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

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Abstract

Inefficient allocation of production across heterogeneous firms is a major source of welfare loss, but frameworks generally ignore policies that reduce the misallocation. We study the welfare effects of policies that target the selection of surviving firms. As an example of such policies, we focus on product standards that force the small, low-quality firms to exit the market. Using data from Chile, we find that more restrictive standards are associated with a reallocation of domestic sales from small to large firms. Guided by this evidence, we study the welfare effects of standards in a model with monopolistically competitive, heterogeneous firms, and a general demand system. The standard improves welfare if low-quality firms over-produce in the market allocation relative to the efficient allocation. We estimate our model across Chilean industries and