quality standard that can eliminate potential producers of low-quality poultry.

TRAINS has recently made available a comprehensive database of technical measures imposed by WTO members. The database includes *all* domestic regulations found in official texts that can be classified as non-tariff measures (NTMs).[13] The 2012 NTM classification separates measures into 16 chapters (labeled A-P), and we make use of the sanitary and phythosanitary (SPS) measures, to construct our measure of quality regulation. SPS standards – along with technical barriers to trade (TBT) – are chapters defined by UNCTAD (2017) as "technical measures." We believe SPS standards fit most closely with our regulations in the theory, although robustness results include TBT as well.

For each country, TRAINS reports all SPS standards imposed and reports them along with their respective NTM code(s).[14] For each standard, the dataset reports the starting year and which products are affected, where a product is a HS 6-digit (HS6) code. We construct a frequency index at the industry level – ISIC(i)-year(t) – as our measure of restrictiveness, labeled TM_{it}, which can be merged to our domestic firm production data (described above). To construct this index, we first count the number of SPS standards (unique codes) in each product-year. We sum the total number of regulations for each 4-digit ISIC (revision 3) industry, controlling for the number of products in the industry by dividing the previous sum by the number of HS6 products in the 4-digit industry.[15] Table 8 in Appendix 6.1.4 lists the top 25 industries ranked by the restrictiveness in the 1995-2007 period, where just

[13] TRAINS collects official measures imposed by countries that might affect international trade, that are mandatory, and are currently applied. National governments or local consultants hired by the World Bank collect regulations from official government sources, such as Customs Agencies or Government Ministries.

[14] The codes are comprised of the chapter plus three numerical digits. Since the same standard might be reported with multiples codes, we use only the first numerical digit in order to avoid double counting the same standard in multiple codes. A standard is counted as a unique resulting code in a product-year.

[15] See Appendix 6.1.3 for a detailed description of the data and construction of the frequency index. We use the starting year for time variation, as we use a flow measure of standards.

for this table we sum up all measures imposed across all years. We rank these using both SPS and TBT standards, as well as only SPS. Unsurprisingly, these rankings are populated by food and pesticide products, along with chemicals and equipment machinery.

2.2 Product Standards and Chilean Firms

The data described above allows us to test the distributional effects of technical measures within industries. To do so, we run the following specification:

$$y_{fit} = \alpha_{it} + \alpha_f + \beta_M TM_{it} * Char_f + \beta_X X_{it} * Char_f + \epsilon_{fit}, \tag{1}$$

where y_{fit} is a performance measure for firm f in industry i at year t, such as a dummy for positive sales ("survival premium"), plus other continuous outcomes. TM_{it} is the measure of industry restrictiveness based on the imposition of SPS measures as reported in Table 8. $Char_f$ is a dummy that we interpret as the firm characteristic. The goal of this exercise is to capture reallocation across firms with a specification that identifies only the heterogeneous effects. The indicator labels a firm as "large" or "high-quality" if it is above the median in domestic sales and various quality proxies within its industry in 1995. Since the firm indicator is fixed over time, and absorbed by the firm fixed effect, it is not correlated with the error term. The main coefficient of interest is β_M, which identifies the high- versus low-quality differential response to the imposition of regulations in an industry-year.[16] In the appendix, we extend this specification to customs data in order to test the differential response of survival rates and export prices across a set of exporters to Chile.

We include industry-year (α_{it}) and firm (α_f) fixed effects to control for the variety of time-varying industry and macroeconomic shocks, plus time invariant firm characteristics. This restrictive specification only captures the relative firm outcomes that are due to changes in technical measures and not due to the various industry characteristics that might drive the firm sales distribution.[17] The time-varying controls, $X_{it} * Char_f$, capture changes in non-regulatory industry characteristics that might drive relative outcomes between firms of different characteristics. These include an interaction of industry openness, as well as import tariffs, with the firm indicator to control for differences in competition introduced by trade.

The OLS specification controls for possible omitted variable bias with its set of fixed effects; however, it is difficult to know the reasons behind the imposition of standards and

[16] The results on the "survival" outcome might be affected by the fact that firms with less than 10 employees are not forced to participate to the survey. However, given that we find exit to be more prevalent among the smallest firms (β_M is in the direction that we expect), the censoring of the data likely *understates* the magnitude of the firm churning.

[17] For example, fixed effects control for differences in product differentiation and demand elasticities across firms and industries.

for this reason one might worry about reverse causality. For example, sales dispersion may reflect Chilean consumers' changing preferences for quality in certain industries, or lobbying by large firms,[18] and the government responds by imposing standards. For that reason we also report an IV specification where TM_{it} is instrumented using the same measure in Peru and Mexico, interacted with the same firm indicator. This is in the spirit of Kee and Nicita (2016), who use TM's of related countries – in that case those with a common language or border in a gravity framework. Peru and Mexico allow for both a border effect and varying distance in the case that the fixed cost due to regulations is correlated with variable costs. Although the IV results provide added evidence, we note that for all specifications, a Hausman test for endogeneity cannot reject the null that the Chilean TMs are exogenous.

Our OLS and IV results are shown in Table 2 and are summarized as follows:

Stylized Fact 2. *A larger amount of new regulatory measures forces out small, low-quality firms (an extensive margin effect).*

The coefficient in the first row of column (1) implies that imposing one standard affecting every product in an industry increases the survival rate of an average large firm by 1.2 percentage points relative to an average small firm.[19] The three proxies for quality yield similar results and coefficients of similar magnitudes. In column (2), imposing a regulation for every product in an industry results in a rise of 0.8 percentage points of the average survival rate of a firm with above-median capital intensity relative to one with below-median capital intensity. Given the relatively higher exit rate of small firms with lower average factor expenditures, we interpret that imposing new SPS standards in an industry generates a reallocation from the smallest to larger firms, and also from low- to high-quality firms.

In the IV specification, the standard errors and coefficients are both slightly larger, but qualitatively the results are consistent with the OLS estimation. Survival rates are relatively higher for firms that start out as bigger, and this shows up as raising sales heterogeneity, although differential effects are indistinguishable from zero (at conventional confidence intervals) using capital intensity and material cost proxies.

Next, we examine the implication that the exit of small firms has on the response of surviving firms. In Table 3, the above specification is expanded to outcomes of surviving firms by using continuous measures of the sales, markups, the three proxies for quality, and outcomes related to production choices. We identify high-quality firms only with their ranking in sales, so that the results are comparable to column (1) of Table 2.

The first column of Table 3 extends the analysis above for domestic sales as an outcome.

[18] In a robustness test, we drop the most concentrated sectors for this reason.

[19] Robustness exercises also test for expanded definitions of "large" versus "small".

Table 2: Survival Heterogeneity: Effect of Technical Measures

	Dummy for Positive Sales							
	OLS				IV			
	(Sales)	(K/L)	(W/L)	(M/L)	(IV-Sales)	(IV-K/L)	(IV-W/L)	(IV-M/L)
TM*Char	0.012***	0.008*	0.012*	0.009**	0.029**	0.013	0.028*	0.014
	(0.004)	(0.005)	(0.007)	(0.003)	(0.013)	(0.012)	(0.015)	(0.011)
# Observations	68122	68122	68122	68122	68122	68122	68122	68122
Fixed Effects	Firm, I-Y	Firm, I-Y	Firm, I-Y	Firm, I-Y	Firm, I-Y	Firm, I-Y	Firm, I-Y	Firm, I-Y
Controls	F-I-Y	F-I-Y	F-I-Y	F-I-Y	F-I-Y	F-I-Y	F-I-Y	F-I-Y
R^2	0.65	0.65	0.65	0.65				
F-stat (first stage)					11.4	11.4	11.4	11.4

In this table, we conduct the specification displayed in (1), using technical measures imposed in Chile (top), and also instrumenting Chile's measures with Peru's and Mexico's technical measures (last four columns). In all cases, the outcome is a dummy for whether the firm has positive sales in that year. To construct the frequency index of technical measures, we allow technical measure for the SPS chapter only, but drop those geared towards imports. The NTM measures are aggregated to the 4-digit ISIC industry level. The total number of measures in each industry-year are summed and then divided by the number of HS6 products in the industry. Each column interacts the TM measure with a dummy for above median in 1995 in terms of sales and quality, where quality is proxied by capital per worker, total wages per worker, and materials expenditure per worker respectively. To construct "survival", all firms alive in 1995 are "potential" producers in all years. In all specifications, we include an interaction of industry openness with the quality indicator, an interaction of the quality indicator measure with the industry import tariff, plus firm and industry-year interacted fixed effects. Standard errors – clustered by 4-digit industry – are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Note that in this case some firms drop out of the sample over time.[20] Not surprisingly, as regulations are felt most strongly by the smallest, lowest-quality firms, the ratio of sales between small and large firms (based on 1995 sales) is magnified as industries become more regulated. Having established the exit result, sales heterogeneity could conceivably be driven by two channels: extensive margin effects (small firms exit and market power increases) or intensive margin effects (large firms raise quality and sell more). As the direct implication of standards in our framework is an extensive margin effect, it is important to verify the relevance of the extensive margin channel and the sources of the intensive margin channel. Our findings are summarized as:

Stylized Fact 3. *A larger amount of new regulatory measures raises relative market power of high-quality firms but not their input expenditure.*

Regulations appear to raise markup heterogeneity (column (2), measured as a Lerner index[21]), as implied by a variable markup model where firms respond to reduced competition. However, there is no rise in dispersion of capital intensity, wages per worker, material cost per worker, skill intensity,[22] nor TFP. Notice the last two outcomes are not quality proxies but outcomes that can be plausibly altered by firms in response to regulations. The latter results are therefore consistent with firms *not* responding along the intensive margin, such as

[20] The appendix reports a specification with $\log(1 + sales)$ as the outcome, allocating zero sales to exiters.

[21] Using logged price-cost margin yields almost identical results.

[22] Ratio of skilled to unskilled employment. We note that the input proxies *are* strongly positively correlated with this ratio – a (rough) measure created with reported workers categorized as unskilled (or "no calificados" in Spanish) by firms in the data.

high-quality firms investing in quality upgrading or due to differential changes in unit costs, but instead rising sales dispersion driven by extensive margin-led reallocation.

Table 3: Alternative Outcome Heterogeneity: Effect of Technical Measures

	Sales	Lerner Index	K/L	Wages/L	Inputs/L	SL/UL	TFP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
TM*Char	0.011**	0.003***	0.021	0.005	0.003	0.004	0.000
	(0.005)	(0.001)	(0.013)	(0.004)	(0.007)	(0.015)	(0.005)
Fixed Effects	Firm, I-Y	Firm, I-Y	Firm, I-Y	Firm, I-Y	Firm, I-Y	Firm, I-Y	Firm, I-Y
Controls	F-I-Y	F-I-Y	F-I-Y	F-I-Y	F-I-Y	F-I-Y	F-I-Y
R^2	0.956	0.856	0.830	0.861	0.869	0.687	0.912
# Observations	42844	38186	38186	38186	38186	32169	38186

This table reports the specification displayed in (1), but for alternative outcomes: log domestic sales, markups (represented by Lerner Index), capital per worker, total wages per worker, materials expenditure per worker, the ratio of skilled to unskilled employment, and TFP. All outcomes are continuous and all except markups (a ratio) are in logs. Relative to the sales outcome (first column), the Lerner sample is smaller due to winsorization. We then keep the same sample for the rest of the intensive margin outcomes (columns 3-7) for comparison with markups. In all specifications the TM is interacted with a quality proxy equal to one for a firm above the median in 1995 in terms of sales only, and we include an interaction of industry openness with the quality indicator, an interaction of the quality indicator measure with the industry import tariff, plus firm and industry-year interacted fixed effects. Standard errors – clustered by 4-digit industry – are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Robustness. See Appendix 6.1.4 for a set of sensitivity results to the analysis above. As a more expanded check on our main analysis, we also employ customs data from the Exporter Dynamic Database (EDD), a dataset from the World Bank that draws on the universe of exporter transactions obtained directly from customs agencies (Fernandes et al., 2016). For the sake of brevity, details of the data and our results are in Appendix 6.1.5.

3 Theory

This section builds a theory for the welfare effects of standards. We begin by presenting the description of the environment, with a standard supply side and a general demand system that nests several preferences common in the literature. Policy makers have the option of imposing a quality standard as a fixed cost, whose effects on the distribution of firms are consistent with the evidence documented in the previous section. We derive an expression for welfare as a function of the standard, and show that under some parameterizations, a standard more restrictive than the market allocation is optimal. We also highlight how the optimal standard varies with demand features that control the markup responses of firms. Finally, we extend our model to include a consumption externality.

3.1 Framework

Consider a closed economy, where L consumers enjoy the consumption of varieties of a differentiated good. We normalize per capita income to 1. The varieties are produced by a

mass of single-product firms, which differ in terms of their quality z. We assume that quality z is a demand shifter: consumers exhibit a higher willingness to pay for higher-quality goods. There is perfect information: consumers, firms, and the government costlessly distinguish between the quality offered in the market.

As in the Melitz (2003) model, there is a pool of potential entrants. Upon entry, firms pay a fixed cost of entry f_E in labor units and discover their quality z. Quality is drawn from an unbounded Pareto distribution with shape parameter κ and shift parameter b. The CDF of the distribution is $H(z) = 1 - \left(\frac{b}{z}\right)^{\kappa}$, while the pdf is $h(z) = \frac{\kappa b^{\kappa}}{z^{\kappa+1}}$. Only a mass J of firms pays the fixed cost of entry. Free entry drives expected profits equal to f_E.

The market is monopolistically competitive. All firms produce their goods with the same marginal cost of production c, in labor units. These assumptions imply that size heterogeneity is linked to the exogenous quality draws. The direct mapping of quality to size might seem stark, but it is a convenient feature that is also present in Kugler and Verhoogen (2012) and finds quantitative support in the empirical findings of Hottman et al. (2016). Our results also generalize to a framework with productivity heterogeneity in which high-productivity firms are able to produce high-quality goods, and marginal costs depend on product quality as in Manova and Zhang (2017) (see Appendix 6.2.7).

The government of the closed economy imposes regulations which are modeled as a fixed cost of production f in labor units. The fixed cost f rationalizes the compliance costs that firms must incur due to the regulation, or the costs associated with inspections for quality levels. Through the fixed cost, the government effectively achieves the outcome of a minimum quality standard: higher fixed costs force the exit of low-quality firms.

3.1.1 Consumer Problem

We adopt the Generalized Translated Power (GTP) preferences proposed by Bertoletti and Etro (2018):

$$U = \int_{\Omega} \left(az(\omega)\xi q(\omega)) - \frac{(\xi q(\omega))^{1+\frac{1}{\gamma}}}{1+\frac{1}{\gamma}} \right) d\omega + \frac{\xi^{-\eta} - 1}{\eta} \tag{2}$$

where $a > 0$ and $\gamma \geq 0$ are constants, $q(\omega)$ is the quantity consumed of variety ω, $z(\omega)$ is a variety specific demand shifter, which we interpret as quality, and Ω is the set of varieties available for consumption. ξ is a quantity aggregator that satisfies:

$$\xi^{-\eta} = \int_{\Omega} \left(az(\omega)\xi q(\omega) - (\xi q(\omega))^{1+\frac{1}{\gamma}} \right) d\omega \tag{3}$$

The GTP utility follows the generalized Gorman-Pollak demand system (Gorman, 1972; Pollack, 1972), and nests several preferences based on the value of the parameter $\eta \in [-1, \infty]$. For $\eta = -1$, preferences are indirectly additive (IA) as described by Bertoletti et al. (2018). For $\eta = 0$, preferences become homothetic with a single aggregator. For $\eta \to \infty$, preferences become directly additive (DA), and generalize the preferences used by Melitz and Ottaviano (2008).[23] Fally (2018) describes the regularity conditions for these preferences.

The consumer's budget constraint is:

$$\int_{\Omega} p(\omega)q(\omega)dz \leq 1$$

where $p(\omega)$ is the price of variety ω and per capita income is normalized to 1. The consumer chooses $q(\omega)$, $\omega \in \Omega$, to maximize its utility subject to the budget constraint. The consumer's inverse demand is:

$$p(\omega) = \xi^{1+\eta}\left[az(\omega) - (\xi q(\omega))^{\frac{1}{\gamma}}\right] \tag{4}$$

3.1.2 Firm Problem

Given the quality draw z, a firm maximizes its profits by choosing quantity $q(z)$ taking ξ as given. Profits are given by:

$$\pi(z) = L\xi^{1+\eta}\left[azq(z) - \xi^{\frac{1}{\gamma}}(q(z))^{1+\frac{1}{\gamma}}\right] - Lcq(z) - f \tag{5}$$

The first order condition with respect to $q(\omega)$ equals:

$$\xi^{1+\eta}\left[az - \left(1 + \frac{1}{\gamma}\right)(\xi q(z))^{\frac{1}{\gamma}}\right] = c$$

We denote by z^* the level of quality such that a firm with quality $z \leq z^*$ has zero demand. By setting $q(z^*) = 0$ in the first order condition, we obtain:

$$z^* = \frac{c}{a}\xi^{-(1+\eta)} \tag{6}$$

We refer to z^* as the market-determined quality cutoff because, in the absence of regulations, i.e. $f = 0$, firms with quality below the cutoff z^* exit. In the presence of a positive compliance cost, the marginal firm that is indifferent between producing and exiting must sell a positive quantity to break even. Therefore, z^* no longer controls the selection of firms in the presence of regulations, but it retains the useful property of simplifying the analytical expressions for

[23] The case where $\gamma = 1$ generates linear demand as in the separable case of Melitz and Ottaviano (2008).

firm level variables and of incorporating the effects of competition and income.[24]

The parameter η controls how the general equilibrium object ξ affects the cutoff z^* and, thus, competition levels. For instance, $\eta = -1$ is a limit case such that changes in ξ do not affect z^*, which remains constant. Instead, if $\eta \neq -1$, variations in ξ that reflect changes in the competitive environment also affect z^*. Thus, the parameter η is the key determinant that controls the anti-competitive effect of the standard.

Substituting the cutoff (6) into the first order condition yields the optimal quantity:

$$q(z) = \left(\frac{a\gamma}{1+\gamma}\right)^{\gamma} \frac{(z^*)^{\gamma}}{\xi} \left(\frac{z}{z^*} - 1\right)^{\gamma} \tag{7}$$

As $q(z)$ is increasing in z, active firms with higher quality sell larger quantities of their products. Substituting (7) into (4) yields the optimal pricing rule:

$$p(z) = c \underbrace{\frac{1}{1+\gamma}\left(\frac{z}{z^*} + \gamma\right)}_{\text{Markup}} \tag{8}$$

Markups are increasing in z: higher-quality firms charge higher prices. This is in line with the relationship we document in *Stylized Fact 1*, as well as exporters to Chile with larger export revenues charging higher prices in the EDD. The positive relationship between prices and quality also receives empirical support from Bastos and Silva (2010), Martin (2012), Dingel (2017), and Manova and Zhang (2012). Furthermore, markups are declining in z^*: tougher competition, represented by a higher market-determined cutoff, reduces markups.

Firm z revenues $r(z)$ and profits $\pi(z)$ are given by:

$$r(z) = \frac{Lc}{1+\gamma}\left(\frac{a\gamma}{1+\gamma}\right)^{\gamma} \frac{(z^*)^{\gamma}}{\xi} \left(\frac{z}{z^*} - 1\right)^{\gamma} \left(\frac{z}{z^*} + \gamma\right) \tag{9}$$

$$\pi(z) = \frac{Lc}{1+\gamma}\left(\frac{a\gamma}{1+\gamma}\right)^{\gamma} \frac{(z^*)^{\gamma}}{\xi} \left(\frac{z}{z^*} - 1\right)^{1+\gamma} - f \tag{10}$$

Substituting the cutoff condition (6) into (10), we obtain:

$$\pi(z) = \frac{L\gamma^{\gamma} c^{\frac{\eta}{1+\eta}} a^{\gamma+\frac{1}{1+\eta}}}{(1+\gamma)^{1+\gamma}} (z^*)^{\gamma+\frac{1}{1+\eta}} \left(\frac{z}{z^*} - 1\right)^{1+\gamma} - f \tag{11}$$

[24] In terms of cutoff (6), our model is isomorphic to one with productivity heterogeneity as shifts in c can be obtained with shifts in z and vice-versa. To generate a model isomorphic to one with productivity heterogeneity, the utility function is: $U = \int_{\Omega} \left(az(\omega)\xi q(\omega)) - \frac{z(\omega)(\xi q(\omega))^{1+\frac{1}{\gamma}}}{1+\frac{1}{\gamma}} \right) d\omega + \frac{\xi^{-\eta}-1}{\eta}$. Although our results hold, our baseline model is better able to match the distribution of sales for the largest firms.

3.2 Quality Standard, Selection, and Prices

The imposition of a fixed cost f forces some firms, which would have been able to produce in the market allocation, to exit, as they cannot generate large enough revenues to pay for the fixed cost. In particular, for a given f there exists a firm with quality $\bar{z}$ such that $\pi(\bar{z}) = 0$. We refer to $\bar{z}$ as the government cutoff, which is implicitly defined as:

$$\frac{L\gamma^{\gamma} c^{\frac{\eta}{1+\eta}} a^{\gamma+\frac{1}{1+\eta}}}{(1+\gamma)^{1+\gamma}} (z^*)^{\gamma+\frac{1}{1+\eta}} \left(\frac{\bar{z}}{z^*} - 1\right)^{1+\gamma} = f \tag{12}$$

The government policy can be represented as a minimum quality standard, since the imposition of the fixed cost has the effect of making sure that firms with quality $z < \bar{z}$ are not allowed to sell in the economy. Since firms' quality is exogenously determined, the policy affects the selection of firms into the domestic market. The larger the fixed cost – the larger is $\bar{z}$ – the more low-quality firms are forced out of the market. *Stylized Fact 2* confirmed that more restrictive regulations cause the exit of smaller, low-quality firms and a reallocation of production towards larger, high-quality firms. Furthermore, the imposition of the fixed cost has an effect on z^*, which in turn affects the performance of all surviving firms.

Of particular interest for our analysis is the price response of the surviving firms, which depends on z^*. To see how the regulation affects z^*, it is convenient to write our variables as a function of $g = \frac{\bar{z}}{z^*} \in [1, \infty)$, a measure of the restrictiveness of the quality standard. If $g = 1$, the standard is ineffective: the market-determined quality cutoff z^* is equal to the minimum allowed $\bar{z}$. For $g > 1$, the government is enforcing a higher quality standard than the market. The measure g is related to the probability of a firm being active under the restriction, relative to the same probability without the restriction: $\frac{P(z \geq \bar{g} | g > 1)}{P(z \geq \bar{g} | g = 1)} = g^{-\kappa}$.

The measure g is implicitly defined by the zero-profit condition on the cutoff firm $\bar{z}$:

$$\frac{L\gamma^{\gamma} c^{\frac{\eta}{1+\eta}} a^{\gamma+\frac{1}{1+\eta}}}{(1+\gamma)^{1+\gamma}} (z^*)^{\gamma+\frac{1}{1+\eta}} (g-1)^{1+\gamma} = f \tag{13}$$

Since g is also a function of z^*, equation (13) does not pin down the value of g given a level of f. We therefore solve for the equilibrium value of z^* using the free entry condition – with the derivations in the appendix. Equating the expected profits to the fixed cost of entry

yields the quality cutoff z^* as a function of g and model's parameters[25]:

$$z^* = \left[\frac{Lc^{\frac{\eta}{1+\eta}} \gamma^\gamma b^\kappa a^{\gamma + \frac{1}{1+\eta}}}{f_E (1+\gamma)^{1+\gamma}} g^{-\kappa} (G_1(g) - (g-1)^{1+\gamma}) \right]^{\frac{1}{\kappa - \gamma - \frac{1}{1+\eta}}} \tag{14}$$

Substituting (14) into (13) yields:

$$\left[\frac{b^\kappa}{f_E} \right]^{\frac{\gamma + \frac{1}{1+\eta}}{\kappa - \gamma - \frac{1}{1+\eta}}} \left[\frac{Lc^{\frac{\eta}{1+\eta}} \gamma^\gamma a^{\gamma + \frac{1}{1+\eta}}}{(1+\gamma)^{1+\gamma}} \right]^{\frac{\kappa}{\kappa - \gamma - \frac{1}{1+\eta}}} \left[g^{-\kappa} (G_1(g) - (g-1)^{1+\gamma}) \right]^{\frac{\gamma + \frac{1}{1+\eta}}{\kappa - \gamma - \frac{1}{1+\eta}}} (g-1)^{1+\gamma} = f \tag{15}$$

Thus, the relationship between g and the fixed cost f only depends on other fundamental parameters of the model. In the appendix, we show numerically that the left-hand-side of (15) is monotonically increasing in g. Hence, there exists a unique value of the fixed cost that generates a given level of restrictiveness g. For this reason, in the remainder we assume that the government directly chooses g, even though the policy aims at a specific level of the fixed cost. This change in the government policy variable has two important advantages. First, it allows us to find a parsimonious formula for the optimal level of restrictiveness of regulations that only depends on three parameters of the model: κ, γ, and η. Using the fixed cost would require us to make assumptions over the values of the other parameters as well. Second, and more importantly, g is a scale free measure that allows us to estimate the restrictiveness of regulations in Section 4 without having to estimate directly the fixed costs, which are notoriously hard to measure.

Finally, let us discuss the relationship between z^* and g expressed in (14). Figure 5 of the appendix shows that an increase in g is associated with a reduction in z^*. Recall that an increase in z^* can be interpreted as an increase in the toughness of competition. As more restrictive regulations force out smaller firms, the number of surviving firms declines, and competition weakens, thus reducing z^*. Lower competition then leads to higher markups from surviving firms. The extent by which markups respond to changes in competition is controlled by the elasticity $\frac{1}{\kappa - \gamma - \frac{1}{1+\eta}}$, which is the elasticity of the market cutoff with respect to size. Conditional on the parameters κ and γ, the elasticity depends on $\frac{1}{1+\eta}$. As a reference to the main preferences discussed above, take the IA case ($\frac{1}{1+\eta} \to \infty$). This represents the limit case where the elasticity equals zero and the standard leaves the markups of surviving firms unchanged. As $\frac{1}{1+\eta}$ decreases there is a positive elasticity of the market cutoff with respect to size, and in these cases the standard increases the markups of surviving firms.

[25] $G_1(g) = \kappa g^{1+\gamma} \left[\frac{F_1(g)}{\kappa - \gamma - 1} - g^{-1} \frac{F_2(g)}{\kappa - \gamma} \right]$. $F_1(g) = {}_2F_1 \left[\kappa - \gamma - 1, -\gamma; \kappa - \gamma, g^{-1} \right]$ and $F_2(g) = {}_2F_1 \left[\kappa - \gamma, -\gamma; \kappa - \gamma + 1, g^{-1} \right]$, where ${}_2F_1[a, b; c, d]$ is the hypergeometric function.

Not only can regulations increase markups, but they do so disproportionately more for the largest firms as established in *Stylized Fact 3*. Consider the ratio of prices between a high-quality firm z_H and a low-quality firm z_L, with $z_H > z_L$. Since the two firms have the same unit costs, the ratio of prices is equivalent to the ratio of markups: $\frac{p(z_H)}{p(z_L)} = \frac{\frac{z_H}{z^*}+\gamma}{\frac{z_L}{z^*}+\gamma}$. It is straightforward to show that the ratio is declining with z^*: as an increase in g reduces z^*, the ratio of markups between high-quality firms and low-quality firms is magnified.

3.3 Quality Standard and Welfare

We are now ready to express welfare as a function of the quality standard. After integrating over the two terms in (2), the utility becomes:

$$U = \left[\frac{Lb^{\kappa}a^{\kappa}c^{\kappa-\gamma-1}\gamma^{\gamma}}{f_E(1+\gamma)^{1+\gamma}}g^{-\kappa}(G_1(g)-(g-1)^{1+\gamma})\right]^{\frac{\eta}{(1+\eta)(\kappa-\gamma)-1}}\left[(1+\gamma)\frac{G_3(g)}{G_2(g)}-\frac{\gamma^2}{1+\gamma}\frac{G_1(g)}{G_2(g)}+\frac{1}{\eta}\right]-\frac{1}{\eta} \tag{16}$$

where we leave the derivations to the appendix.[26]

There are two main channels through which regulations affect welfare. First, regulations affect the selection of firms since the government-imposed $\bar{z}$ is larger than the market cutoff z^*. Second, regulations impose a wasteful fixed cost on surviving firms. Below, we discuss how the first channel raises welfare for a standard that is not too large, but this is mitigated – or even dominated, depending on parameters – by the second channel.

Selection Effect. The change in selection has a positive welfare effect of reallocating production from exiting low-quality firms to surviving high-quality firms, which we call the *composition effect* of the standard. However, the quality standard reduces the number of varieties available for consumption, which is welfare reducing (*variety effect*), and the reduction in the number of varieties may cause a change in the markups of surviving firms, through a change in z^* (8). We call this the *anti-competitive* effect of the standard.

In Appendix 6.2.5, we only consider the selection effect of the standard, by assuming that the government imposes exogenously the cutoff $\bar{z}$.[27] We show that for "small" levels of restrictiveness, the composition effect dominates the reduction in the number of varieties and the anti-competitive effects. Note that the channel by which welfare increases is novel to the literature on quality standards and is possible *only* due to the endogenous distortion

[26] We restrict the parameter space such that $\kappa-\gamma-1>0$. $G_2(g) = \kappa g^{1+\gamma}\left[\frac{F_1(g)}{\kappa-\gamma-1}+\gamma g^{-1}\frac{F_2(g)}{\kappa-\gamma}\right]$. $G_3(g) = \kappa g^{1+\gamma}\left[\frac{F_1(g)}{\kappa-\gamma-1}\right]$.

[27] In this extension, we can prove analytically that $g > 1$ improves welfare under the assumption of linear demand ($\gamma = 1$). Details are available upon request.

that arises in the presence of variable markups. In the often-explored case where markups are constant (Gaigné and Larue, 2016; Bastos et al., 2018; Mei, 2020), the variety and anti-competitive effects always dominate. The discussion in the appendix clarifies the sources of the allocative inefficiency in the market allocation, whereby high-quality firms under-produce as their markups are too high and low-quality firms over-produce, relative to the efficient allocation. Finally, the *degree* to which selection can improve welfare depends on the strength of the anti-competitive effect.

Fixed Cost. A second welfare channel is driven by the payment of a fixed cost of compliance by all firms.[28] Such a channel is welfare reducing since workers are reallocated within firms from output production to the fixed labor requirement. As a result, the purchasing power of consumers declines and so does welfare. For this reason, we view our baseline model as a conservative way to evaluate the effects of a regulation. For instance, if the fixed cost is a lump-sum tax payment, the welfare effects would be larger as the tax revenues would be redistributed in the economy while the fixed cost is not. Because of the presence of the fixed cost, there are parameterizations under which the government standard is welfare reducing and, thus, the market allocation is preferred.

Discussion. As an example, in Figure 1, we show the relationship between welfare (combining both the selection effect and the fixed cost) and the standard under two values for η that represent alternative limit cases. Under IA preferences ($\eta = -1$), and the chosen values for the other two parameters, a standard improves welfare: the relationship between welfare and the standard is hump-shaped, reflecting the two channels previously discussed. We contrast this to the case of homothetic preferences ($\eta = 0$), in which, given the other chosen parameters, the standard only reduces welfare since the benefits from the reallocation are not enough to cover the costs associated with the payment of the fixed cost.[29]

The optimal level of the restrictiveness measure of the standard, $g^{opt}(\kappa, \gamma, \eta)$, only depends on the parameters κ, γ, and η. Intuitively, whether or not the regulation can improve welfare, and what is the level of the optimal level of regulations, crucially depend on the extent of the anti-competitive effects, which are captured by the parameter η, as shown in Figure 1 and previously discussed. In Figure 2, we relate the optimal restrictiveness of standards to the possible parameter assumptions. The larger the anti-competitive effects, the lower the optimal restrictiveness. Furthermore, if the anti-competitive effects are large enough the market allocation is preferred to the regulation.[30]

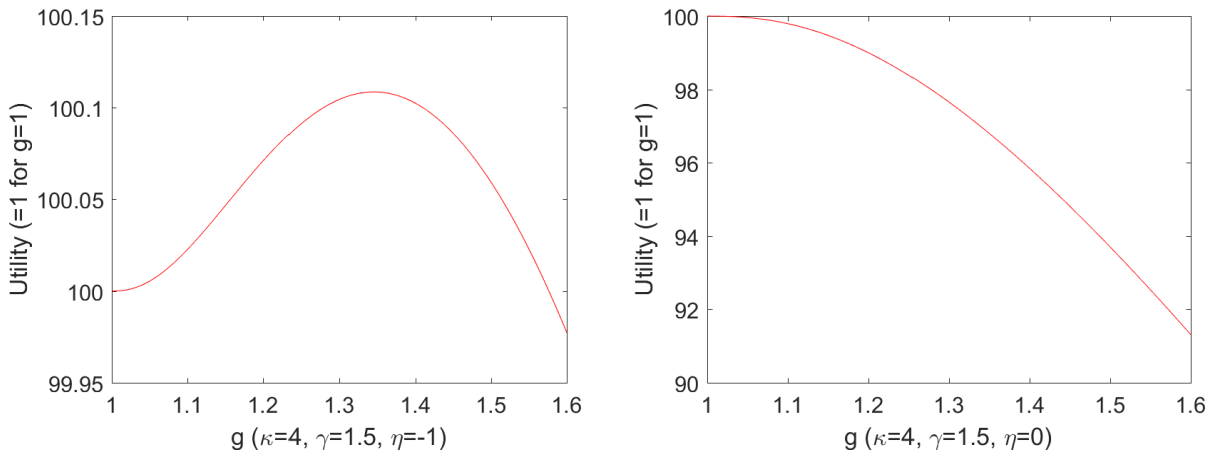
[28] Notice also that as U declines in c, if the standard or other policies only increase the marginal cost of production c, their welfare effect would be unambiguously negative.

[29] We note that the selection effect is positive for homothetic preferences (a markup distortion exists), but is weaker due to the strong anti-competitive response. Under some values of κ and γ, welfare does increase.

[30] In Appendix 6.2.6, we briefly discuss the differences between the market and the planner's allocation

Figure 1: Minimum Quality Standard and Welfare

(a) IA Preferences $\eta = -1$ **(b)** Homothetic Preferences $\eta = 0$



The optimal degree of restrictiveness also depends on the parameters γ and κ which determine the distribution of firms' markups and, more generally, the aggregation of firm level variables. The optimal g increases in γ, which governs market power. In fact, in the extreme case in which $\gamma = 0$, demand is fully rigid, and, thus, there are no distortions across firms. Moreover, the optimal g decreases in κ, which is inversely related to the dispersion in quality across firms. Higher levels of κ reduce firm heterogeneity and, thus, the degree of allocative inefficiency across firms: in the extreme case where $\kappa \to \infty$, the model collapses to the case of homogeneous firms.

3.4 Quality Standards and Consumption Externalities

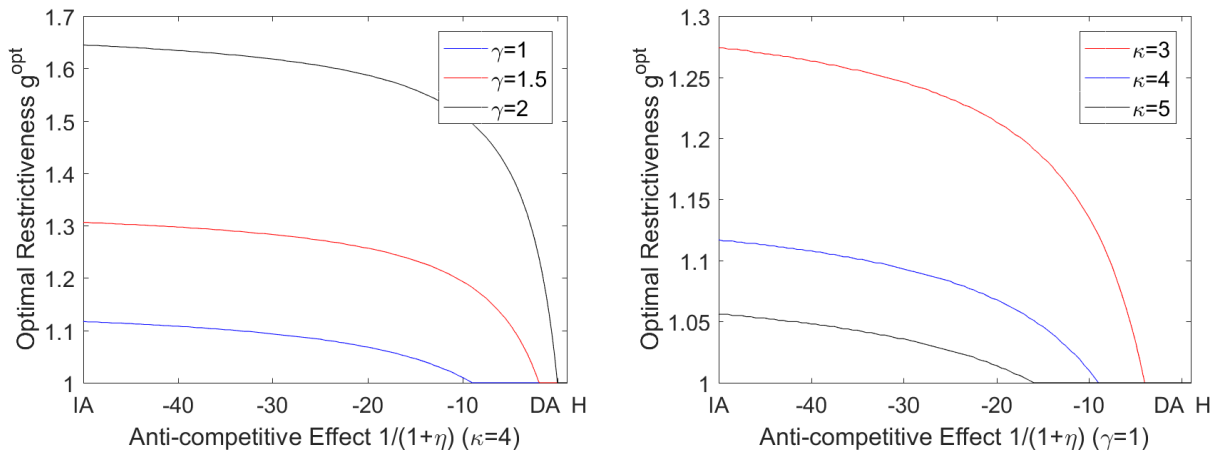
In this section, we study how the presence of a consumption externality interacts with the allocative inefficiency of the market allocation and, thus, affects the optimal level of restrictiveness of the standards. Let us rewrite the utility of the representative consumer as:

$$\tilde{U} = U + \ln(E) \tag{17}$$

across the three different preferences. The ranking of optimal g as a function of the degree by which markups depend on the number of competitors is respected across other preferences not included in GTP. In the online appendix, we provide a detailed discussion of the (IA) addilog preferences (Bertoletti et al., 2018), (DA) Stone-Geary (Simonovska, 2015), and (homothetic) Quadratic Mean of Order R (Feenstra, 2018). Finally, we explore the effects of a variety externality in the Benassy-CES preferences (Benassy, 1996).

Figure 2: Optimal g Across Preferences

(a) As a function of γ **(b)** As a function of κ



where E is the externality associated with the consumption of goods of higher quality and is modeled as quantity weighted average quality:

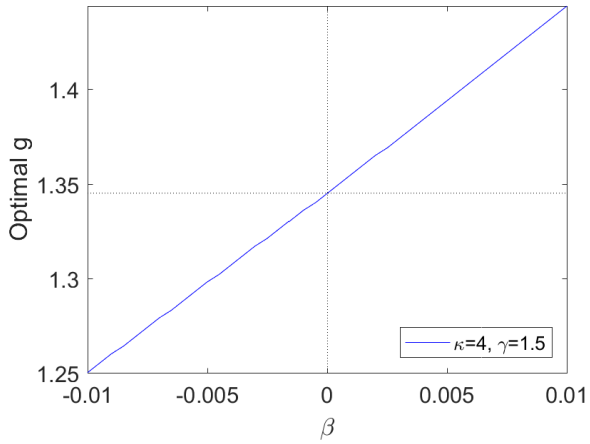
$$E = \frac{\int_{\bar{z}}^{\infty} q(z) z^{\beta} dz}{\int_{\bar{z}}^{\infty} q(z) dz} \tag{18}$$

where β controls the relationship between z and the consumption externality. For $\beta > 0$, larger values of z are associated with a larger positive externality. This is the case in which society is better off when consumers purchase high-quality goods. In this case, high-quality for consumers is also equivalent to a higher positive externality, although the externality implies that the average quality in the market is too low. This could represent the case of environmental externalities, where consumers partially internalize the externality by exhibiting higher demand, conditional on prices, for environmentally conscious products.[31] For $\beta < 0$, larger values of z are associated with a smaller positive externality. This is the case in which higher firm quality is associated with some negative externality.

We compute the optimal g with the externality and compare it to the baseline model for different values of β – with derivations left to the appendix. Figure 3 shows that, for positive values of β, the optimal regulation is higher than the baseline case, as the regulation improves allocative efficiency and the externality at the same time. We believe such a scenario to be the most realistic, as recent research in the management literature has found a positive relationship between firm sales performance and sustainability practices (Kronthal-Sacco et

[31] Such a setup represents the gap between what consumers intend to purchase, as they declare it in surveys, and what they actually purchase in stores (Kronthal-Sacco et al., 2020).

Figure 3: Optimal g and Externality ($\eta = -1$)



For parameter values shown, we plot the optimal regulation for varying β. The dotted horizontal line marks the optimal g in the baseline case without an externality.

al., 2020; Atz et al., 2020).[32] In contrast, for negative values of β, the regulation worsens the externality, but it improves allocative efficiency and, thus, the optimal regulation is smaller than the baseline case. The figure reports the results under IA preferences ($\eta = -1$), and in the appendix we also show other common preferences.

4 Model Estimation

In this section, we leverage the theoretical framework to estimate the regulatory restrictiveness in Chile, which provides concrete welfare implications for the quality standard described in the previous section. The estimation has two tiers. In the first tier, the "upper" parameter, η, is estimated to match the elasticity of prices to both income and market size. In the second tier, we match the empirical sales distribution constructed with the firm data described in Section 2. Instead of relying on the SPS data, we employ a simulated method of moments (SMM) procedure that estimates (g, κ, γ) to minimize the difference between percentiles of the model and data sales distribution. Using moments from the sales distribution to back out demand and supply parameters is a widely used approach in the trade literature (Eaton et al., 2011; Jung et al., 2019). Furthermore, our strategy to estimate the implied survival restrictions in Chilean industries is similar to Behrens et al. (2020), who estimate the distortions present within French industries with only the distribution of firm

[32] Kronthal-Sacco et al. (2020) find high growth in sales of sustainability-marketed consumer packaged goods, and that the growth is mainly driven by large and established brands. Atz et al. (2020) document that sustainability practices are associated with better financial performance in a meta-analysis of the literature.

revenues/employment.[33]

The estimation yields not only an implied level of restrictiveness – which we call g in the model – but also the optimal level of restrictiveness at the manufacturing and industry level given the supply and demand parameters. Hence, we provide a meaningful interpretation of welfare losses from sub-optimal policy, while uncovering considerable heterogeneity across sectors. While various sectors can be made more restricted, several are estimated to be *too* restrictive. Finally, we stress that the extent of anti-competitive effects, along with the payment of fixed costs, are crucial in determining optimal restrictiveness.

4.1 Strategy

Our goal is to estimate the parameter set $(g, \kappa, \gamma, \eta)$, which can be done at different levels of aggregation (e.g. sectors, manufacturing). These are sufficient to characterize "restrictiveness", as given by g/g^{opt}, as well as the possible welfare gains from imposing the optimal policy. We solve the model via simulation because the moments in the model that pin down these parameters are created using simulated firms. In other words, for a guess of the parameters, we simulate firm-level outcomes and attempt to reproduce moments of price elasticities and the empirical domestic sales distribution.

First, we simulate a large enough number of draws so as to best approximate the entire continuum of firms that exist in the model. We follow the insights of Eaton et al. (2011) and relabel firm-level indicators that can be simulated from a parameter-free uniform distribution. Recall that the pdf of the quality distribution is given by $h(z) = \frac{\kappa b^{\kappa}}{z^{\kappa+1}}$. We draw 250,000 realizations of the uniform distribution on the [0; 1] domain, $U \sim [0; 1]$, we order them in increasing order, and find the maximum realization, denoted by u_{max}. Then, the firm quality indicator is $z = (u/u_{max})^{-1/\kappa} z^*$. Given that there exists restrictions on the survival of low-quality firms, the set of producing firms is chosen from $z \in [g, \infty]$.

We adopt an over-identification strategy that targets separately the price elasticities with respect to income and market size, as well as 99 moments from the empirical domestic sales distribution. In the first tier, we make a guess for η, estimate the 3 other parameters given the guess (described below), and then produce two sales-weighted price elasticities:

$$\bar{\epsilon}_x = \frac{d \ln p(z)}{d \ln x} = \left(\frac{d \ln z^*}{d \ln x} \right) (G_2(g))^{-1} \frac{g^{1+\gamma} \kappa F_1(g)}{\kappa - \gamma - 1}, \tag{19}$$

[33] We avoid using our data on SPS standards for two reasons. First, as noted in Section 2, our dataset may include both vertical and horizontal norms, and it only provides the number of regulations and no information on their level of restrictiveness. Second, our algorithm captures the restrictiveness of *any* regulation that affects selection, consistent with our general theoretical results.

where $x \in \{L, y\}$ and $G_2(g)$ is a function that depends on the targeted parameters. The appendix provides details on the solution for the elasticities of the cutoff (first term in parenthesis). As targets, we produce these elasticities with customs Chilean exports data which allows us to regress unit values on destination-level per-capita income and population within firm-HS6 product combinations (see Appendix 6.4.2 for the full specification). We find a price elasticity of income equal to 0.084 and that of market size equal to -0.012.[34]

In the second tier, given η and a set of potential producers in the simulation, namely those with $z > g$, we compute firm revenues normalized by mean revenues[35]:

$$\tilde{r}(z|z > g) = \frac{r}{\bar{r}} = (G_2(g))^{-1} \left(\frac{z}{z^*} - 1\right)^{\gamma} \left(\frac{z}{z^*} + \gamma\right) \tag{20}$$

The theoretical relative sales as well as price elasticities are matched to their counterpart in the data in order to identify the model parameters. We outline the approach for relative sales, which follows Sager and Timoshenko (2019), with an equivalent procedure done for the price elasticity moments in the first tier. Let $F_q^m(g, \kappa, \gamma) = \log(\tilde{r})_q$ be the q-th quantile of the simulated log domestic sales distribution. Then, let F_q^d denote the corresponding value of the empirical CDF. Our identification consists of choosing the parameter set that minimizes the sum of the squared errors between empirical and theoretical quantiles:

$$\min_{g,\kappa,\gamma} \sum_{q=1}^{99} \left(F_q^d - F_q^m(g, \kappa, \gamma)\right)^2. \tag{21}$$

Finally, we compute bootstrap standard errors by running the estimation above 100 times, each time taking a bootstrap sample of the data. We take the average parameter estimates $(\hat{g}, \hat{\kappa}, \hat{\gamma})$, and use the standard deviation of estimates to compute a 95% confidence interval.

Our strategy to estimate the parameter set is based on the separate ways that each parameter is identified. First, we report $\frac{1}{1+\eta}$ since this statistic determines the extent of anti-competitive effects, and therefore is identified from price elasticities (see Section 3.3). The second set of parameters are identified within the sales distribution. κ governs the shape of the quality distribution, which is proportional to the shape in the sales distribution only in special cases (Mrazova et al., 2021), which do not apply to our GTP specification. The

[34]Notice these moments are also a central result of Simonovska (2015) (Table 5), which finds a price (market size) elasticity of income equal to 0.14 (-0.021). Our data allows us to produce targets related to sales of Chilean firms, with the caveat that products sold by the same firm to separate destinations are not necessarily identical. A earlier working paper presents results with Simonovska (2015)'s parameters, with very similar quantitative implications. The domestic census does not allow for cross-destination variation since only total exports are reported.

[35]Although relative sales are independent of η, z^* does depend on η. However, in results below we find that parameters from the sales distribution, (g, κ, γ) are quantitative very similar even for large swings in η.

divergence in the sales and quality distribution is due to the distribution of markups. Since firm markup levels are a function of γ (see (8)), this parameter affects the mapping from the quality to the sales distribution and is not collinear with κ.[36] Finally, as is argued above, the standard not only eliminates low-quality firms but reallocates resources to higher-quality firms. Therefore, relative sales across percentiles of the sales distribution are a function of g. For this reason, we use a general strategy to match sales across the firm distribution, with each parameter being identified by different parts of the distribution.

4.2 Estimation Results

4.2.1 Manufacturing-Wide Results by Year

For expositional purposes, we start by employing the procedure outlined in the previous section to estimate $(\hat{g}, \hat{\kappa}, \hat{\gamma}, \frac{1}{1+\hat{\eta}})$ for the universe of Chilean manufacturing firms in each year. The estimated level of the quality standard $\hat{g}$ has a 95% confidence interval above one in every year, with the standard peaking at 1.13 (with standard error of .01) through 1998-2000, before dropping every year thereafter to 1.02 in 2007. The estimates imply that regulations reduce the probability of a firm being active between 30-40% in the first half of the period $(-\hat{g}^{\hat{\kappa}})$, and between 5-20% in the second half. $\hat{\eta}$ implies that prices behave most similarly to IA preferences, although we show below that this is sensitive to using the price elasticity with respect to income separately from the elasticity to market size.

Panel A of Table 4 displays the results for the parameter estimates in 1995, 2000, and 2005. In Panel B, we report the data value and the simulated value for 5 moments that are indirectly targeted.[37] The parameter for demand curvature $\hat{\gamma}$ ranges between 1.3 and 2.4, rejecting the simple linear demand model in every year. The Pareto shape parameter of the quality distribution $\hat{\kappa}$ varies between 4-5 for the majority of the sample (consistent with estimates in Jung et al. (2019) and Simonovska and Waugh (2014)), and below 3 after 2004. It is evident that we can match moments from the sales distribution closely. Finally, the model implied average markups are 14%, 13%, and 30% in the three displayed years. These are in line with the empirical average markup estimates, which are not targeted in the estimation.[38]

Next, we explore possible welfare consequences of a change in restrictions. We compute the welfare change associated with a change in regulations as the equivalent variation in

[36] As is not the case, for example, if preferences were CES and the distribution of quality is Pareto.

[37] In the appendix, Figure 11 displays the model and empirical sales distributions, which allows us to visually compare the model and empirical sales distributions, which are reassuringly close. We also conduct tests of distributional fit.

[38] The markup estimation follows the procedure used in Section 2. We take a weighted average using the firms' share of total employment in the economy.

Table 4: Estimation Results: Manufacturing-wide in 1995, 2000, and 2005

Panel A: Parameter Estimates

Year	Data Targets	$\hat{g}$	$\hat{\kappa}$	$\hat{\gamma}$	$\frac{1}{1+\hat{\eta}}$
1995	Sales Percentiles, Income+Size Elasticity	1.1 (.008)	4.45 (.48)	1.94 (.10)	-21
2000	Sales Percentiles, Income+Size Elasticity	1.12 (.014)	4.68 (1.1)	2.28 (.30)	-27
2005	Sales Percentiles, Income+Size Elasticity	1.02 (.015)	2.50 (.38)	1.32 (.20)	-64

Panel B: Moments: Data versus Model (Using Both Elasticities)

	1995		2000		2005	
Moment	Data	Model	Data	Model	Data	Model
Sales Advantage	2.41	2.42	2.57	2.57	2.88	2.87
90-10 Sales	3.89	3.88	4.15	4.13	4.71	4.66
99-90 Sales	2.02	2.06	2.25	2.25	2.26	2.34
Skewness	.67	.71	0.78	.78	.43	.34
Average Markup	22%	14%	20%	13%	38%	30%

Panel A reports the parameter estimates when estimating the model for all manufacturing firms in each year (results also available per industry or sector, but are not reported as they would contain too many estimates for each parameter per year). The first step is to estimate $\frac{1}{1+\hat{\eta}}$ with an over-identified procedure that targets both the size and income price elasticities from customs data. Given $\frac{1}{1+\hat{\eta}}$, we estimate $(\hat{\gamma}, \hat{\kappa}, \hat{g})$ by targeting the sales percentiles. We compute bootstrap standard errors (in parenthesis) by running the estimation 100 times, each time taking a bootstrap sample of the data. In Panel B, we compute 5 moments in the data and using the simulated firms. "Sales Advantage" reflects the log difference between the average sales of firms in the to 50% relative to the bottom 50%. "90-10" and "99-90" are log differences in sales between firms in the respective percentiles. The average markup in the data is computed from estimating markups using the De Loecker and Warzynski (2012) procedure and taking a weighted average using the firms' share of total employment in the economy.

income that, if given to consumers in the initial allocation, would leave consumers indifferent between the new allocation and the initial one. This approach is commonly used in the trade literature to compute the gains from trade (Arkolakis et al., 2012, 2019; Bertoletti et al., 2018). Details are in Appendix 6.2.4. At the economy wide level, the optimal restrictiveness (g^{opt}) is larger than the estimated level of restrictiveness. For example, between 1995 and 2001, given the calibrated parameters, the optimal standard in this closed economy is between 1.90 and 2.15. Relating the results to Figure 2, the estimated anti-competitive effect is to the left of DA preferences, which raises the optimal restrictiveness, as does the high value for γ. Between 1995 and 2001, a counterfactual rise in $\hat{g}$ to its optimal level would raise welfare by around 0.10-0.15% all else equal. After 2001, due to the much smaller κ, the optimal restrictiveness increases and possible welfare gains are 0.25-0.30%. At least for the given parameter estimation, this is likely a lower bound due to the way we characterize standards as fixed costs that are paid in wages. Still, there is an economically important possible welfare gain in the range of 0.10-0.30% from raising restrictiveness given their *current* level. For context, notice that, relative to free trade, the welfare gain from setting an optimal tariff in an Armington model is of similar magnitude (Costinot and Rodríguez-Clare (2014),

Figure 4.1). In the next subsection we explore sectoral heterogeneity.

Robustness. The estimation above takes a general approach in terms of attempting to match the whole sales distribution instead of specific moments within the distribution. Next, we apply a similar SMM procedure with specific moments from the sales distribution that are pinned down by our parameters of interest. We construct 4 moments: i) the sales advantage of "high-quality" relative to "low-quality" firms[39]; ii) the skewness of the distribution which captures the composition effect of the standard; and two differences: iii) $\log(\tilde{r})_{99} - \log(\tilde{r})_{90}$, and iv) $\log(\tilde{r})_{90} - \log(\tilde{r})_{10}$. Appendix 6.4.3 includes plots of the simulated sales distribution, their respective estimated parameters, and also reports tests of distributional fit which ranks the benchmark estimation along with alternative specifications. We do not find large discrepancies with our benchmark strategy. However, in the alternative calibration, the fit with the sales data distribution is clearly not as close which is evident in comparing the plots of the estimated CDFs and the distributional test results.[40]

We also consider fixing some parameters to estimate restrictiveness, with plots of the sales distribution. We set $\gamma = 1.8$ and $\kappa = 4$ as deep parameters constant over time, in order to estimate only the outer parameter and the restrictiveness. $\hat{g}$ still ranges between 1.02 and 1.1, falling in the 2000's, though the graphical analysis shows that this specification is not able to match the dispersion in the sales data of the latter years.[41]

The last robustness check provides intuition for the importance of the anti-competitive channel. Our price elasticity moments imply a clear but modest income effect on prices ($\bar{\epsilon}_y$) – which pushes η towards DA and homothetic preferences – but also a negligible market size effect ($\bar{\epsilon}_L$), as implied by IA preferences.[42] We therefore take a somewhat middle ground in disciplining the benchmark analysis. Table 19, shown in Appendix 6.4.4 along with a more detailed discussion, reports calibration results for the cases where we match each of the two price elasticities individually.

[39] This moment is related to that used to identify the elasticity of substitution in Bernard et al. (2003).

[40] We compare model-implied sales distributions (including the next robustness) with the sales data. In none of the cases do we reject the null that the data and the model simulated distributions are the same.

[41] We have also estimated (with similar results) the addilog model of Bertoletti and Etro (2017) and the linear, separable Melitz and Ottaviano (2008) (MO) model. The former is similar to the IA case in our GTP framework. The latter is nested in our DA case with $\gamma = 1$. In a previous working paper, we fixed γ to 1 as in MO and report results for the general model. A small γ results in too little sales dispersion and the implied average markups are larger than reasonable markup estimates as the substitution across goods is too low. Jung et al. (2019) discuss the limitations of linear demand. The effect on $\hat{g}$ is small.

[42] Simonovska (2015) is the first paper we are aware of that documents the positive effect of destination income on prices, along with a negligible effect from the destination population (for *one firm* that sells to multiple destinations). This result is also found in Dingel (2017) for US producers across multiple destinations, and it is used as motivation for the introduction of the IA preferences in Bertoletti et al. (2018). Although we rationalize these results qualitatively in our benchmark calibration with a small anti-competitive effect, this implies a price elasticity of income larger than the moment we target due to being over-identified.

Two results stand out from targeting separate moments for $\frac{1}{1+\eta}$. First, the anti-competitive effect is sensitive to targeting only the low price elasticity of income (and implicitly very strong price elasticity to market size), or only the negligible size elasticity (and implicitly a large elasticity to income). In the former case $\frac{1}{1+\hat{\eta}}$ is between 0.50 and 1, closest to homothetic preferences, while in the latter case we are even closer to IA demand. Second, the sales moments parameters $(\hat{\kappa}, \hat{\gamma}, \hat{g})$ are almost identical regardless of the level of the anti-competitive effect. However, the optimal restrictiveness decreases significantly as $\frac{1}{1+\hat{\eta}}$ increases, as the anti-competitive effect starts to dominate at much lower levels of restrictiveness.

International Trade. Although this paper does not attempt to identify why the level of restrictiveness has changed over time, we point out a possible mechanism for the lower estimated restrictiveness observed in Table 4. As an example, take the food and beverage sector (ISIC 15). The ratio of average domestic sales of the top 50% of firms relative to the smallest 50% is 2.70 in the first half of our sample period, and increases to 3.1 in the second half (reflected by the "Sales Advantage" in Panel B of Table 4). The results suggest that the expansion of the large firms is concurrent with a lower estimated restrictiveness after 2004. This is captured by the reduction in $\hat{\kappa}$ between 2000 and 2005, which highlights an increase in the underlying quality dispersion.

A greater openness to trade might have contributed to the reallocation and is related to the drop in observed restrictiveness. Edmond et al. (2015) argue that trade reduces misallocation through competition, and in fact we confirm that the standard in this paper works as a complement to lower trade costs in an open economy setting in a companion paper (Macedoni and Weinberger, 2020). Although disentangling trade policy from our measure of restrictiveness of standards is beyond the scope of this paper, in the appendix we report suggestive evidence for the importance of trade.

4.2.2 Estimation Results by Sector

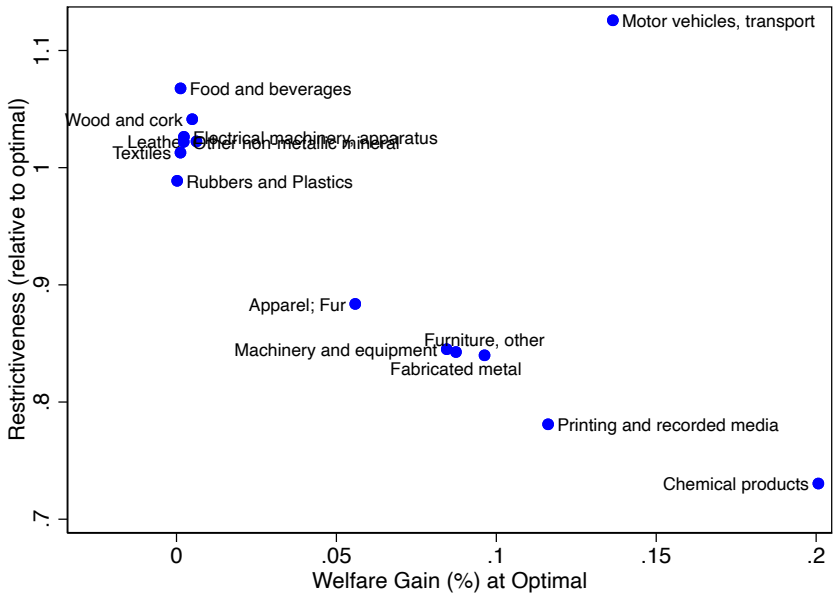
The estimated restrictiveness of the standard $\hat{g}$ is highly heterogeneous across sectors. In order to compute possible welfare gains by sector, which is likely more practical in setting standards, we repeat the estimation strategy detailed above for 16 two-digit ISIC sectors in 2000. This level of aggregation allows for at least 100 firms in each estimation. It is difficult to judge the relationship to the regulation data with such few sectors, but we point out that there is a positive correlation between the frequency index of SPS regulations constructed by sector as in Section 2 and the estimated standard (equal to 0.39).

Figure 4 plots the welfare gains in each sector that are possible by setting the optimal standard (horizontal axis), along with the level of restrictiveness across sectors (vertical axis), computed by normalizing the estimated $\hat{g}_i$ by the optimal level of regulations implied by the

model.[43] There are several industries clustered around zero possible welfare gains where the restrictiveness is *above* one, as these industries have current standards slightly above their optimal restrictiveness. There is also one industry, motor vehicles, which is significantly overly restrictive and there are large possible gains from reducing regulations.

However, there are several industries where a policymaker can obtain welfare gains from a rise in restrictiveness. Chemical products, metal, furniture, machinery, apparel, and media sectors have an estimated restrictiveness 10-30% lower than optimal (given estimated parameters), and would therefore generate welfare gains from higher regulation up to 0.20%. With value added sector weights – and the assumption of only independent within-sector distortions – we find that the economy wide welfare gains of moving each sector to its optimal restrictions is equal to 0.05%, about half as big as we found by treating manufacturing as one sector.[44] The lower aggregate gains highlight that the distribution of quality and demand vary by industry. Our theory section highlighted the possible welfare gains once one accounts for markup distortions, but a clear advantage of our framework is to identify in which sectors more restrictiveness is beneficial.

Figure 4: Sectoral Restrictiveness and Possible Welfare Gains in 2000.



The horizonal axis plots the welfare gains achieved by moving to the optimal standard (a proportional change in g_i equal to $\frac{g_i^{opt}}{\hat{g}_i}$). The vertical axis is the estimated $\hat{g}_i$ normalized by the optimal level of regulations implied by the model (g_i^{opt}).

[43] We cannot directly compare $\hat{g}_i$ across sectors (i), since the distribution of quality and demand features vary, and thus the same $\hat{g}_i$ in two sectors might have very different welfare implications. The index bears a close resemblance to the estimated industry distortions in Behrens et al. (2020).

[44] Aggregate welfare gains are once again 2-3 times larger, closer to 0.15%, if we used estimates from 2005.

Finally, in Appendix 6.4.6, we compare the sectoral level of restrictiveness in the case where imposing a standard does not entail a fixed cost (Figures 16 and 17), as well as targeting individual price elasticities. It is clear that fixed costs have a significant effect in shifting down optimal restrictiveness as they reallocate labor away from production. If policymakers could impose a standard without a fixed cost, it would imply that *every* industry would gain from more restrictions – although the ranking across industries in terms of their optimal change in restrictiveness is unchanged. The aggregate welfare gain from optimal regulations is 0.75%, or 15 times larger. This highlights that policymakers have much more leverage in imposing quality standards if it can be done in a way that restricts the survival of low-quality firms but minimizes the wastefulness of the compliance costs.

5 Conclusion

In this paper, we argue that a key channel is missed in rationalizations of regulations and product standards: a reallocation that raises average quality, which has novel ambiguous welfare implications when the market allocation is inefficient. In fact, the past literature focuses on settings where the allocation is efficient and thus these reallocations cannot raise welfare. To motivate the welfare-enhancing reallocation that occurs in the model, we rely on a panel of Chilean manufacturing firms and compare the distribution of sales across industries that differ in their level of regulation over time. Our findings that technical measures skew domestic sales towards high-quality firms complements the findings in trade studies that have found these measures to reduce the extensive margin of export flows.

Our model shows that whether or not standards improve welfare depends on the extent of the anti-competitive effect of standards, namely the increase in markups that follows the exit of firms with more restrictive regulations. We estimate the model to fit the observed distribution of domestic sales and conduct a policy-relevant evaluation that compares the estimated level of restrictiveness with the optimal standard as predicted by our model. We find that welfare gains are possible by moving policy towards the optimal standards, although these vary by sector.

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6 Appendix

6.1 Empirics Details and Extensions

6.1.1 Sales and Input Proxies for Quality.

Table 5 regresses log sales on the input measures for quality that we detail in the main text. Clearly, capital intensity, wages per worker, material costs per worker are strongly correlated with sales. For this reason, in terms of differentiating "high" and "low" quality firms in 1995, we categorize them as below or above the median in all 4 measures (the input proxies and sales).

Table 5: Relationship Between Input Measures and Sales

	Log Domestic Sales		
	(K/L)	(W/L)	(M/L)
Input Measure	0.559***	1.869***	0.943***
	(0.013)	(0.034)	(0.017)
Fixed Effects	Sector-Year	Sector-Year	Sector-Year
R^2	0.364	0.483	0.507
# Observations	41422	43466	43264

In this table, we report results of a regression of log domestic sales on other measures of quality. Column headers in parenthesis represent the logged continuous measure used as the explanatory variable. These are log capital per worker, log wages per worker, and log materials expenditure per worker. In all cases we control for sector (ISIC 2 digit)-year interacted fixed effects. Standard errors (in parenthesis) are clustered at the firm level, which is the variation exploited. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

6.1.2 Markup Estimation and Summary Statistics

Estimating markups as in De Loecker and Warzynski (2012) (DLW) relies on the textbook result that only in the presence of perfect competition are the revenue and cost shares of an input equal to each other. Therefore, the approach sets the markup as a wedge between the revenue share of a variable factor of production and its cost share. As in the literature, we use materials as a variable factor of production and denote with superscript x the variables related to materials. Let α^x_{ft} denote the cost share of materials for a firm f in year t, which is observed in the data and measured as the ratio between expenditures on variable inputs and sales:

$$\alpha^x_{ft} = \frac{P^X_{ft} X_{ft}}{P_{ft} Y_{ft}}, \tag{22}$$

where $P^X_{ft} X_{ft}$ is the value of materials used in production by firm f in year t, with X_{ft} denoting the quantity, and $P_{ft} Y_{ft}$ is the firm's total revenues. Therefore, the numerator is recovered using the nominal value of material expenditure for a firm while the denominator is given by total sales (both deflated using their respective year-industry deflator).

Cost minimization implies that the revenue share is equal to the factors' output elasticity. Therefore, we estimate a firm-level production function by sector with the approach of Ackerberg et al. (2015). That estimation yields an output elasticity of materials (a flexible

input) so that the ratio of this elasticity to its cost share is interpreted as the price-cost markup. The production function is written as:

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

β is the vector of output coefficients, ω_{ft} is a firm's (f) productivity at time t, ϵ_{ft} the measurement error, and $\{L_{ft}, X_{ft}\}$ are the set of variable inputs (labor and materials), and K_{it} is fixed capital. We take logs and use a Gross Output, Translog production function:

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

y, l, k, x refer to the logged value of gross output, labor, capital and intermediate inputs respectively. Labor is number of workers[45]. Capital and materials are both expressed as total deflated value, while gross output is deflated sales. Each 2-digit industry is estimated separately, using 4-digit industry input and output deflators provided by the Chilean Statistics Institution (INE). Notice that this Translog production specification allows for heterogeneous firm level output coefficients. Given the production function above, the output elasticity of materials is:

$$\theta_{ft}^x = \frac{\partial y_{ft}}{\partial x_{ft}} = \beta_x + 2\beta_{xx} x_{ft} + \beta_{lx} l_{ft} + \beta_{kx} k_{ft} + \beta_{lkx} l_{ft} k_{ft} \tag{23}$$

Estimated βs are constant by sector for all years, however notice that θ_{ft}^x depends on firm and year specific input values. Output elasticities are therefore firm and year specific.

We 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 De Loecker and Warzynski (2012) (they use export status similarly). Specifically, in the first step of the ACF procedure for the production function estimation, we add imports and exports into the intermediate input demand function of the firm.[46] 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.[47] Results of the production function estimation and the resulting median markup for each year and sector – for the full set of firms including those we drop in the main samples – are shown in Table 6.

Firm level markups represent 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. Therefore, the price-cost markup is represented by[48]:

$$m_{ft} = \frac{p_{ft}}{c_{ft}} = \frac{\theta_{ft}^x}{\alpha_{ft}^x} \tag{24}$$

[45] We combine skilled and unskilled workers although they can be split up using a subjective classification of labor categories.

[46] For a full account of the 2-step procedure see Ackerberg et al. (2015).

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

[48] 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.

Table 6: Factor Coefficients and Markups by 2-digit ISIC Sectors

	(1)					
	Obs	Labor Coeff	Capital Coeff	Mat. Coeff	Ret. Scale	Med. Markup
15	19475	0.218	0.073	0.757	1.048	1.192
17	3462	0.336	0.083	0.666	1.085	1.206
18	3846	0.349	0.047	0.665	1.062	1.219
19	2095	0.433	0.054	0.657	1.145	1.034
20	4382	0.240	0.051	0.773	1.064	1.264
21	1803	0.187	0.089	0.745	1.020	1.358
22	3017	0.285	0.111	0.633	1.029	1.323
24	3740	0.283	0.105	0.667	1.055	1.360
25	4085	0.221	0.072	0.734	1.027	1.352
26	2837	0.191	0.064	0.802	1.057	1.540
27	1503	0.128	0.139	0.747	1.015	1.412
28	4760	0.243	0.059	0.675	0.977	1.189
29	2923	0.508	0.098	0.489	1.095	0.993
31	1199	0.246	0.074	0.682	1.002	1.260
33	365	0.178	0.046	0.778	1.002	1.774
34	752	0.490	0.091	0.656	1.237	1.529
35	595	0.338	0.074	0.603	1.016	1.119
36	3229	0.180	0.033	0.812	1.025	1.544
N	68870					

Production function coefficients and median markups calculated using the methods of Ackerberg et al. (2015) and De Loecker 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.

Finally, the Lerner Index is given by:

$$Lerner_{ft} = 1 - \frac{1}{m_{ft}} \tag{25}$$

Summary Statistics. Table 7 reports summary statistics for markups as well as other measures from the firm-level data for the sample of firms in the main sample (which conditions on firms being alive in 1995).

6.1.3 Database of Non-Tariff Measures

The database is available at https://i-tip.wto.org/goods/default.aspx?language=en. It is also made available on the TRAINS database, but we downloaded the full set of measures for all measures and all reporters from the WTO site. Then, we kept only the cases where the "reporter" is Chile, the "partner" is the World, the starting year is within 1995-2007, and the NTM chapter is either SPS (Chapter A), TBT (Chapter B), or pre-shipment inspections (Chapter C). In the main analysis we use only SPS measures. Also, we drop classifications A1 within the SPS standards, as these are most likely to include regulations that only affect imported goods. Finally, the data is provided with a "Start Year" of the NTM. We use this year as the year that the measure is imposed which allows for time variation in TM_{it} (which is a flow measure).

Notice that this is not the same data used in Fontagné et al. (2015). They are interested in

Table 7: Summary Statistics

	mean	sd	p10	p50	p95
Log Domestic Sales	13.62	1.790	11.62	13.30	16.96
Log K/L	8.362	1.707	6.294	8.495	10.90
Log W/L	8.082	0.682	7.275	8.033	9.261
Log M/L	8.799	1.283	7.439	8.668	11.00
Markup (P/C)	1.310	0.379	1.018	1.243	1.842
Markup (Lerner)	0.199	0.168	0.0179	0.195	0.457
Log TFP	2.380	0.683	1.572	2.322	3.467

These summary statistics reflect the sample of firms in the baseline specification of the paper, but before winsorizing markups. Winsorizing markups (as explained in the main text) reduces the sample size for the specifications with markups.

"specific trade concerns" (STCs), which are complaints to the WTO made by trade partners about NTMs that are applied by the imposing country. Those NTMs are a subset of this data, but we count every single SPS that is imposed by Chile, which is a much larger set of measures than the ones with a reported STC. The drawback of course is that there is less information about these measures, and what their real "purpose" is.

Once the data is cleaned so that there are only SPS measures, with Chile as the imposing country and World as the partner, the most important step is how to create an industry measure of regulation. There are many observations for the imposition of each measure for two reasons. First, each regulation can affect multiple products. We do want to keep every product affected. Second, each regulation is categorized with a specific code in terms of the type of standard imposed. The standard code is one letter (chapter), plus 3 digits. Of the 3 digits, we use only the first digit. For example, if the same product in 2001 is affected by a measure "A330" and "A310", we count this as only one measure and delete duplicates. We do this in order to not double count measures, as it seems likely that this is the same measure categorized as two different types of SPS codes.

Finally, we aggregate the data to have an industry-year index of regulations. First, since the firm data is at the 4-digit ISIC level, we concord the product-level (HS6) to the ISIC level. Then, we aggregate to get a total number of measures imposed for each industry in each year. To control for the number of products within an industry, the total number of measures is divided by the number of HS6 products in that industry. This is therefore calculated as what is called a Frequency Index in the trade literature.[49] We construct a Frequency Index in industry i which can be written as:

$$F_i = \frac{\sum_{p \in i} D_p M_p}{\sum_{p \in i} M_p} \tag{26}$$

where D_p is equal to the number of unique 2-digit NTM codes imposed in product p, within industry i. M_p is a dummy for a product produced within the industry. The trade literature

[49] A similar calculation could be done where we weight the products by their importance in production (a Coverage Ratio). Since we are not attempting to measure the effect on aggregate flows, we do not believe the coverage ratio is the correct measure for our purposes (although it would be trivial to construct).

typically treats M_p as a dummy for a product being imported by a country. In our case, we take into consideration *all* products within industry i.

Table 8: Top 25 Most Regulated Industries

	SPS and TBT Rank		SPS Rank	
Rank	ISIC	Industry Name	ISIC	Industry Name
1	2421	Pesticides	1511	Meat products
2	1520	Dairy products	1513	Fruit and vegetables
3	1531	Grain products	1513	Fruit and vegetables
4	1552	Wine	1549	Other Food
5	1511	Meat products	1520	Dairy products
6	1513	Fruit and vegetables	1512	Fish products
7	1551	Alcohol production	1531	Grain products
8	1554	Soft drinks	1532	Starch products
9	1532	Starch products	2429	Other Chemicals
10	1533	Animal feeds	1553	Beer
11	1549	Other Food	1542	Sugar
12	1512	Fish products	1711	Textiles
13	1514	Oils and fats	2423	Wood
14	2424	Cleaning products	2010	Domestic appliances
15	2010	Wood	1533	Animal Feeds
16	1544	Farinaceous products	1554	Soft drinks
17	1543	Candy bars	2029	Manufacture of other products of wood
18	2021	Plywood, etc	1543	Chocolate and Sugar Confectionery
19	3230	TV and radio receivers	2412	Fertilisers and Nitrogen Compounds
20	3150	Lighting equipment	1544	Farinaceous products
21	3190	Other electrical equipment	2021	Plywood, etc
22	2912	Pumps	2411	Basic Chemicals
23	3311	Medical equipment	1429	Other Mining
24	2423	Pharmaceuticals	1911	Tanning and Dressing of Leather
25	2023	Wooden containers	2320	Manufacture of refined petroleum products

This table ranks industries by frequency index. We count the total number of standards imposed over all years (although in the regression we take the annual number of measures imposed). On the left we rank industries using both SPS and TBT standards. On the right, we rank industries using only SPS standards.

6.1.4 Robustness of Stylized Facts 2 and 3 with Chilean Domestic Sales Data

The NTM dataset may contain both vertical and horizontal norms, although our theoretical framework only considers vertical norms. As a way to deal with this issue, in the baseline results, we use only SPS. In Table 9 in the Appendix we replace the set of technical measures used in specification (1) with a more general definition, using TBT measures as well. The results are almost identical, and more precise in some cases, which suggests that neither SPS or TBT are driven by horizontal norms.[50]

To extend the definition of "large" and "small" firms, the firm characteristic can be expanded beyond above and below the median. For the survival outcome, we do this in two ways. First by extending the binary firm dummies to size terciles (small, medium, large), and second by creating a continuous measure of size (again, in 1995). We only use the second measure for the survival outcome because it is likely that the value of sales in the first year is correlated to the *growth* in outcomes related to sales (both sales itself and the markup) that

[50]The presence of measures based on horizontal norms likely biases our results towards zero. These don't discriminate on quality, which means "treated" industries will receive no distributional impact.

is captured in our specification. The first two columns in Table 10 report the results using the separate firm characteristic measures on the survival outcome. In the case of terciles (as in column (1)), we drop the "small" indicator so that the coefficients for "medium" and "large" can be interpreted relative to small firms. We see that both measures reflect the fact that the larger the firm in 1995, the higher the survival rate when new SPS measures are introduced. The last two columns reproduce the tercile specification for domestic sales and markups. In both cases, it is clear that SPS measures reallocate sales to larger firms and this is driven by the rise in markups.

Given the ability of (a small number of) large firms to potentially lobby policymakers (Blanga-Gubbay et al., 2021), the next set of results repeats the main specification when the most concentrated industries are dropped. We first compute Herfindahl Indices for each industry in 1995, rank industries by concentration, then drop industries with the highest concentration such that 5% of firms are dropped (according to their industry). Table 11 reports results when we test the effect of technical measures on relative outcomes, using survival, sales, and markups. We do this using the sales ranking as the firm characteristic. The results are almost identical to the baseline sample, which suggests that lobbying by large firms is not driving the industry-specific changes in regulation after 1995 (since in that case, we would expect the large firms to have the most power in these industries).

Table 12 provides robustness tests for the effect of regulations on sales with alternative samples. First, we use the same sample used in the specification with survival as outcome, in which all firms alive in 1995 are present for all years. Exiting firms are allocated 0 sales in the data. In this way, we might more clearly identify the reallocation of sales from the exiting firms (their sales mechanically decrease to zero) to the surviving firms (which we know from the survival rates, tend to be larger). Second, a common issue with data on regulations is the high level of measurement error. For instance, there could be a mismatch between the date of initial enforcement of a regulation, and the date of its listing in the dataset. To address the concern, we run a specification where regulations are aggregated across all years so that there is *one* restrictiveness measure for each industry. In this case (column 2), the specification is a repeated cross-section, with sales as the outcome within industry-year, and ran on an unbalanced panel. We obviously cannot do this for survival rates. The main drawback in this case is that we cannot control for firm fixed effects.[51] We add an interaction with industry trade elasticities (from Broda and Weinstein (2006)) to control for the effect of demand characteristics on the sales distribution – which was controlled for in the previous specification by firm fixed effects. Table 12, column 1, confirms our main findings that as smaller, low-quality firms exit, the sales of the initially larger firms increase relative to the smaller firms. In the repeated cross-section, we once again find that more regulated industries exhibit higher skewness in sales towards high-quality firms, which suggests that the possible mismatch between date of enforcement and listing of the regulation does not drive the results.[52]

[51] Since the regulations are aggregated from the HS 6 product level, firms within the same 4-digit ISIC might actually be exposed to different levels of regulation.

[52] Relatedly, we checked that the results are robust to a balanced panel with a different start date, e.g. 1998, and the coefficients are very similar (results available upon request).

Table 9: Firm Outcome Heterogeneity: Technical Measures include TBT

Panel A: Survival

	OLS				IV			
	(Sales)	(K/L)	(W/L)	(M/L)	(IV-Sales)	(IV-K/L)	(IV-W/L)	(IV-M/L)
TM*Char	0.015***	0.010**	0.009	0.006	0.029*	0.010	0.035*	0.005
	(0.004)	(0.004)	(0.006)	(0.004)	(0.015)	(0.012)	(0.018)	(0.010)
# Observations	68122	68122	68122	67409	68122	68122	68122	67409
Fixed Effects	Firm, I-Y	Firm, I-Y	Firm, I-Y	Firm, I-Y	Firm, I-Y	Firm, I-Y	Firm, I-Y	Firm, I-Y
Controls	F-I-Y	F-I-Y	F-I-Y	F-I-Y	F-I-Y	F-I-Y	F-I-Y	F-I-Y
R^2	0.65	0.65	0.65	0.65				
F-stat (first stage)					7.3	7.3	7.3	7.3

Panel B: Mechanisms

	Sales	Lerner Index	K/L	Wages/L	Inputs/L	SL/UL	TFP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
TM*Char	0.013**	0.003**	0.025*	0.002	-0.004	0.008	-0.000
	(0.006)	(0.001)	(0.015)	(0.004)	(0.006)	(0.015)	(0.002)
Fixed Effects	Firm, I-Y	Firm, I-Y	Firm, I-Y	Firm, I-Y	Firm, I-Y	Firm, I-Y	Firm, I-Y
Controls	F-I-Y	F-I-Y	F-I-Y	F-I-Y	F-I-Y	F-I-Y	F-I-Y
R^2	0.956	0.856	0.830	0.861	0.869	0.687	0.995
# Observations	42844	38186	38186	38186	38186	32169	37833

In this table, we conduct the specification displayed in (1), using technical measures imposed in Chile. Compared to the Table in the main text, here we construct the frequency index of technical measures allowing technical measure to be SPS *or* TBT NTMs. We still drop those geared towards imports. The NTM measures are aggregated to the 4 digit ISIC industry level. The total number of measures in each industry-year are summed and then divided by the number of HS6 products in the industry. Each row interacts the TM measure with a dummy for above median in 1995 in terms of sales and quality, where quality is proxied by capital per worker, total wages per worker, and materials expenditure per worker respectively. For the results on survival, all firms alive in 1995 are "potential" producers in all years, which is why the number of observations is much larger. In all specifications, we include an interaction of industry openness with the quality indicator, an interaction of the quality indicator measure with the industry import tariff, plus firm and industry-year interacted fixed effects. Standard errors – clustered by 4-digit industry – are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 10: Firm Outcome Heterogeneity: Medium and Large Firms relative to Small

	Survive		Log Domestic Sales	Lerner Index
	(1)	(2)	(3)	(4)
TM*Char (Continuous)	0.005**			
	(0.002)			
TM*Char (Medium)		0.008	-0.001	-0.000
		(0.005)	(0.008)	(0.001)
TM*Char (Large)		0.016***	0.014**	0.002*
		(0.006)	(0.007)	(0.001)
Fixed Effects	Firm, I-Y	Firm, I-Y	Firm, I-Y	Firm, I-Y
R^2	0.648	0.648	0.956	0.856
# Observations	68122	68122	42844	38186

In this table, we conduct the specification displayed in (1), using technical measures imposed in Chile (top). Compared to the Tables in the main text, here we extend the "characteristic" dummy measures beyond just above and below median. First by extending the binary firm dummies to size terciles (small, medium, large), and second by creating a continuous measure of size. The second measure we only use for the survival outcome because it is likely that the value of sales in the first year is correlated to the *growth* in outcomes related to sales (both sales itself and the markup) that is captured in our specification. In the case of terciles (as in column (1), (3) and (4)), we drop the "small" indicator so that the coefficients for "medium" and "large" can be interpreted relative to small firms. In all specifications, we include an interaction of industry openness with the quality indicator, an interaction of the quality indicator measure with the industry import tariff, plus firm and industry-year interacted fixed effects. Standard errors – clustered by 4-digit industry – are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 11: Firm Outcome Heterogeneity: Drop Most Concentrated Industries

	Survive	Log Domestic Sales	Lerner Index
	(Sales)	(Sales)	(Sales)
TM*Char	0.012***	0.011**	0.003***
	(0.004)	(0.005)	(0.001)
Fixed Effects	Firm, I-Y	Firm, I-Y	Firm, I-Y
R^2	0.647	0.955	0.856
# Observations	64146	40150	36005

In this table, we conduct the specification displayed in (1), using technical measures imposed in Chile (top). Compared to the Tables in the main text, here we drop the most concentrated industries. We first compute Herfindahl Indices for each industry in 1995, rank industries by concentration, then drop industries such that 5% of firms are dropped (according to their industry). In all specifications, we include an interaction of industry openness with the quality indicator, an interaction of the quality indicator measure with the industry import tariff, plus firm and industry-year interacted fixed effects. Standard errors – clustered by 4-digit industry – are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 12: Firm Sales Heterogeneity: Balanced Sample and Repeated Cross-Sections

	Log Domestic Sales	
	(Balanced Samples)	(Repeated Cross Sections)
TM*Char	0.139**	0.151***
	(0.066)	(0.031)
Fixed Effects	Firm, I-Y	I-Y
Controls	Yes	Yes
R^2	0.675	0.595
# Observations	68122	39266

In this table, we conduct two alternative specifications with log sales as the outcome. The first column is the specification displayed in (1), using technical measures imposed in Chile, where we do not drop firms that exit the sample (following procedure in the case for survival). Compared to the the main text Table 3, here the sales of exiting firms are made equal to 0 so that we include all firms alive in 1995 for all 13 years. The outcome is $\log(1 + sales)$. As in the main text, we include an interaction of industry openness with the quality indicator, an interaction of the quality indicator measure with the industry import tariff, plus firm and industry-year interacted fixed effects. In the second column, regulations are aggregated by industry across all years, so variation is only at the industry level (a repeated cross section using annual data on firm sales). TM_i (restrictiveness) is measured at the 4 digit ISIC industry level. In this specification, we control for the firm indicator interacted with 3 different industry controls: openness, average tariffs, and the industry demand elasticity (this is the only one not used in the benchmark specification, since it is subsumed by firm fixed effects.), along with include industry-year interacted fixed effects. Standard errors – clustered by 4-digit industry – are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

6.1.5 Expanded Analysis With Customs Data

For the following, we expand our analysis to customs data from the Exporter Dynamics Database (EDD).[53] The EDD is a dataset from the World Bank that draws on the universe of exporter transactions obtained directly from customs agencies. It contains transaction-level export values and quantities for exporters of 12 countries, although once we condition on *exporters to Chile* we are left with exporters from Peru (year 1993-2009 available), Mexico (2000-2009), Uruguay (2001-2012), and Guatemala (2003-2010). The data for Mexico contains only values and no quantities, so results with prices as the outcome exclude Mexican exporters. Log prices are constructed as unit values: $p_{ofpt} = \frac{v_{ofpt}}{q_{ofpt}}$, where o is origin, f firm, p HS6 product, and t refers to year. The specification is the following:

$$y_{ofpt} = \alpha_{opt} + \alpha_{ft} + \beta_M TM_{pt} * Quality_f + X_{opt} * Quality_f + Competency_{fpt} + \epsilon_{ofpt}, \quad (27)$$

where y_{ofpt} includes log prices, values and quantities. Notice that the data is at the origin-firm-product (HS6)-year level, so there are potentially multiple firm observations per year for multi-product exporters. In all specifications, we include firm-year and origin-product-year interacted fixed effects to capture relative price differences in products hit with a regulation relative to products that are not. This is similar to the Chilean firm level specifications with a few advantages. First, we can control for time-varying firm shocks by making use of the multi-product firms – though we point out that we lose observations by restricting ourselves to multi-product firms. Second, regulations are allowed to vary at the HS6 level and do not have to be aggregates to the industry level. We use a simple coverage measure provided by the TRAINS database, which is the fraction of HS8 products covered by a regulation found in year t. We control for any product-year shocks with fixed effects. The variation includes both the cross-section of price dispersion within firms across products with different levels of regulation, as well as time-series variation in prices of high- versus low-quality firms as products become more or less regulated.

Firm quality is determined by the *total* exports to Chile across all products of a firm. $Quality_f$ is an indicator equal to one for firms whose total exports are above the median exports for each origin o. To fix quality across time, we let a firm be of high-quality in all the years it appears in the data if it was above the median in total exports in any year.[54] We control for two product characteristics interacted with the firm quality dummy: Chile's import tariff on the product and the share of total Chilean imports that are of product p. We also control for the product-level $Competency_{fpt}$ by sorting all firm sales within a year and ranking them by value. In this way, we take into account the fact that firms with large scope might produce products away from its core-competency, which might distort the comparison of the same product by another firm with a different catalog of products. A higher value of competency signifies a product closer to the core.

Table 13 displays the main results for customs transactions. The first four columns display results for unit values as the outcome. In the first column, we include the quantity

[53] See Fernandes et al. (2016) for details on the data.

[54] Since we cannot match this data to business sheet information, our firm information is limited. We take the approach of Asprilla et al. (2019) to use all firm transaction to determine its quality level. They use firm scope, while we use total firm exports since we control for the $Competency_{fpt}$ a firm has in each product.

of the transaction to control for price effects that might be related to certain types of orders. Our benchmark specification is in column (2), where the results are almost the same as the previous column. Export prices differences between high- and low-quality firms from the same origin are heightened as products become more regulated in Chile. Since the number of observations for Uruguay and Guatemala are small, and there is no quantity data for Mexico, a reasonable interpretation of these results is they are mainly driven by the *Peruvian* exports to Chile. In the third column, we show that in fact the results are unchanged if we use only Peruvian exporters. In an even more restrictive specification, we add firm-product fixed effects in column (4), which restricts us to firms selling the same product in consecutive years. In this case, we lose about half the observations, however, results are qualitatively similar. In columns (5)-(6), we use log values on the left hand side and find similar results, although only significant at the 13% level with the benchmark sample and strongly significant when Mexican data is included. The last column displays quantity on the left hand side, and explains the discrepancy between the price and value results. Regulations do *not* raise the dispersion in quantity sold between high and low-quality firms. Notice finally that product-level prices and quantities within firms rise with the "competency" of a firm in a product, as is predicted by multi-product models (Macedoni and Xu, 2020).

The result for prices is robust and implies that regulated products see a larger dispersion in prices between high and low-quality firms. It is consistent with the domestic results which find higher sales and markup dispersion in more regulated industries. We point out the results could be due to a reallocation effect towards high-price firms, as well as an intensive margin effect where high-quality firms raise their quality and therefore their unit cost. With this data it is not possible to tease this out. The differences between price and quantity results could be consistent with either interpretation of reallocation to firms with higher prices or high-quality firms raising their unit costs. However, given the consistent findings in the literature that point to the extensive margin (Fontagné et al. (2015), Asprilla et al. (2019), and Macedoni and Weinberger (2020), plus our results in Section 2), we believe these findings are likely not due to a differential rise in costs.

We also repeat the specifications above when there is no time-variation in the NTMs (Table 14). We construct product level TM_p measures by taking the average across all years, a measure similar to the one in NTM-MAP Gourdon (2014). This robustness test could be important if it is hard to tell when Chile actually *implements* a regulation.[55] The variation now is only cross-sectional, across products, although we still include data for all years and control for firm-year and product-year shocks. Although the coefficients are smaller, which comes from the fact we don't account for changes in prices within firms across years, the interpretation is the same as above in Table 13. Once again there is strong evidence that dispersion in the value of sales for high- versus low-quality firms is higher in more regulated products, and this is all from price differences. We point out again the restrictive fixed effects that accounts for any within-year and across-time differences in products and firms, capturing only the *relative* firm differences.

Table 15 displays *across-firm* descriptive results of how transaction prices and quantities vary with firm quality. We include only origin-industry-year fixed effects, thus allowing for

[55] In the data, there is a year associated with each NTM, but there does seem to be jumps in some years, whereas other years show very few regulations.

Table 13: Pass-through Heterogeneity in Customs Data: Effect of Technical Measures

	Log Prices				Log Value		Log Quantity
	(1)	(2)	(Peru only)	(4)	(5)	(With Mexico)	(7)
TM*Quality	0.346***	0.328**	0.328**	0.717***	0.450	0.663***	0.122
	(0.124)	(0.140)	(0.139)	(0.272)	(0.300)	(0.238)	(0.340)
Tariff*Quality	-2.226***	-2.138***	-2.170***	0.608	-2.722*	-5.696***	-0.584
	(0.672)	(0.744)	(0.745)	(1.866)	(1.481)	(1.524)	(1.652)
ProdShare*Quality	3.345	-1.920	-2.149	0.638	33.120**	48.544***	35.040**
	(5.412)	(6.656)	(6.636)	(7.726)	(14.263)	(12.396)	(17.475)
Log quantity	-0.150***						
	(0.010)						
Competency	0.007***	0.001**	0.001**	0.001**	0.045***	0.012***	0.044***
	(0.001)	(0.000)	(0.000)	(0.001)	(0.005)	(0.004)	(0.005)
Fixed Effects	F-Y, O-P-Y	F-Y, O-P-Y	F-Y, O-P-Y	F-Y, F-P, O-P-Y	F-Y, O-P-Y	F-Y, O-P-Y	F-Y, O-P-Y
R^2	0.910	0.897	0.889	0.968	0.841	0.798	0.836
# Observations	38849	38849	36666	18494	38849	65356	38849

In this table, we test the heterogeneous pass-through of unit values, sales values, and quantities across low- and high-quality firms in industries differentiated by NTM regulations. The results are based on customs data from the Exporter Dynamics Database (EDD), where we keep only Chile as the destination. The origins that are left are Peru (year 1993-2009 available), Mexico (2000-2009), Uruguay (2001-2012), and Guatemala (2003-2010). Log prices, the outcome in first four columns, are constructed as unit values with transaction value over quantity. Quantity data is not available for Mexico, so for most specifications (other than column 5), Mexico is not included. In all specifications, we include firm-year and origin-produce-year interacted fixed effects. Standard errors – clustered by firms – are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

variation across firms. Although not including firm-year FEs could raise the number of observations, we restrict the sample to be the same as the previous table for comparison. A firm with a quality indicator equal to one has on average 35% higher unit values and sells 85% higher quantities than low-quality firms. The result is consistent with Equation (8) of the theory and past studies such as Manova and Zhang (2012).

Relative Survival. We also check whether the extensive margin seems to play a role in the customs database. To do so, we follow the Fontagné et al. (2015) method, similar to our method for domestic firms, to keep a subsample of firms and create a balanced panel with those firms. First, we aggregate the data to the 4-digit HS sector, and second, keep all firm-product pairs that are in the data for at least 4 years. In this way, we minimize the amount of firm churning, which should go against us, and account for firms that have minor changes in their products which might alter their HS classification (also accounts for possible classification changes across years although we do map all data to the 1996 HS classification). Then, we ran an identical specification as the price-level regressions above, with "survival" as the outcome. Survival is defined as having positive sales in year t, whereas this turns to zero in years where the firm-product pair is not in the customs database.

The first column of Table 16 confirms that higher quality firms have a higher survival rate, when we exclude firm-year fixed effects. In the second column, the survival rate of high-quality firms is relatively higher than in sectors without regulations. Again, this is consistent with the results in Section 2 and suggest that there is an important extensive margin response to a rise in regulations in a product. In more regulated markets, low-quality firms are more likely to exit, in conjunction with the higher dispersion in export values and export prices.

Table 14: Pass-through Heterogeneity in Customs Data: Effect of Technical Measures (No Time Variation)

	Log Prices		Log Value		Log Quantity
	(1)	(2)	(3)	(With Mexico)	(5)
TM*Quality	0.109***	0.113***	0.086	0.105	-0.026
	(0.031)	(0.032)	(0.067)	(0.065)	(0.070)
Tariff*Quality	-2.045***	-1.949***	-2.583*		-0.634
	(0.669)	(0.742)	(1.480)		(1.655)
ProdShare*Quality	2.029	-3.215	31.725**		34.940**
	(5.444)	(6.670)	(14.227)		(17.408)
Log quantity	-0.150***				
	(0.010)				
Competency	0.007***	0.001**	0.045***	0.012***	0.044***
	(0.001)	(0.000)	(0.005)	(0.003)	(0.005)
Fixed Effects	F-Y, O-P-Y	F-Y, O-P-Y	F-Y, O-P-Y	F-Y, O-P-Y	F-Y, O-P-Y
R^2	0.910	0.897	0.841	0.806	0.836
# Observations	38849	38849	38849	72908	38849

In this table, we test the heterogeneous pass-through of unit values, sales values, and quantities across low- and high-quality firms in industries differentiated by NTM regulations. The results are based on customs data from the Exporter Dynamics Database (EDD), where we keep only Chile as the destination. The origins that are left are Peru (year 1993-2009 available), Mexico (2000-2009), Uruguay (2001-2012), and Guatemala (2003-2010). Log prices, the outcome in first three columns, are constructed as unit values with transaction value and quantity. Quantity data is not available for Mexico, so for most specifications (other than column 4), Mexico is not included. In all specifications, we include firm-year and origin-produce-year interacted fixed effects. Standard errors – clustered by firms – are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 15: Descriptive Correlations in EDD Data

	Log Prices	Log Value	Log Quantity
	(1)	(2)	(3)
Quality	0.347***	1.201***	0.854***
	(0.074)	(0.091)	(0.085)
Fixed Effects	O-P-Y	O-P-Y	O-P-Y
R^2	0.587	0.550	0.599
# Observations	38849	38849	38849

The results are based on customs data from the Exporter Dynamics Database (EDD), where we keep only Chile as the destination. The origins that are left are Peru (year 1993-2009 available), Mexico (2000-2009), Uruguay (2001-2012), and Guatemala (2003-2010). Quality is defined as in the main text, at the firm-level using total sales by an exporter across all products. We control for $Competency_{fpt}$, but it is not reported in the Table because its interpretation with across-firm variation is not clear. Log prices are constructed as unit values with transaction value and quantity. The sample in this table excludes Mexico due to lack of quantity data. In all specifications, we include origin-product-year interacted fixed effects. Standard errors – clustered by firms – are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 16: Survival Heterogeneity in Customs Data: Effect of Technical Measures

	Survive	
	(1)	(2)
Quality (Tot Exports)	0.080***	
	(0.019)	
TM*Quality		0.068*
		(0.039)
Competency	-0.001***	-0.001**
	(0.000)	(0.001)
Fixed Effects	O-P-Y	F-Y, O-P-Y
R^2	0.428	0.831
# Observations	31897	31897

The results are based on customs data from the Exporters Dynamics Database (EDD), where we keep only Chile as the destination. The origins that are left are Peru (year 1993-2009 available), Mexico (2000-2009), and Uruguay (2001-2012). Log prices are constructed as unit values with transaction value and quantity. The sample in this table excludes Mexico due to lack of quantity data. In all specifications, we include origin-industry-year interacted fixed effects. Standard errors – clustered by firms – are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

6.2 Model's Derivations

6.2.1 Consumers' Problem

Recall the Generalized Translated Power (GTP) preferences:

$$U = \int_{\Omega} \left(az\xi q(\omega) - \frac{(\xi q(\omega))^{1+\frac{1}{\gamma}}}{1+\frac{1}{\gamma}} \right) d\omega + \frac{\xi^{-\eta} - 1}{\eta} \tag{28}$$

where ξ is a quantity aggregator that is implicitly defined as:

$$\xi^{-\eta} = \int \left(az\xi q(\omega) - (\xi q(\omega))^{1+\frac{1}{\gamma}} \right) d\omega \tag{29}$$

The first order conditions of the consumers' problem are:

$$az\xi - \xi^{1+\frac{1}{\gamma}} q(\omega)^{\frac{1}{\gamma}} + \left[\underbrace{\int \left(azq(\omega) - \xi^{\frac{1}{\gamma}} (q(\omega))^{1+\frac{1}{\gamma}} \right) d\omega - \xi^{-\eta-1}}_{=0 \text{ by } (29)} \right] \frac{\partial \xi}{\partial q(\omega)} = \lambda p(\omega)$$

$$az\xi - \xi^{1+\frac{1}{\gamma}} q(\omega)^{\frac{1}{\gamma}} = \lambda p(\omega) \tag{30}$$

By multyplying both sides of (30) by $q(\omega)$ and integrating across all varieties $\omega \in \Omega$, we obtain the marginal utility of income λ.

$$\lambda = \frac{1}{y} \int \left(az\xi q(\omega) - (\xi q(\omega))^{1+\frac{1}{\gamma}} \right) d\omega = \frac{\xi^{-\eta}}{y} \tag{31}$$

Using (31) in (30) yields the inverse demand:

$$p(\omega) = \frac{\xi}{\lambda} \left[az(\omega) - (\xi q(\omega))^{\frac{1}{\gamma}} \right] = y\xi^{1+\eta} \left[az - (\xi q(\omega))^{\frac{1}{\gamma}} \right] \tag{32}$$

As we consider a closed economy, we normalize per capita income to unity.

6.2.2 Quality Standard and Aggregate Variables

Recall that g is implicitly defined as:

$$\frac{Lc}{1+\gamma} \left(\frac{a\gamma}{1+\gamma} \right)^{\gamma} \frac{(z^*)^{\gamma}}{\xi} (g-1)^{1+\gamma} = f \tag{33}$$

The average profits of firms with $z > \bar{z}$ are:

$$\bar{\pi} = \int_{\bar{z}}^{\infty} \pi(z) \frac{\kappa \bar{z}^{\kappa}}{z^{\kappa+1}} dz - f =$$

$$= \frac{Lc}{1+\gamma} \left(\frac{a\gamma}{1+\gamma} \right)^{\gamma} \frac{(z^*)^{\gamma}}{\xi} \int_{\bar{z}}^{\infty} \left(\frac{z}{z^*} - 1 \right)^{1+\gamma} \frac{\kappa \bar{z}^{\kappa}}{z^{\kappa+1}} dz - f =$$

$$= \frac{Lc}{1+\gamma}\left(\frac{a\gamma}{1+\gamma}\right)^{\gamma}\frac{(z^*)^{\gamma}}{\xi}G_1(g) - f = \tag{34}$$

$$= \frac{Lc}{1+\gamma}\left(\frac{a\gamma}{1+\gamma}\right)^{\gamma}\frac{(z^*)^{\gamma}}{\xi}(G_1(g) - (g-1)^{1+\gamma}) \tag{35}$$

where we substitute (33) into (34). $G_1(g)$ is a function of κ, γ, and of the restrictiveness of the standard g:

$$\begin{aligned} G_1(g) &= \int_{\bar{z}}^{\infty} \kappa\left(\frac{z}{z^*} - 1\right)^{1+\gamma}\frac{\bar{z}^{\kappa}}{z^{\kappa+1}}dz = \\ &= \int_{\bar{z}}^{\infty} \kappa\left(1 - \frac{z^*}{z}\right)^{1+\gamma}\frac{\bar{z}^{\kappa}}{(z^*)^{1+\gamma}z^{\kappa-\gamma}}dz = \\ &= \kappa g^{1+\gamma}\left[\frac{F_1(g)}{\kappa-\gamma-1} - g^{-1}\frac{F_2(g)}{\kappa-\gamma}\right] \end{aligned} \tag{36}$$

$F_1(g)$ and $F_2(g)$ are two hypergeometric functions given by:

$$F_1(g) = {}_2F_1\left[\kappa-\gamma-1, -\gamma; \kappa-\gamma, g^{-1}\right]$$

$$F_2(g) = {}_2F_1\left[\kappa-\gamma, -\gamma; \kappa-\gamma+1, g^{-1}\right].$$

The probability of a firm being active is:

$$P(z \geq \bar{z}) = \frac{b^{\kappa}}{\bar{z}^{\kappa}} = \frac{b^{\kappa}}{(z^* g)^{\kappa}} \tag{37}$$

The zero expected profit condition is:

$$\begin{aligned} P(z \geq \bar{z})\bar{\pi} &= f_E \\ \frac{Lc}{1+\gamma}\left(\frac{a\gamma}{1+\gamma}\right)^{\gamma}\frac{b^{\kappa}}{(z^*)^{\kappa-\gamma}g^{\kappa}\xi}(G_1(g) - (g-1)^{1+\gamma}) &= f_E \end{aligned} \tag{38}$$

from which we obtain:

$$(z^*)^{\kappa-\gamma}\xi = \frac{Lcb^{\kappa}}{f_E(1+\gamma)}\left(\frac{a\gamma}{1+\gamma}\right)^{\gamma} g^{-\kappa}(G_1(g) - (g-1)^{1+\gamma}) \tag{39}$$

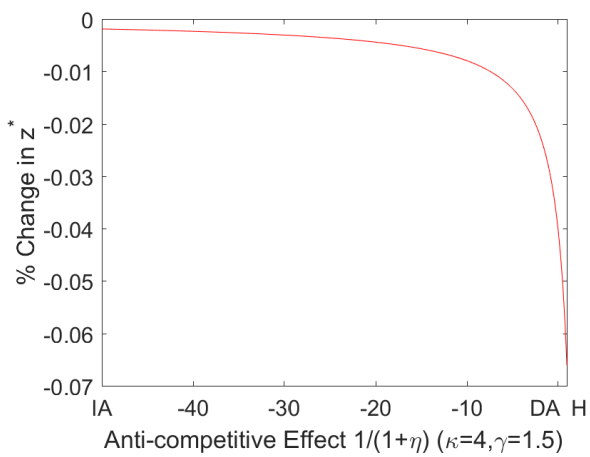
Substituting the quality cutoff $z^* = \frac{c}{a}\xi^{-(1+\eta)}$ into (39) yields the quality cutoff z^* as a function of g and model's parameters:

$$z^* = \left[\frac{Lc^{\frac{\eta}{1+\eta}}\gamma^{\gamma}b^{\kappa}a^{\gamma+\frac{1}{1+\eta}}}{f_E(1+\gamma)^{1+\gamma}}g^{-\kappa}(G_1(g) - (g-1)^{1+\gamma})\right]^{\frac{1}{\kappa-\gamma-\frac{1}{1+\eta}}} \tag{40}$$

where $g^{-\kappa}(G_1(g) - (g-1)^{1+\gamma})$ is decreasing in g. The parameter η controls the elasticity of the quality cutoff with respect to market size L and marginal costs c. In particular, the elasticity of the cutoff with respect to size is $\frac{\partial \ln z^*}{\partial \ln L} = \frac{1}{\kappa-\gamma-\frac{1}{1+\eta}}$. An increase in market size

induces selection effects, namely it increases the minimum level of quality allowed by the market, if such an elasticity is positive. Such a condition is satisfied for homothetic ($\eta = 0$) and DA preferences ($\eta = \infty$). However, under IA preferences ($\eta = -1$), where the cutoff is only dependent on income ($z^*_{\text{IA}} = \frac{c}{a}$), there are no selection effects due to market size.

Figure 5: z^* and Regulatory Restrictiveness



Percentage change in z^* following a 5% increase in g, from 1 to 1.05.

The market aggregator ξ equals:

$$\xi = \left[\frac{Lb^{\kappa}a^{\kappa}\gamma^{\gamma}}{f_E(1+\gamma)^{1+\gamma}c^{\kappa-\gamma-1}}g^{-\kappa}(G_1(g)-(g-1)^{1+\gamma})\right]^{-\frac{1}{(1+\eta)(\kappa-\gamma)-1}} \tag{41}$$

which equals one under DA preferences, decreases in g under IA preferences, and increases in g under homothetic preferences. The aggregator ξ is a quantity shifter that affects the volumes of production, along with z^*, of all surviving firms.

Substituting both (41) and (40) in the implicit definition of g (33), we obtain the expression shown in the main text

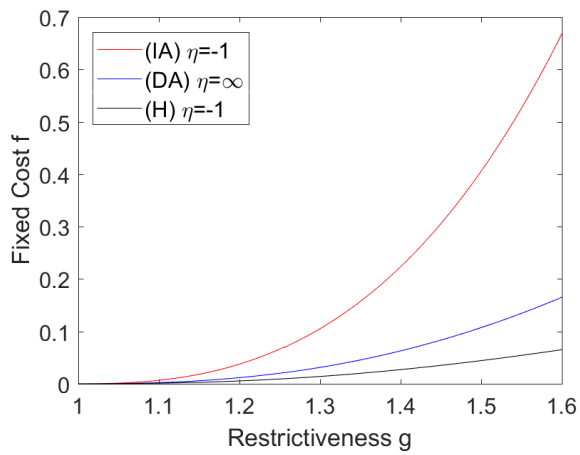
$$\left[\frac{b^{\kappa}}{f_E}\right]^{\frac{\gamma+\frac{1}{1+\eta}}{\kappa-\gamma-\frac{1}{1+\eta}}}\left[\frac{Lc^{\frac{\eta}{1+\eta}}\gamma^{\gamma}a^{\gamma+\frac{1}{1+\eta}}}{(1+\gamma)^{1+\gamma}}\right]^{\frac{\kappa}{\kappa-\gamma-\frac{1}{1+\eta}}}\left[g^{-\kappa}(G_1(g)-(g-1)^{1+\gamma})\right]^{\frac{\gamma+\frac{1}{1+\eta}}{\kappa-\gamma-\frac{1}{1+\eta}}}(g-1)^{1+\gamma} = f \tag{42}$$

which shows the mapping of f into g. We show numerically that the function

$$\left[g^{-\kappa}(G_1(g)-(g-1)^{1+\gamma})\right]^{\frac{\gamma+\frac{1}{1+\eta}}{\kappa-\gamma-\frac{1}{1+\eta}}}(g-1)^{1+\gamma}$$

is monotonically increasing in g in figure 6, for the most common values of the parameter η used in the literature. This supports our approach of examining the effects of g on welfare rather than the effects of the fixed cost f on welfare, since given the parameters of the model, there is only one value of the fixed cost that generates the restriction g.

Figure 6: Fixed Cost and Regulatory Restrictiveness



Mapping of the restrictiveness of regulation g into the fixed cost f (42). We compute $\left[g^{-\kappa}(G_1(g)-(g-1)^{1+\gamma})\right]^{\frac{\gamma+\frac{1}{1+\eta}}{\kappa-\gamma-\frac{1}{1+\eta}}}(g-1)^{1+\gamma}$ as a function of g. This leads to the fixed cost f, by normalizing $\left[\frac{b^{\kappa}}{f_E}\right]^{\frac{\gamma+\frac{1}{1+\eta}}{\kappa-\gamma-\frac{1}{1+\eta}}}\left[\frac{Lc^{\frac{\eta}{1+\eta}}\gamma^{\gamma}a^{\gamma+\frac{1}{1+\eta}}}{(1+\gamma)^{1+\gamma}}\right]^{\frac{\kappa}{\kappa-\gamma-\frac{1}{1+\eta}}}$ to one.

Firms' average revenues are:

$$\bar{r}=\int_{\bar{z}}^{\infty}r(z)\kappa\frac{\bar{z}^{\kappa}}{z^{\kappa+1}}dz=\frac{Lc}{1+\gamma}\left(\frac{a\gamma}{1+\gamma}\right)^{\gamma}\frac{(z^*)^{\gamma}}{\xi}G_2(g) \tag{43}$$

where $G_2(g)$ is a function of κ, γ, and g:

$$\begin{aligned}G_2(g)&=\int_{\bar{z}}^{\infty}\kappa\left(\frac{z}{z^*}-1\right)^{\gamma}\left(\frac{z}{z^*}+\gamma\right)\frac{\bar{z}^{\kappa}}{z^{\kappa+1}}dz=\\&=\int_{\bar{z}}^{\infty}\kappa\left(1-\frac{z^*}{z}\right)^{\gamma}\left(1+\gamma\frac{z^*}{z}\right)\frac{\bar{z}^{\kappa}}{(z^*)^{1+\gamma}z^{\kappa-\gamma}}dz=\\&=\kappa g^{1+\gamma}\left[\frac{F_1(g)}{\kappa-\gamma-1}+\gamma g^{-1}\frac{F_2(g)}{\kappa-\gamma}\right]\end{aligned} \tag{44}$$

Revenues normalized by average revenues, which we use in the calibration exercise, become:

$$\frac{r(z)}{\bar{r}}=(G_2(g))^{-1}\left(\frac{z}{z^*}-1\right)^{\gamma}\left(\frac{z}{z^*}+\gamma\right) \tag{45}$$

By market clearing:

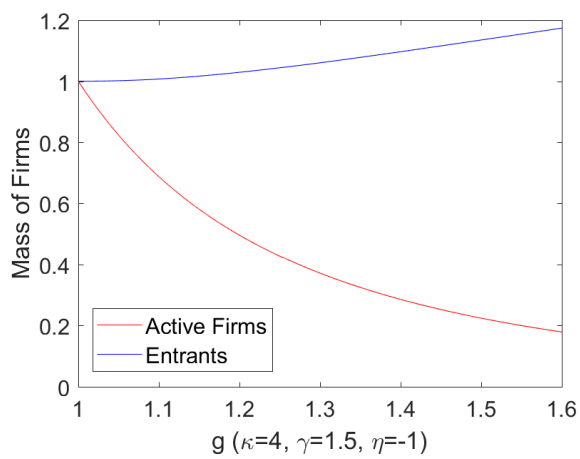
$$\frac{c}{1+\gamma}\left(\frac{a\gamma}{1+\gamma}\right)^{\gamma}\frac{Jb^{\kappa}}{(z^*)^{\kappa-\gamma}g^{\kappa}\xi}G_2(g)=1 \tag{46}$$

Dividing (46) by (38) yields the equilibrium mass of entrants, which is independent of η:

$$J = \frac{L}{f_E} \frac{G_1(g)}{G_2(g)}$$

As shown in Figure 7, market entry J is increasing in the restrictiveness of the standard. As an increase in g increases the average profits in the economy, more firms enter. However, the total number of active firms in the economy $N = P(z > \bar{z})J$ is declining in the restrictiveness of the standard.

Figure 7: Effects of a Standard on Entry and Selection



6.2.3 Welfare

To derive the utility, we need to derive the two integrals in (28) and (29). First, we obtain:

$$\int_{\bar{z}}^{\infty} a\xi z q(z) = a \left(\frac{a\gamma}{1+\gamma}\right)^{\gamma} \frac{Jb^{\kappa}}{(z^*)^{\kappa-\gamma} g^{\kappa}} z^* G_3(g) \tag{47}$$

where $G_3(g)$ is given by:

$$\begin{aligned} G_3(g) &= \int_{\bar{z}}^{\infty} \kappa \frac{z}{z^*} \left(\frac{z}{z^*} - 1\right)^{\gamma} \frac{\bar{z}^{\kappa}}{z^{\kappa+1}} dz = \\ &= \int_{\bar{z}}^{\infty} \kappa \left(1 - \frac{z^*}{z}\right)^{\gamma} \frac{\bar{z}^{\kappa}}{(z^*)^{1+\gamma} z^{\kappa-\gamma}} dz = \\ &= \kappa g^{1+\gamma} \left[\frac{F_1(g)}{\kappa - \gamma - 1}\right] \end{aligned} \tag{48}$$

Rearranging the market clearing condition,

$$\left(\frac{a\gamma}{1+\gamma}\right)^{\gamma} \frac{Jb^{\kappa}}{(z^*)^{\kappa-\gamma} g^{\kappa} \xi} = \frac{(1+\gamma)\xi}{cG_2(g)} \tag{49}$$

Using (49) into (47) yields:

$$\int_{\bar{z}}^{\infty} a\xi z q(z) = (1+\gamma)\frac{az^*\xi}{c}\left(\frac{G_3(g)}{G_2(g)}\right) \tag{50}$$

Following the same steps, we obtain the second integral:

$$\begin{aligned}\int_{\bar{z}}^{\infty} (\xi q(z))^{1+\frac{1}{\gamma}} &= \left(\frac{a\gamma}{1+\gamma}\right)^{1+\gamma}\frac{Jb^{\kappa}}{(z^*)^{\kappa-\gamma}g^{\kappa}}z^*G_1(g)\\ &= \frac{az^*\xi}{c}\gamma\left(\frac{G_1(g)}{G_2(g)}\right)\end{aligned} \tag{51}$$

Substituting (50) and (51) into the utility function (28) yields:

$$\begin{aligned}U &= \int_{\Omega}\left(az\xi q(\omega) - \frac{(\xi q(\omega))^{1+\frac{1}{\gamma}}}{1+\frac{1}{\gamma}}\right)d\omega + \frac{\xi^{-\eta}-1}{\eta}\\ &= \frac{az^*\xi}{c}\left[(1+\gamma)\frac{G_3(g)}{G_2(g)} - \frac{\gamma^2}{1+\gamma}\frac{G_1(g)}{G_2(g)}\right] + \frac{\xi^{-\eta}-1}{\eta}\end{aligned}$$

By the cutoff condition (6), $\xi^{-\eta} = \frac{a\xi z^*}{c}$. Thus, the utility becomes:

$$U = \frac{az^*\xi}{c}\left[(1+\gamma)\frac{G_3(g)}{G_2(g)} - \frac{\gamma^2}{1+\gamma}\frac{G_1(g)}{G_2(g)} + \frac{1}{\eta}\right] - \frac{1}{\eta}$$

The term $(1+\gamma)\frac{G_3(g)}{G_2(g)} - \frac{\gamma^2}{1+\gamma}\frac{G_1(g)}{G_2(g)}$, which is a component of the average utility, is always increasing in g. On the other hand, the product of the quality cutoff z^* and the aggregator ξ is declining in g. Finally, by the cutoff condition, $z^* = \frac{c}{a}\xi^{-1-\eta}$. Thus, the utility becomes:

$$U = \xi^{-\eta}\left[(1+\gamma)\frac{G_3(g)}{G_2(g)} - \frac{\gamma^2}{1+\gamma}\frac{G_1(g)}{G_2(g)} + \frac{1}{\eta}\right] - \frac{1}{\eta} \tag{52}$$

Substituting (41) into (52) yields:

$$U = \left[\frac{Lb^{\kappa}a^{\kappa}c^{\kappa-\gamma-1}\gamma^{\gamma}}{f_E(1+\gamma)^{1+\gamma}}g^{-\kappa}(G_1(g)-(g-1)^{1+\gamma})\right]^{\frac{\eta}{(1+\eta)(\kappa-\gamma)-1}}\left[(1+\gamma)\frac{G_3(g)}{G_2(g)} - \frac{\gamma^2}{1+\gamma}\frac{G_1(g)}{G_2(g)} + \frac{1}{\eta}\right] - \frac{1}{\eta}$$

which is the expression shown in the main text. For the IA, DA, and homothetic case, the utility equals:

$$\begin{aligned}U_{DA} &= \left[\frac{Lb^{\kappa}a^{\kappa}c^{\kappa-\gamma-1}\gamma^{\gamma}}{f_E(1+\gamma)^{1+\gamma}}g^{-\kappa}(G_1(g)-(g-1)^{1+\gamma})\right]^{\frac{1}{\kappa-\gamma}}\left[(1+\gamma)\frac{G_3(g)}{G_2(g)} - \frac{\gamma^2}{1+\gamma}\frac{G_1(g)}{G_2(g)}\right]\\ U_{IA} &= \left[\frac{Lb^{\kappa}a^{\kappa}c^{\kappa-\gamma-1}\gamma^{\gamma}}{f_E(1+\gamma)^{1+\gamma}}g^{-\kappa}(G_1(g)-(g-1)^{1+\gamma})\right]\left[(1+\gamma)\frac{G_3(g)}{G_2(g)} - \frac{\gamma^2}{1+\gamma}\frac{G_1(g)}{G_2(g)} - 1\right] + 1\end{aligned}$$

$$U_H = \frac{\ln\left[\frac{L\gamma^\gamma b^\kappa a^{\gamma+1}}{f_E(1+\gamma)^{1+\gamma}}\right]}{\kappa-\gamma-1} + \ln\left(\frac{a}{c}\right) + (1+\gamma)\frac{G_3(g)}{G_2(g)} - \frac{\gamma^2}{1+\gamma}\frac{G_1(g)}{G_2(g)} - \frac{\kappa \ln g}{\kappa-\gamma-1} + \frac{\ln(G_1(g)-(g-1)^{1+\gamma})}{\kappa-\gamma-1}$$

With the fixed cost, the government chooses $\bar{z}$. The equilibrium value of $z^*(g)$ is determined by the equation that describes the cutoff as a function of $z^*(g)$. The measure of the restrictiveness of the standard as the ratio between $\bar{z}$ and the market cutoff under no restriction $z^*(1)$ is given by:

$$\tilde{g} = \frac{\bar{z}}{z^*(1)} = \frac{\bar{z}}{z^*(g)}\frac{z^*(g)}{z^*(1)} = g\left[\frac{g^{-\kappa}(G_1(g)-(g-1)^{1+\gamma})}{G_1(1)}\right]^{\frac{1}{\kappa-\gamma-\frac{1}{1+\eta}}} \tag{53}$$

and exactly equals g under IA preferences.

The optimal level of the standard $\bar{z}^{opt}$ is then proportional to the market-determined cutoff:

$$\bar{z}^{opt} = g^{opt}(\kappa,\gamma,\eta)z^* \tag{54}$$

If we interpret z^* as a market determined preference for quality, markets with higher preference for quality have higher optimal quality standards while markets with a lower preference for quality have a lower optimal level of $\bar{z}$. To derive some quantitative intuition for the result, let us focus on the IA case, in which z^* is a constant. For $\kappa = 4$ and $\gamma = 1.5$, welfare is maximized at $g = 1.34$: the government sets a standard which reduces the probability of a firm being active by $|1.34^{-4} - 1| = 69\%$ relative to the market allocation.[56]

6.2.4 Equivalent Variation in Income

Let us consider $\tilde{U}$ as:

$$\tilde{U} = U + \frac{1}{\eta} = \left[\frac{Lb^\kappa a^\kappa \gamma^\gamma g^{-\kappa}(G_1(g)-(g-1)^{1+\gamma})}{f_E(1+\gamma)^{1+\gamma}c^{\kappa-\gamma-1}}\right]^{\frac{\eta}{(1+\eta)(\kappa-\gamma)-1}}\left[(1+\gamma)\frac{G_3(g)}{G_2(g)} - \frac{\gamma^2}{1+\gamma}\frac{G_1(g)}{G_2(g)} + \frac{1}{\eta}\right] \tag{55}$$

To spare some notation, let $G_4(g) = (1+\gamma)\frac{G_3(g)}{G_2(g)} - \frac{\gamma^2}{1+\gamma}\frac{G_1(g)}{G_2(g)} + \frac{1}{\eta}$, and $G_5(g) = G_1(g) - (g-1)^{1+\gamma}$ so that

$$\tilde{U} = \left[\frac{Lb^\kappa a^\kappa \gamma^\gamma g^{-\kappa} G_5(g)}{f_E(1+\gamma)^{1+\gamma}c^{\kappa-\gamma-1}}\right]^{\frac{\eta}{(1+\eta)(\kappa-\gamma)-1}} G_4(g) \tag{56}$$

Let $\hat{x} = x_{new}/x_{old}$. The change in the utility $\hat{\tilde{U}}$, due to a change in the restrictiveness of regulations $\hat{g}$ can be written as:

$$\hat{\tilde{U}} = \left(\hat{g}^{-\kappa}\widehat{G_5(g)}\right)^{\frac{\eta}{(1+\eta)(\kappa-\gamma)-1}}\widehat{G_4(g)}$$

[56] Under homothetic and DA preferences, z^* is a function of $\bar{z}$. Hence, the reduction in the probability of being active becomes $|(\tilde{g})^{-\kappa} - 1|$, where $\tilde{g} = \frac{\bar{z}}{z^*(1)} = g\left[\frac{g^{-\kappa}G_1(g)}{G_1(1)}\right]^{\frac{1}{\kappa-\gamma-\frac{1}{1+\eta}}}$.

Let us now consider the indirect utility function. First, we substitute $\xi^{-\eta}$ into the utility function. Second, using the inverse demand function, we substitute $\xi q(z) = \left(az - \frac{p(z)}{W\xi^{1+\eta}}\right)^{\gamma}$, where $W = y + EV$ and EV is the equivalent variation in income. Thus, we obtain:

$$\begin{aligned}\tilde{U} &= \int \left[a\left(1+\frac{1}{\eta}\right) z(\xi q(z)) - \left(\frac{1}{\eta}+\frac{\gamma}{1+\gamma}\right)(\xi q(z))^{1+\frac{1}{\gamma}}\right] f(z)dz = \\ &= \int \left[a\left(1+\frac{1}{\eta}\right) z\left(az - \frac{p(z)}{W\xi^{1+\eta}}\right)^{\gamma} - \left(\frac{1}{\eta}+\frac{\gamma}{1+\gamma}\right)\left(az - \frac{p(z)}{W\xi^{1+\eta}}\right)^{\gamma+1}\right] f(z)dz\end{aligned}$$

So, the indirect utility function equals:

$$V(W,\mathbf{p}) = \frac{Jb^{\kappa}}{\bar{z}^{\kappa}} \int_{\bar{z}}^{\infty} \left[a\left(1+\frac{1}{\eta}\right) z\left(az - \frac{p(z)}{W\xi^{1+\eta}}\right)^{\gamma} - \left(\frac{1}{\eta}+\frac{\gamma}{1+\gamma}\right)\left(az - \frac{p(z)}{W\xi^{1+\eta}}\right)^{\gamma+1}\right] f(z)dz$$

We now take the derivative of $V(W,\mathbf{p})$ with respect to W holding prices constant. Since $z^* = \frac{c}{a}\xi^{-(1+\eta)}$, and z^* affects markups, it follows that we keep ξ constant as well.

$$\begin{aligned}\frac{dV(W,\mathbf{p})}{dW} &= \frac{Jb^{\kappa}}{\bar{z}^{\kappa}} \int_{\bar{z}}^{\infty} \left[a\gamma\left(1+\frac{1}{\eta}\right) z\left(az - \frac{p(z)}{W\xi^{1+\eta}}\right)^{\gamma-1} \frac{p(z)}{W^2\xi^{1+\eta}} + \right. \\ &\left. - (1+\gamma)\left(\frac{1}{\eta}+\frac{\gamma}{1+\gamma}\right)\left(az - \frac{p(z)}{W\xi^{1+\eta}}\right)^{\gamma} \frac{p(z)}{W^2\xi^{1+\eta}}\right] f(z)dz = \\ &= \frac{Jb^{\kappa}}{W\bar{z}^{\kappa}} \int_{\bar{z}}^{\infty} \left[\left(az - \frac{p(z)}{W\xi^{1+\eta}}\right)^{\gamma} \frac{p(z)}{W\xi^{1+\eta}} \left(a\gamma\left(1+\frac{1}{\eta}\right) z\left(az - \frac{p(z)}{W\xi^{1+\eta}}\right)^{-1} + \right.\right. \\ &\left.\left. -(1+\gamma)\left(\frac{1}{\eta}+\frac{\gamma}{1+\gamma}\right)\right)\right] f(z)dz = \\ &= \frac{Jb^{\kappa}}{W\bar{z}^{\kappa}} \int_{\bar{z}}^{\infty} \left[\left(az - \frac{p(z)}{W\xi^{1+\eta}}\right)^{\gamma} \frac{p(z)}{W\xi^{1+\eta}} \left(\frac{az\gamma(1+\eta)}{\eta\left(az - \frac{p(z)}{W\xi^{1+\eta}}\right)} - \left(\frac{1+\gamma}{\eta}+1\right)\right)\right] f(z)dz\end{aligned}$$

Hence, expressing the derivative in log terms, i.e. the derivative of $d\ln V$ with respect to $d\ln W$, we obtain:

$$d\ln V = \frac{\int_{\bar{z}}^{\infty} \left[\left(az - \frac{p(z)}{W\xi^{1+\eta}}\right)^{\gamma} \frac{p(z)}{W\xi^{1+\eta}} \left(\frac{az\gamma(1+\eta)}{\eta\left(az - \frac{p(z)}{W\xi^{1+\eta}}\right)} - \left(\frac{1+\gamma}{\eta}+1\right)\right)\right] f(z)dz}{\int_{\bar{z}}^{\infty} \left[a\left(1+\frac{1}{\eta}\right) z\left(az - \frac{p(z)}{W\xi^{1+\eta}}\right)^{\gamma} - \left(\frac{1}{\eta}+\frac{\gamma}{1+\gamma}\right)\left(az - \frac{p(z)}{W\xi^{1+\eta}}\right)^{\gamma+1}\right] f(z)dz} d\ln W \tag{57}$$

Substituting $\frac{p(z)}{\xi^{1+\eta}} = y(az - (\xi q(z))^{\frac{1}{\gamma}}$ and solving the expression generates hypergeometric functions that depend both on g and EV. Integrating for $EV \in [0, W-y]$ yields the equivalent change in welfare. However, such an expression is quite complicated and requires numerical integration. Thus, we use the local approximation, which can be obtained by

setting $y = W$. Recall that

$$p(z) = \frac{c}{1+\gamma}\left(\frac{z}{z^*} + \gamma\right)$$

and

$$\frac{1}{\xi^{1+\eta}} = \frac{az^*}{c}$$

which implies that

$$az - \frac{p(z)}{\xi^{1+\eta}} = az - \frac{acz^*}{c(1+\gamma)}\left(\frac{z}{z^*} + \gamma\right) = \frac{a\gamma}{1+\gamma}(z - z^*)$$

Substituting these two results yields:

$$d\ln V = \frac{\int_{\bar{z}}^{\infty}(z-z^*)^{\gamma}(z+\gamma z^*)\left(\left(\frac{1+\eta}{\eta}\right)z(z-z^*)^{-1} - \frac{1}{1+\gamma} - \frac{1}{\eta}\right)f(z)dz}{\int_{\bar{z}}^{\infty}\left[\left(\frac{1+\eta}{\eta}\right)z(z-z^*)^{\gamma} - \left(\frac{1}{\eta} + \frac{\gamma}{1+\gamma}\right)\left(\frac{\gamma}{1+\gamma}\right)(z-z^*)^{\gamma}\right]f(z)dz} d\ln W \tag{58}$$

Let's solve each integral separately:

$$\begin{aligned}
&\int_{\bar{z}}^{\infty}(z-z^*)^{\gamma-1}(z+\gamma z^*)\kappa z^{-\kappa}\bar{z}^{\kappa}dz = \int_{\bar{z}}^{\infty}\left(1-\frac{z^*}{z}\right)^{\gamma-1}\left(1+\gamma\frac{z^*}{z}\right)\kappa z^{-\kappa+\gamma}\bar{z}^{\kappa}dz = \\
&\quad = \kappa\bar{z}^{\gamma+1}\left(\frac{F_3(g)}{\kappa-\gamma-1} + \frac{g^{-1}\gamma F_4(g)}{\kappa-\gamma}\right) \\
&\int_{\bar{z}}^{\infty}(z-z^*)^{\gamma}(z+\gamma z^*)\kappa dz = \int_{\bar{z}}^{\infty}\left(1-\frac{z^*}{z}\right)^{\gamma}\left(1+\gamma\frac{z^*}{z}\right)\kappa z^{-\kappa+\gamma}\bar{z}^{\kappa}dz \\
&\quad = \kappa\bar{z}^{1+\gamma}\left[\frac{F_1(g)}{\kappa-\gamma-1} + \gamma g^{-1}\frac{F_2(g)}{\kappa-\gamma}\right] = G_2(g)(z^*)^{1+\gamma} \\
&\int_{\bar{z}}^{\infty}(z-z^*)^{\gamma}\kappa z^{-\kappa+\gamma}\bar{z}^{\kappa}dz = \int_{\bar{z}}^{\infty}\left(1-\frac{z^*}{z}\right)^{\gamma}\kappa z^{-\kappa+\gamma}\bar{z}^{\kappa}dz = \\
&\quad = \kappa\bar{z}^{1+\gamma}\frac{F_1(g)}{\kappa-\gamma-1} \\
&\int_{\bar{z}}^{\infty}(z-z^*)^{\gamma}\kappa z^{-\kappa-1}\bar{z}^{\kappa}dz = \int_{\bar{z}}^{\infty}\left(1-\frac{z^*}{z}\right)^{\gamma+1}\kappa z^{-\kappa+\gamma}\bar{z}^{\kappa}dz = \\
&\quad = \kappa\bar{z}^{1+\gamma}\left[\frac{F_1(g)}{\kappa-\gamma-1} - g^{-1}\frac{F_2(g)}{\kappa-\gamma}\right] = G_1(g)(z^*)^{1+\gamma}
\end{aligned}$$

where

$$\begin{aligned}
F_3(g) &= {}_2F_1(1-\gamma, \kappa-\gamma-1; \kappa-\gamma; g^{-1}) \\
F_4(g) &= {}_2F_1(1-\gamma, \kappa-\gamma; \kappa-\gamma+1; g^{-1})
\end{aligned}$$

Hence,

$$d\ln V = \frac{\left(\frac{1+\eta}{\eta}\right)\left(\frac{F_3(g)}{\kappa-\gamma-1}+\frac{g^{-1}\gamma F_4(g)}{\kappa-\gamma}\right)-\left(\frac{1}{1+\gamma}+\frac{1}{\eta}\right)\left[\frac{F_1(g)}{\kappa-\gamma-1}+\gamma g^{-1}\frac{F_2(g)}{\kappa-\gamma}\right]}{\left(\frac{1+\eta}{\eta}\right)\frac{F_1(g)}{\kappa-\gamma-1}-\left(\frac{1}{\eta}+\frac{\gamma}{1+\gamma}\right)\left(\frac{\gamma}{1+\gamma}\right)\left[\frac{F_1(g)}{\kappa-\gamma-1}-g^{-1}\frac{F_2(g)}{\kappa-\gamma}\right]} d\ln W \tag{59}$$

Therefore, to compute the welfare effect of changes in regulation we use the following formula:

$$d\ln W = \frac{\left(\frac{1+\eta}{\eta}\right)\frac{F_1(g)}{\kappa-\gamma-1}-\left(\frac{1}{\eta}+\frac{\gamma}{1+\gamma}\right)\left(\frac{\gamma}{1+\gamma}\right)\left[\frac{F_1(g)}{\kappa-\gamma-1}-g^{-1}\frac{F_2(g)}{\kappa-\gamma}\right]}{\left(\frac{1+\eta}{\eta}\right)\left(\frac{F_3(g)}{\kappa-\gamma-1}+\frac{g^{-1}\gamma F_4(g)}{\kappa-\gamma}\right)-\left(\frac{1}{1+\gamma}+\frac{1}{\eta}\right)\left[\frac{F_1(g)}{\kappa-\gamma-1}+\gamma g^{-1}\frac{F_2(g)}{\kappa-\gamma}\right]}\hat{\bar{U}}$$

6.2.5 Product Standards as Exogenous Cutoff

In this section, we briefly outline the welfare effects of product standards modeled as an exogenous cutoff $\bar{z}$, which does not require all active firms to pay a fixed cost f. This is equivalent to having all firms below the minimum quality standard pay a prohibitive fixed cost, which forces their exit. Analytically, the only change is in the average profits, which equal

$$\bar{\pi} = \frac{Lc}{1+\gamma}\left(\frac{a\gamma}{1+\gamma}\right)^{\gamma}\frac{(z^*)^{\gamma}}{\xi}G_1(g) \tag{60}$$

The utility of consumer equals:

$$U = \left[\frac{Lb^{\kappa}a^{\kappa}\gamma^{\gamma}}{f_E(1+\gamma)^{1+\gamma}c^{\kappa-\gamma-1}}g^{-\kappa}G_1(g)\right]^{\frac{\eta}{(1+\eta)(\kappa-\gamma)-1}}\left[(1+\gamma)\frac{G_3(g)}{G_2(g)}-\frac{\gamma^2}{1+\gamma}\frac{G_1(g)}{G_2(g)}+\frac{1}{\eta}\right]-\frac{1}{\eta} \tag{61}$$

In figure 8, we plot the optimal level of the regulations as a function of the anti-competitive effect captured by the term $1/(1+\eta)$. By comparing Figures 2 and 8, it is clear that the effect of imposing the change in cutoff via a fixed cost is a downward shift in the optimal regulation.

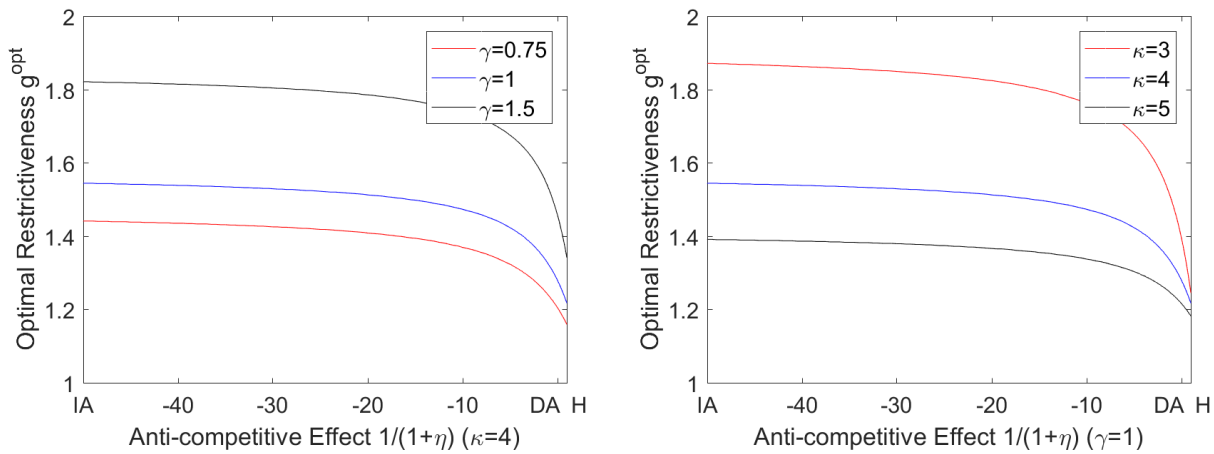
Since a quality standard $\bar{z}$ can improve welfare because the market allocation is inefficient, the rest of the subsection is devoted to understand in detail which distortions are reduced by a standard, and how these differ across the types of preferences. There are three possible margins through which the market equilibrium is inefficient: entry, selection, and the distribution of markups across active firms. However, the assumption of Pareto distributed quality and monopolistic competition constrains the margins of inefficiency present in our model to the allocation of production across entrants (the latter two).[57]

To understand these two margins, we recap the two biases identified in Dhingra and Morrow (2019) (DM). The first type of distortion is due to lack of appropriability: in making their production decision, firms do not take into account the social gains from an increase in variety. Letting z_P^* denote the optimal cutoff chosen by a planner, this "appropriation

[57] The mass of entrants J is always efficient in the market allocation (Arkolakis et al., 2019).

Figure 8: Optimal g as a function of $1/(1+\eta)$

(a) As a function of γ **(b)** As a function of κ



bias" causes an excessive degree of firms' selection, whereby $z^* > z^*_{\mathrm{P}}$ all else equal. Firm heterogeneity in market power generates the second distortion: in making their production decision, firms do not take into account how their choice alters production and prices of other firms. This "business stealing" effect (DM and Mankiw and Whinston (1986)) reduces selection below the optimum, i.e. $z^* < z^*_{\mathrm{P}}$, because it allows low-quality firms to steal business from high-quality firms.[58] Moreover, the business stealing bias distorts the quantity of production across firms. High-quality firms under-produce as their markups are too high and low-quality firms over-produce, relative to the efficient allocation.

The quality standard affects welfare in two opposing directions, both of which can be understood through its effect on markups. First, the standard raises the *average markup* through a composition effect which works purely through a reallocation of market shares and bring the economy closer to the socially optimal average markup.[59] That misallocation is reduced when average markups increase might seem counter-intuitive, but in fact allocative efficiency increases as market share is reallocated away from low-quality firms and to high-quality firms, a channel highlighted with productivity heterogeneity in recent work by Edmond et al. (2018), Baqaee and Farhi (2020), and Weinberger (2020). The standard eliminates low-quality firms, reducing the distortion that affects selection, and furthermore causes a reallocation of production towards high-quality firms, therefore reducing the distortion on the distribution of quantities produced. These are the two inefficiency margins discussed above. Second, the standard reduces the number of varieties. Such a reduction, which is welfare reducing in and of itself, can lead to anti-competitive results. As discussed above, the standard can reduce competition and thus raises the markup of *each surviving firm*. For small values of g, the composition effect dominates for any η.[60]

[58] The Dhingra and Morrow (2019) results are in fact applicable to our framework with firms differentiated in quality instead of productivity.

[59] The social planner chooses to equalize markups across firms at $m = \frac{\kappa-\gamma}{\kappa-\gamma-1}$.

[60] We note, the quality standard is not first-best. It raises expected profits, which induces too much entry, and cannot bring the economy to the efficient allocation.

6.2.6 Market Allocation and Planner's Allocation

In the following paragraphs, we describe these market inefficiencies that emerge for each of the three specific cases of GTP preferences. To do so, we compare the main variables of interest between the social planner's allocation and the market's allocation. Details of the planner's allocation are in the Web Appendix.

IA Preferences. Under IA preferences ($\eta = -1$), the market allocation always generates a business stealing bias. The ratio of the planner's quality cutoff relative to the market cutoff is always greater than one: $\left(\frac{z_P^*}{z^*(1)}\right)_{IA} = \frac{\kappa-\gamma}{\kappa-\gamma-1} > 1$. As a result, low-quality firms over-produce and high-quality firms under-produce relative to the planner's allocation. The composition effect of the standard reduces the business stealing bias, by forcing the exit of low-quality firms and increasing the production of surviving firms. Although the anti-competitive effect is absent, the average markup in the economy increases because of the composition effect.

DA Preferences. Under DA preferences ($\eta \to \infty$), the market allocation generates business stealing bias, provided that $\gamma > 0$ and, thus, demand is not fully rigid. The ratio of the planner's cutoff to the market cutoff is $\left(\frac{z_P^*}{z^*(1)}\right)_{DA} = \left(1 + \frac{1}{\gamma}\right)^{\frac{\gamma}{\kappa-\gamma}} \geq 1$. For $\gamma > 0$, a quality standard improves welfare, by reducing the business stealing bias. For $\gamma = 0$, the bias disappears and the standard cannot improve welfare. The main difference relative to the IA case is that a standard has anti-competitive effect under DA preferences: as the standard reduces the number of firms in the market, the lower competitive pressure allows for surviving firms to charge higher markups, limiting the benefits of the standard.

Homothetic Preferences. Under homothetic preferences ($\eta = 0$), the ratio of the planner's cutoff relative to the market cutoff is $\left(\frac{z_P^*}{z^*(1)}\right)_{H} = \left(1 + \frac{1}{\gamma}\right)^{\frac{\gamma}{\kappa-\gamma-1}} \left(1 - \frac{1}{\kappa-\gamma}\right)^{\frac{1}{\kappa-\gamma-1}}$, and it could be smaller or greater than one depending on the parameters of the model.[61] If the ratio is greater than one, the effects of a standard are qualitatively similar to the DA case.

In the presence of a dominating appropriation bias, a quality standard can still improve welfare, although by a somewhat smaller magnitude relative to the case in which there is too little selection. The reason for this seemingly surprising result is that the market allocation generates a markup distribution that is different from the constant markup that a planner would choose. In particular, markups are on average too small in the market relative to the planner's allocation. The quality standard improves upon such misallocation, despite exacerbating the already too high level of selection. Therefore, one important conclusion from our analysis is that the market distortions are driven entirely by the presence of variable markups, and exist in both homothetic and non-homothetic preferences.

[61] The business stealing bias dominates, if $\kappa > \gamma + \left(1 - \left(1 + \frac{1}{\gamma}\right)^{-\gamma}\right)^{-1}$. Since regularity conditions imply that $\kappa > \gamma + 1$, there is a region for small enough κ, in which appropriation bias dominates. For instance, for the linear case $\gamma = 1$, there is too much selection if $\kappa \in (2, 3)$. Such a case is not quantitatively relevant: in the estimation of a model with homothetic preferences (in the robustness figures of Appendix 6.4) we confirm that this case is not present in any of the 16 sectors.

6.2.7 Productivity Heterogeneity and Quality

The baseline model features the simplifying assumption that firms differ exogenously in terms of quality. However, most papers in the literature model firms that differ in terms of productivity and that product quality is a function of firm's productivity (Manova and Zhang, 2017; Feenstra and Weinstein, 2017). This section shows that the results of our baseline model also arise in a model in which quality is a function of firm's productivity. The results of this section rely on the model in which quality standards are represented by an exogenous cutoff.

Consider an extension to the baseline model in which firms differ in terms of productivity ϕ. As it is common in the literature, we assume that ϕ follows a Pareto distribution with CDF: $1 - \left(\frac{\tilde{b}}{\phi}\right)^{\tilde{\kappa}}$. Similarly to the framework of Manova and Zhang (2017), firm's quality is proportional to firm's productivity: $z = \phi^{\frac{1}{\theta}}$, with $\theta > 0$. Moreover, we let the marginal cost of the firm ϕ be proportional to the quality. In particular, marginal costs are equal to cz^{β}. We assume that the elasticity of marginal costs with respect to quality is less than one: $\beta < 1$. This assumption is made for average revenues to be well defined.[62] To obtain a closed form expression for the utility, we restrict the analysis to the linear GTP case, namely $\gamma = 1$.

Firm's profits become

$$\pi(z) = L\xi^{1+\eta}\left[azq(z) - \xi(q(z))^2\right] - Lcz^{\beta}q(\omega)$$

Profit maximization yields the following optimal quantity:

$$q(z) = \left(\frac{a}{2}\right)\frac{z^*}{\xi}\left(\frac{z}{z^*} - \left(\frac{z}{z^*}\right)^{\beta}\right)$$

where the market determined quality cutoff equals:

$$z^* = \left(\frac{c}{a\xi^{1+\eta}}\right)^{\frac{1}{1-\beta}}$$

Using the quality cutoff, we can rewrite the performance variables of the firm as follows:

$$p(z) = \frac{c(z^*)^{\beta}}{2}\left(\frac{z}{z^*} + \left(\frac{z}{z^*}\right)^{\beta}\right)$$
$$r(z) = \frac{Lca}{4}\frac{(z^*)^{\beta+1}}{\xi}\left(\left(\frac{z}{z^*}\right)^2 - \left(\frac{z}{z^*}\right)^{2\beta}\right)$$
$$\pi(z) = \frac{Lca}{4}\frac{(z^*)^{\beta+1}}{\xi}\left(\frac{z}{z^*} - \left(\frac{z}{z^*}\right)^{\beta}\right)^2$$

[62] Modeling an endogenous quality choice as (Gaigné and Larue, 2016), in which firms must also pay a fixed cost is highly intractable under GTP preferences. We verified that such a technological assumption does not generate additional distortions in a model with standard CES preferences.

Let us derive the probability distribution for quality. In particular,

$$Pr(\tilde{z} \leq z) = Pr(\phi^{\frac{1}{\theta}} \leq z) = 1 - \left(\frac{\tilde{b}}{z^{\theta}}\right)^{\tilde{\kappa}}$$

Thus, we can change the notation and derive the same distribution for quality we used in the baseline model. In fact, quality z follows a Pareto distribution with shape parameter $\kappa = \tilde{\kappa}\theta$ and shift parameter $b = \tilde{b}^{\frac{1}{\theta}}$.

Following the same procedure as the baseline model, the utility of the representative consumer becomes:

$$U = \left[\frac{Lb^{\kappa}a^{\kappa-2\beta}}{4f_E c^{\kappa-2}} g^{-\kappa} G_1(g)\right]^{\frac{\eta(1-\beta)}{(1+\eta)(\kappa-1)-1-\beta\eta}} \left[2\frac{G_3(g)}{G_2(g)} - \frac{1}{2}\frac{G_1(g)}{G_2(g)} + \frac{1}{\eta}\right] - \frac{1}{\eta}$$

where

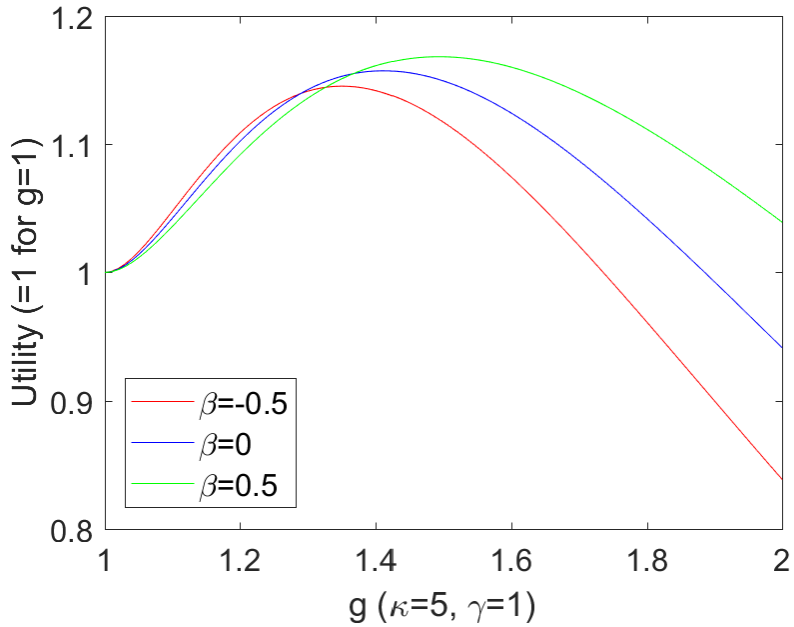
$$G_1(g) = \frac{\kappa g^2}{\kappa - 2} - \frac{2\kappa g^{\beta+1}}{\kappa - \beta - 1} + \frac{\kappa g^{2\beta}}{\kappa - 2\beta}$$
$$G_2(g) = \frac{\kappa g^2}{\kappa - 2} - \frac{\kappa g^{2\beta}}{\kappa - 2\beta}$$
$$G_3(g) = \frac{\kappa g^2}{\kappa - 2} - \frac{\kappa g^{\beta+1}}{\kappa - \beta - 1}$$

Figure 9 shows the relationship between welfare and the restrictiveness of the standard for different values of β, under IA preferences. For $\beta = 0$, this extension becomes identical to the baseline model. This implies that our baseline model with firms heterogeneous in quality is equivalent to a model in which firms differ in terms of productivity, and their productivity is proportional to their product quality. The result is independent of the level of θ, as long as the two models match the same distribution of sales.

For $\beta \neq 0$, the marginal costs of production depends on quality. If $\beta < 0$, firm's with high quality also have lower production costs. This scenario assumes that more productive firms have higher quality and attain cost efficiency. When $\beta < 0$, the sales difference between low-quality firms and high-quality firms increases relative to the baseline model, since high-quality firms are also low-cost firms. In this case, the business stealing bias is reduced relative to the baseline model. Hence, the optimal level of g is smaller.

On the other hand, $\beta > 0$ yields the more realistic scenario in which high-quality firms have higher costs of production than low-quality firms (Manova and Zhang, 2017). In this scenario, the business stealing bias is larger than the baseline case. There are too many low-quality firms operating in the market because 1) their markups are lower and 2) their marginal costs are lower. As a result, when marginal costs and quality are positively correlated the positive welfare effects of the standard are larger. The result also arises under DA and homothetic preferences. Details are available upon request.

Figure 9: Minimum Quality Standard and Welfare ($\eta = -1$)



6.3 Consumption Externality

Solving the integrals of the function E (18), we obtain:

$$\int_{\bar{z}}^{\infty} q(z)dz = \left(\frac{a\gamma}{1+\gamma}\right)^{\gamma} \frac{\kappa(z^*)^{\gamma} g^{\gamma}}{\xi} \left(\frac{F_2(g)}{\kappa-\gamma}\right)$$
$$\int_{\bar{z}}^{\infty} q(z)z^{\beta}dz = \left(\frac{a\gamma}{1+\gamma}\right)^{\gamma} \frac{\kappa(z^*)^{\beta+\gamma} g^{\beta+\gamma}}{\xi} \left(\frac{F_1(\beta,g)}{\kappa-\gamma-\beta}\right)$$

where

$$F_1(\beta, g) =_2 F_1(\kappa-\gamma-\beta, -\gamma; \kappa-\gamma-\beta+1; g^{-1})$$

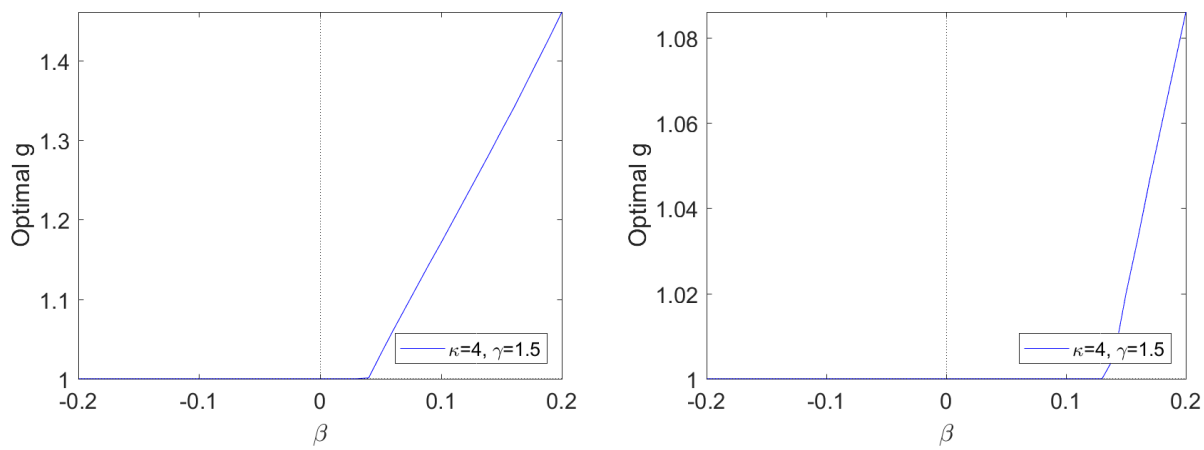
Hence, the externality equals:

$$E = (z^* g)^{\beta} \frac{F_1(\beta, g)(\kappa-\gamma)}{F_2(g)(\kappa-\gamma-\beta)} \tag{62}$$

and we can plug it in the utility of the consumer to find the optimal level of regulations. Figure 10 shows the optimal g under DA and homothetic preferences for different values of β.

Figure 10: Optimal g and Externality

(a) DA **(b)** H



6.4 Estimation

6.4.1 Price Elasticity Moments

Let us first consider the sales-weighted price elasticity with respect to income. In our model, per capita income is normalized to one, since we are looking at a closed economy case. However, it can be shown that the price elasticity of income is identical to (minus) the price elasticity with respect to the unit labor requirements c. The price elasticity with respect to c equals:

$$\epsilon_y(z) = \frac{d\ln p(z)}{d\ln y} = -\frac{d\ln p(z)}{d\ln c} = \left(\frac{d\ln z^*}{d\ln g}\right)\left(1+\gamma\frac{z^*}{z}\right)^{-1} \tag{63}$$

We consider the sales-weighted average price elasticity with respect to c, which equals:

$$\bar{\epsilon}_y = \left(\frac{d\ln z^*}{d\ln c}\right)(G_2(g))^{-1}\frac{g^{1+\gamma}\kappa F_1(g)}{\kappa-\gamma-1}$$

Finally, the elasticity of the cutoff with respect to c is:

$$\frac{d\ln z^*}{d\ln c} = \frac{\frac{\eta}{1+\eta}}{\kappa-\gamma-\frac{1}{1+\eta}} \tag{64}$$

Similarly, the price elasticity with respect to market size, L:

$$\bar{\epsilon}_L(z) = \frac{d\ln p(z)}{d\ln L} = \frac{1}{\kappa-\gamma-\frac{1}{1+\eta}}(G_2(g))^{-1}\frac{g^{1+\gamma}\kappa F_1(g)}{\kappa-\gamma-1} \tag{65}$$

6.4.2 Estimation of Targets for Price Elasticity Moments

As described in the previous subsection, our estimation targets $\frac{d \ln p(z)}{d \ln y}$ and $\frac{d \ln p(z)}{d \ln L}$. The most rigorous attempt we are aware of to estimate these elasticities is Simonovska (2015), which compares prices of identical products (from the same retailer) sold across a variety of destinations. The closest we can get with Chilean firms is through exports from customs data that allows us to compute unit values at the transaction level.[63] Customs export data includes all exports transactions from Chile, and is acquired from the Chilean Central Bank. To restrict to cross-sectional variation we only use 2007 data (the year with the most observations in our data), which includes 53,232 observations with price data. Due to fixed effects, the sample estimated includes only firm-product combinations with multiple destinations (about 60% of the sample).

The Chilean export data is run on the following specification:

$$\ln p_{fpd} = \alpha_{fp} + \beta_y \ln y_d + \beta_L \ln L_d + Z_d + \epsilon_{fpd}, \tag{66}$$

where unit values vary at the firm-product-destination level. We control for firm-product fixed effects to capture only firm-product combinations with sales to multiple destinations. As destination controls, we have a set of "*gravity*" measures relative to Chile (i.e distance, common colony, colonial history, religion, border dummy, and language), as well as average tariffs and NTMs with Chile as the origin. Further we control for Chile's total exports to the destination relative to their GDP, the total number of products Chile sends to the destination (*scope*), and the destination's openness (average of its total imports and exports). The data for destination aggregates is from the Penn World Tables. We cluster our standard error at the destination level (60 destinations).

The coefficient on per-capita income (y) is 0.084 (t-stat = 4.36), while that on market size (L) is -0.012 (which is not significantly different from 0). Compared to Simonovska (2015), the market size elasticity is similarly small and not statistically different from 0 (though our coefficient is slightly smaller). Our income elasticity is also positive, although again smaller. The second columns repeats our specification with no controls and the income elasticity increases marginally to close to 0.10. We do caution that customs data cannot account for the possibility that the same HS6 product sold to different destinations reflects different varieties (not necessarily of equal quality). For that reason, the estimates in Simonovska (2015) provide a useful comparison, and we note that our main results are quantitatively extremely similar if we target estimates from that paper.

6.4.3 Sales Moments

Figure 11 displays the results for the benchmark manufacturing-wide estimation for each year. We show results for the years 1995, 2000, 2005. We compare the CDF of the log sales distribution in the data with that implied by the estimated model. Figure 12 displays the result under the alternative calibration in which we target only 4 moments: the sales

[63] For obvious reasons, these moments cannot be estimated with only Chile as the destination (as in the Chilean census data or the EDD data with Chile as the origin) as it requires variation in income and competition across destinations. We believe the closest possible dataset is to use a dataset with Chilean firms selling to various destinations.

Table 17: Log Price Regressions in Exports Customs Data: Effect of Income and Population

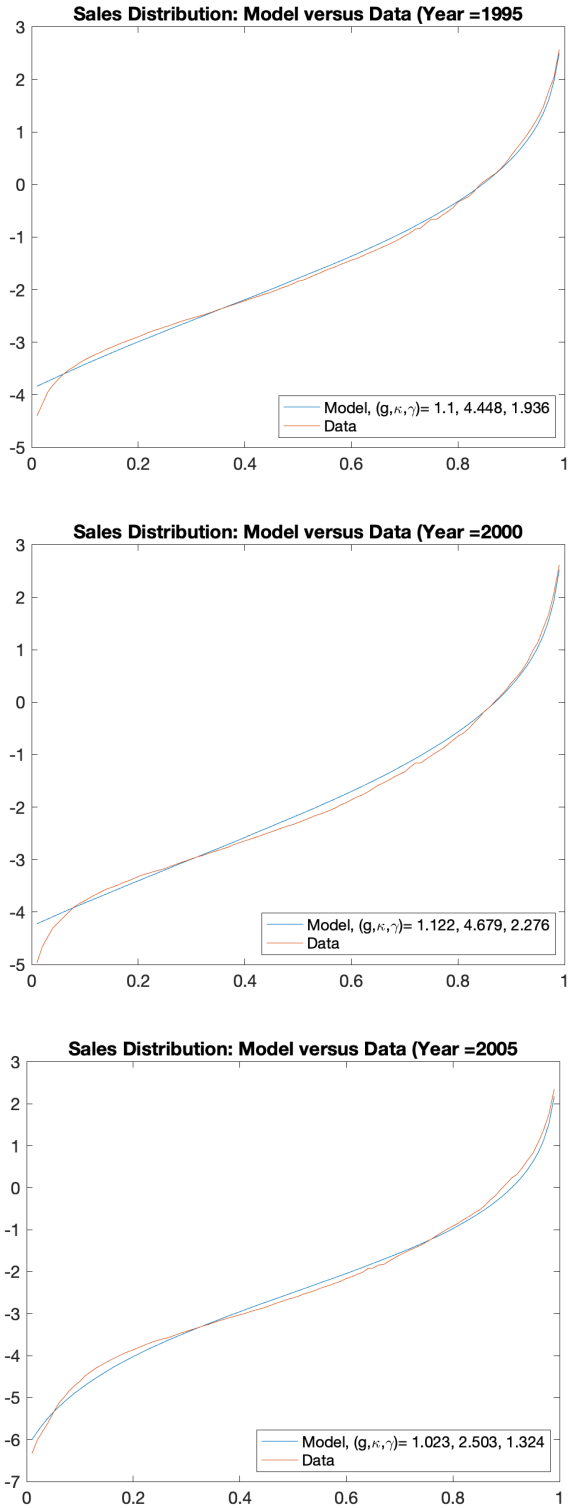
	(1) Log Price - Benchmark	(2) Log Price - No Controls
Log Per-Capital GDP	0.084***	0.098***
	(0.019)	(0.018)
Log Population	-0.012	0.002
	(0.010)	(0.008)
Scope to Dest.	-0.086***	
	(0.015)	
TM's	-0.002	
	(0.006)	
Exports to Dest.	-0.007	
	(0.009)	
Tariffs	0.038	
	(0.261)	
Dest. Openness	-0.121**	
	(0.057)	
Fixed Effects	Firm-Product	Firm-Product
Obs.	30,152	30,978
R2	0.638	0.639

In this table, we estimate the elasticity of prices with respect to income and market size (a proxy for competition). Price is the unit value in customs reports (value over quantity exported). We do not report the gravity controls, which include log distance, indicators for a common colony, whether destination was a colony, a common religion, a common border, and a common language. Customs export data includes all exports transactions from Chile, and is acquired from the Chilean Central Bank. To restrict to cross-sectional variation we only use 2007 data, which includes 53,232 observations with price data. Due to fixed effects (always firm-product interactions), the sample estimated includes only firm-product combinations with multiple destinations (about 60% of the sample). Standard errors – clustered by destination – are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

advantage of "high-quality" relative to "low-quality" firms; the skewness of the distribution; and two differences: $\log(\tilde{r})_{99} - \log(\tilde{r})_{90}$ and $\log(\tilde{r})_{90} - \log(\tilde{r})_{10}$. Figure 13 plots the simulated sales distribution when we set $\kappa = 4$ and $\gamma = 1.8$.

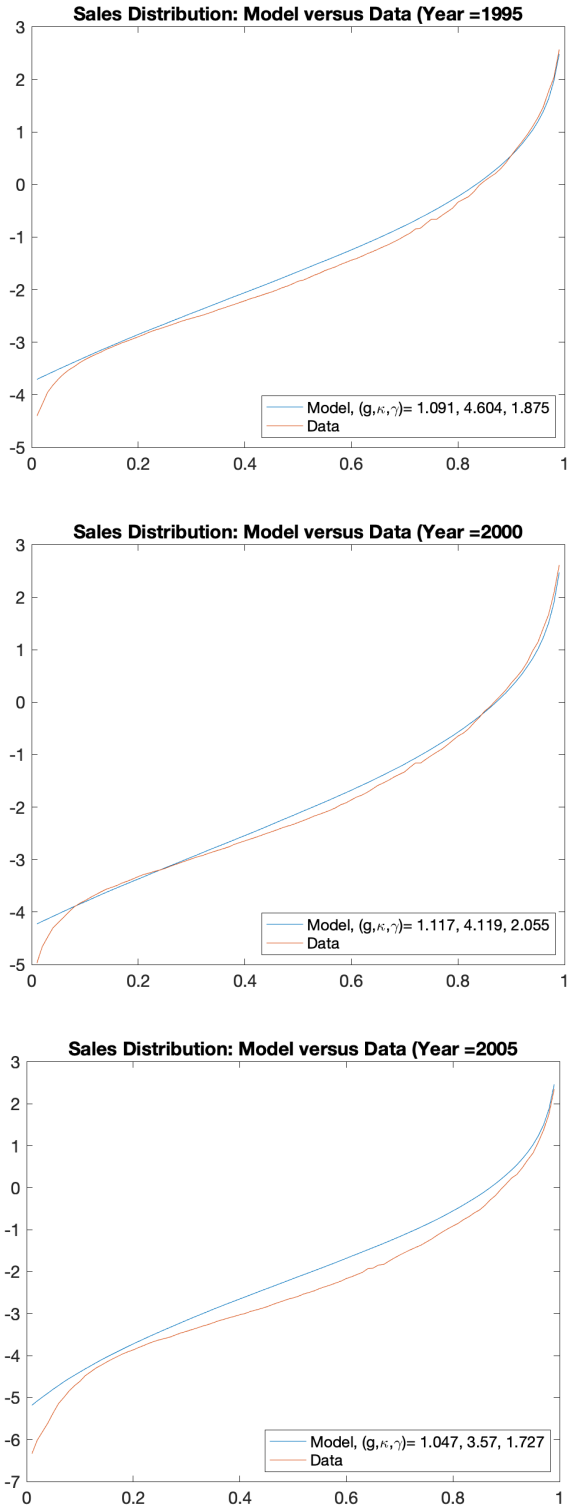
Table 18 reports results of distributional fit for the 3 specifications. The table reports results for Kolmogorov-Smirnov and Kuiper tests of distributional fit. Each model distribution, simulated with parameters estimated for 2000, is compared to the sales data in 2000. This is a quantitative parallel to the plots above. Test statistics are provided for Kolmogorov-Smirnov (KS) and Kuiper tests. The p-value of the KS test corresponds to the null hypothesis that the data sales distribution and the model simulated distribution are the same. Two results stand out. We cannot reject the null in any case, so our estimation allows us to accurately match the sales data, as is implied by visually comparing the CDFs above. Second, both tests reveal that the benchmark estimation has the smallest test statistic of the three, implying the closest fit with the data sales distribution.

Figure 11: Log Domestic Sales Distribution: Model VS Data



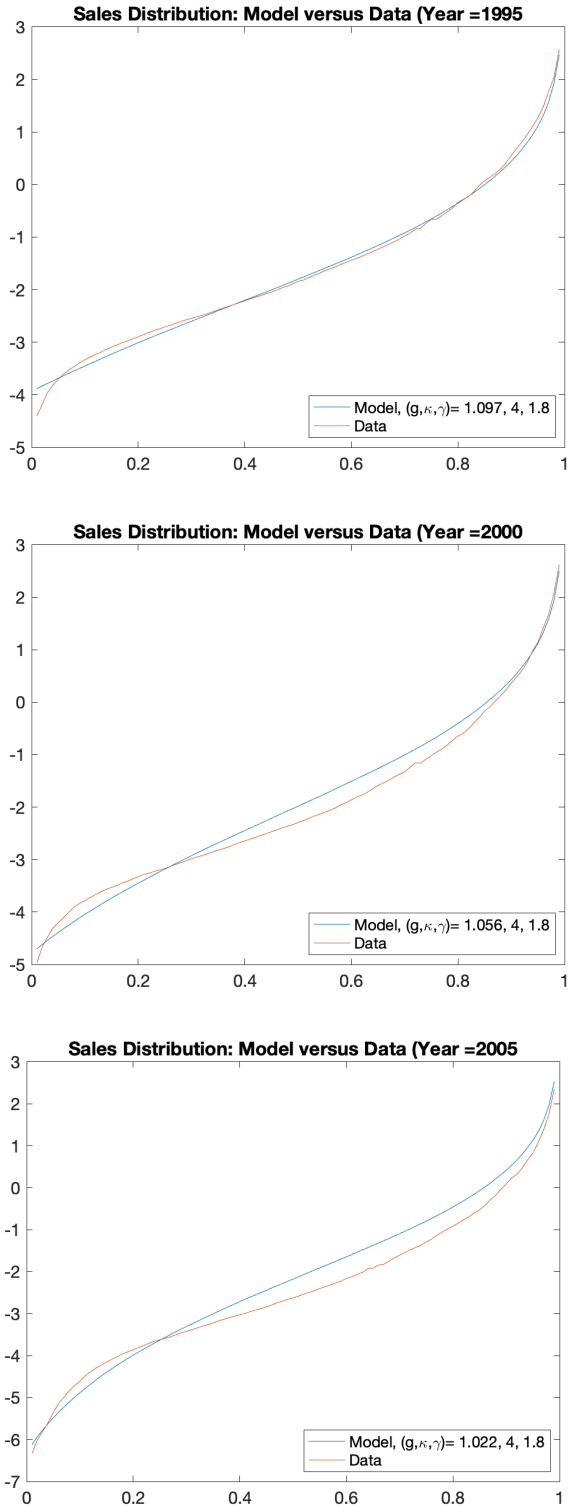
Each figure plots the CDF of the log sales distribution in the data (red) versus the simulated distribution given the estimated parameters. The model is estimated using the universe of manufacturing firms in each year. Although we estimate parameters for all years, we report only 1995, 2000, and 2005.

Figure 12: Log Domestic Sales Distribution: Model (Alternative- 4 moments) VS Data



Each Figure plots the CDF of the log sales distribution in the data (red) versus the simulated distribution given the estimated parameters. The parameters of the model are estimated using *only the 4 moments described in the "alternative calibration"*. The model is estimated using the universe of manufacturing firms in each year.

Figure 13: Log Domestic Sales Distribution: Model ($\gamma = 1.8, \kappa = 4$) VS Data



Each figure plots the CDF of the log sales distribution in the data (red) versus the simulated distribution given the estimated parameters. The parameters of the model are estimated using the main specification, but a fixed $\gamma = 1.8$ and $\kappa = 4$. The model is estimated using the universe of manufacturing firms in each year.

Table 18: Test of Distributional Fit

Specification	Kolmogorov-Smirnov Statistic	p-value	Kuiper Test Statistic
99 Sales moments (Benchmark)	0.13	0.34	0.18
4 Sales moments	0.14	0.26	0.21
Fixed κ and γ	0.14	0.26	0.23

This table reports results for Kolmogorov-Smirnov and Kuiper tests of distributional fit for the benchmark estimation (that targets 99 percentiles of the sales distribution), the robustness estimation with only 4 sales moments, and the robustness estimation with fixed κ and γ. Each model distribution is compared to the sales data in 2000. Test statistics are provided for Kolmogorov-Smirnov (KS) and Kuiper tests. We base the tests on the CDF estimated by the kernel method. The p-value of the KS test corresponds to the null hypothesis that the data sales distribution and the model simulated distribution are the same. We cannot reject the null in any case.

6.4.4 Alternative Calibration of Anti-Competitive Effect

Table 19 compares parameter estimates when we target separate price elasticities individually. It is clear that the value of $\frac{1}{1+\eta}$, the anti-competitive effect, is very sensitive to these moments. In the case that we target only the low price elasticity of income but allow for a large market size elasticity, preferences would be close to homothetic. In the case where we target a very low market size elasticity (as we find and is found in Simonovska (2015) and Dingel (2017)), preferences approach the IA. In the case where we minimize the sum of squared errors of both moments jointly the result is preferences that are closer to IA than homothetic. It is also clear that the sales moments parameters $(\hat{\kappa}, \hat{\gamma}, \hat{g})$ are almost identical regardless of $\frac{1}{1+\hat{\eta}}$, so that the sales moments parameters are orthogonal to the level of the anti-competitive channel.

However, the optimal restrictiveness, as well as possible welfare gains, can decrease significantly as $\frac{1}{1+\hat{\eta}}$ increases, as the anti-competitive effect starts to dominate at much lower levels of restrictiveness. In the case where we target only the low price elasticity of income (and implicitly very strong price elasticity to market size), which implies a strong anti-competitive effect, the welfare gains from imposing the optimal regulation are on average 0.0014%, or about 100 times lower than the benchmark case. The welfare gains from raising restrictiveness are small due to the large rise in firm-level markups as the number of competitors decreases. This is not too surprising given that $\frac{1}{1+\hat{\eta}}$ approaches the extreme of homothetic preferences. In the other extreme, where we target only the very low market size elasticity, $\frac{1}{1+\hat{\eta}}$ is closer to IA than the benchmark estimation and the possible welfare gains increase by a small amount.

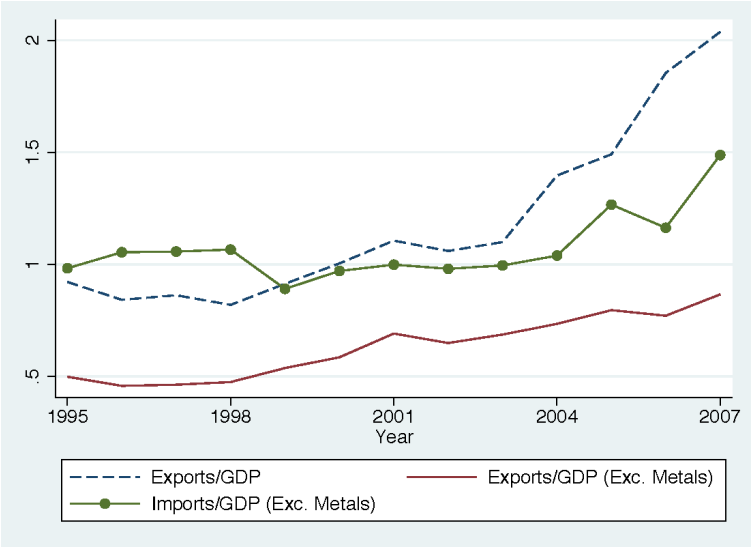
Table 19: Estimation Results: Manufacturing-wide in 1995, 2000, and 2005

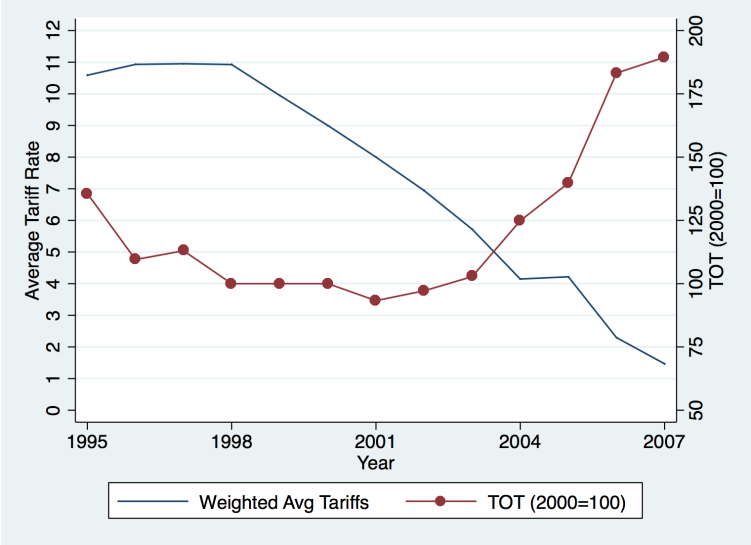
Year	Data Targets	$\hat{g}$	$\hat{\kappa}$	$\hat{\gamma}$	$\frac{1}{1+\hat{\eta}}$
1995	Sales Percentiles, Income Elasticity	1.1 (.01)	4.45 (0.48)	1.94 (0.10)	0.77
2000	Sales Percentiles, Income Elasticity	1.12 (0.01)	4.68 (1.11)	2.28 (0.30)	0.87
2005	Sales Percentiles, Income Elasticity	1.02 (0.02)	2.50 (0.38)	1.32 (0.20)	0.99
1995	Sales Percentiles, Size Elasticity	1.1 (.008)	4.45 (.48)	1.94 (.10)	-49
2000	Sales Percentiles, Size Elasticity	1.12 (.01)	4.68 (1.1)	2.28 (.30)	-54
2005	Sales Percentiles, Size Elasticity	1.02 (.02)	2.50 (.38)	1.32 (.20)	-77
1995	Sales Percentiles, Income+Size Elasticity	1.1 (.008)	4.45 (.48)	1.94 (.10)	-15
2000	Sales Percentiles, Income+Size Elasticity	1.12 (.01)	4.68 (1.1)	2.28 (.30)	-19
2005	Sales Percentiles, Income+Size Elasticity	1.02 (.02)	2.50 (.38)	1.32 (.20)	-39

This table reports the parameter estimates when estimating the model for all manufacturing firms in each year, for 3 separate strategies of price elasticity moments. The first 3 rows target only the price elasticity with respect to income ($\bar{\epsilon_y} = 0.084$), the next 3 rows only the price elasticity with respect to market size ($\bar{\epsilon_L} = -0.012$), and the last three rows target both elasticities jointly as in the main text. We compute bootstrap standard errors (in parenthesis) by running the estimation 100 times, each time taking a bootstrap sample of the data.

6.4.5 Trade Openness, 1995-2007

Figure 14: Chilean Trade Flows, Tariffs, Terms of Trade





6.4.6 Restrictiveness and Optimal Standards by Sector

We cannot directly compare $\hat{g}_i$ across sectors, since the distribution of quality and demand features vary, and thus the same $\hat{g}_i$ in two sectors might have very different welfare implications. As a practical tool, we normalize $\hat{g}_i$ with the optimal standard predicted by our model. We construct a restrictiveness index (RI) using the estimated parameters:

$$RI_i = \frac{\hat{g}_i}{\hat{g}_i^{opt}(\hat{\kappa}_i, \hat{\gamma}_i)}. \tag{67}$$

where i denotes a sector. The interpretation of this index is different from the technical measures in Section 2, as it captures a wide variety of measures – for example one that is meant to be protectionist in the guise of a quality standard – that limits the survival of firms at the bottom of the sales distribution. As we have argued in this paper, although there might be other rationales for why standards are actually imposed, the presence of misallocation creates a further potential benefit. The index bears a close resemblance to the estimated industry distortions in Behrens et al. (2020).

Figure 15 plots the RI in 2000 for each sector, sorted from largest to smallest. For each industry, we derive the 95% confidence interval using the estimated standard error for g in the calibration. Figure 16 plots the welfare gains and RI when we assume the regulation can be imposed without fixed costs, while Figure 17 plots the restrictiveness index in this case. As discussed in the main text, without fixed costs all sectors have a RI index below one, which means they can be made more restrictive. The welfare gain ranges from close to 0 to 2%, so that very large welfare gains are possible when labor is not wasted on compliance activities.

Figure 18 repeat the benchmark estimation for the case where we target only the income elasticity in the upper tier, so that preferences are close to homothetic. As discussed in the main text, these types of preferences produce a much larger anti-competitive effect. Combined with a fixed cost, there would be no sectors in 2000 that benefit from more regulation. Figure 19 takes the parameters estimated in the case where we target just the market size elasticity for η, where results are very similar to the benchmark case. In this case about half the sectors are under-regulated.

Figure 15: Restrictiveness Index: By Sector in 2000.

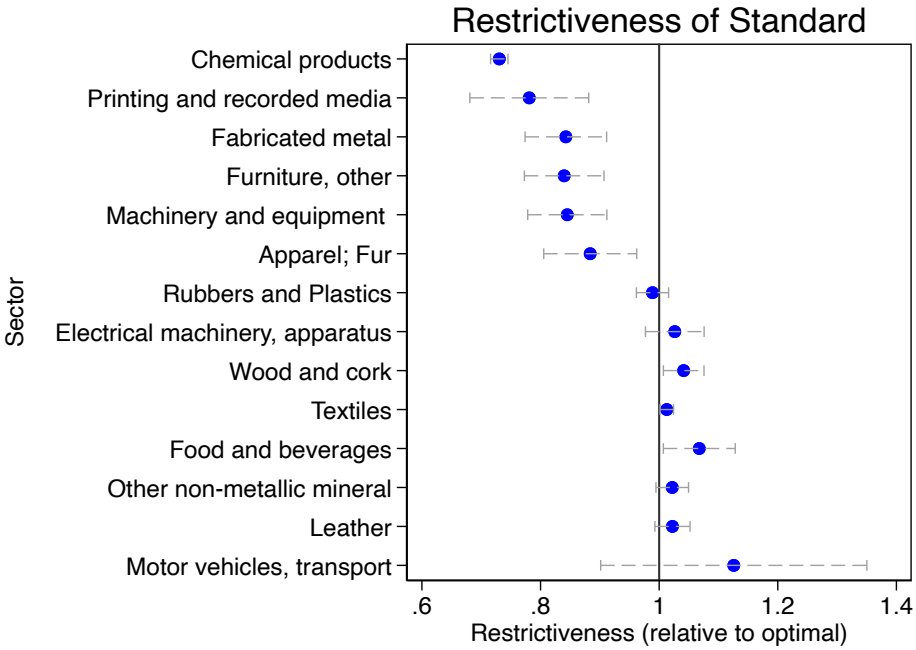


Figure 16: Welfare and Restrictiveness without Fixed Costs: By Sector in 2000.

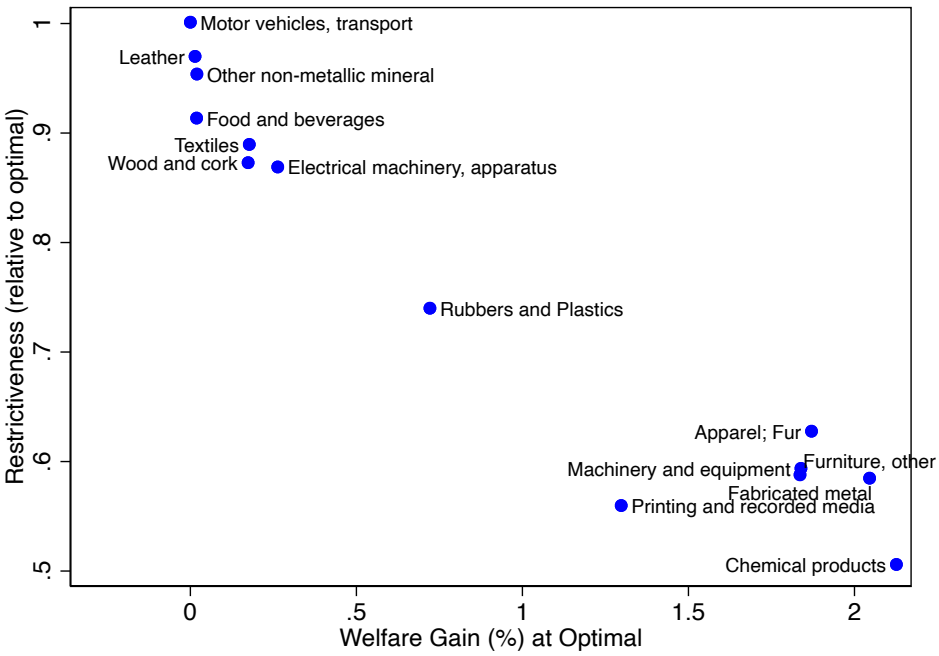


Figure 17: Restrictiveness Index without Fixed Costs: By Sector in 2000.

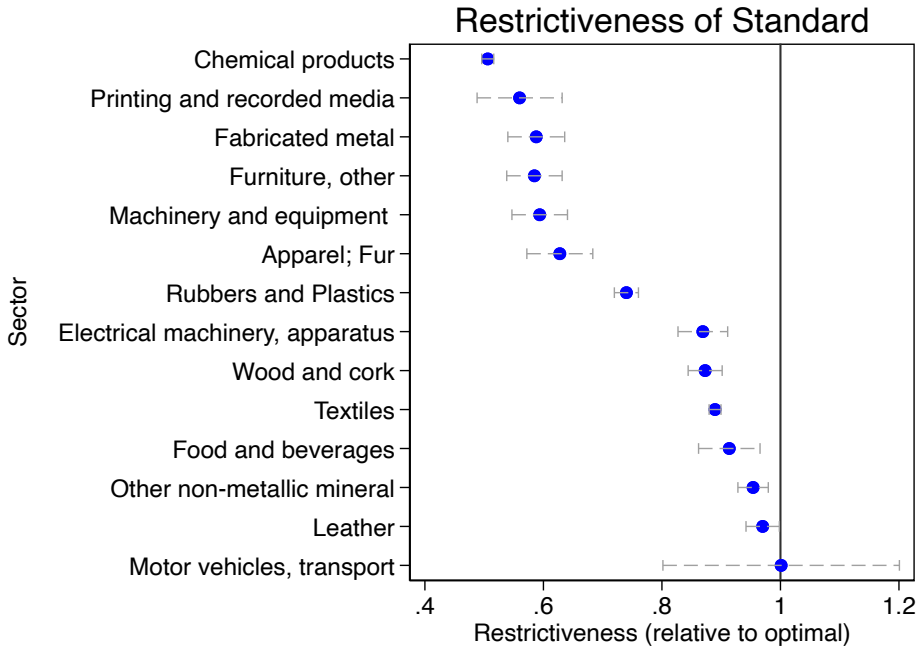


Figure 18: Restrictiveness Index Targeting Income Elasticity: By Sector in 2000.

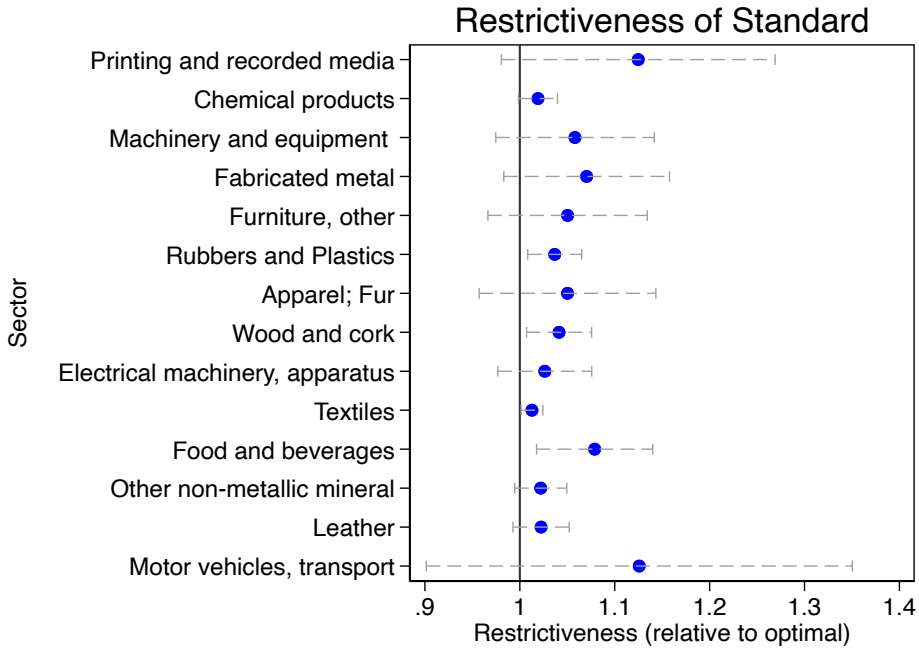


Figure 19: Restrictiveness Index Targeting Market Size Elasticity: By Sector in 2000.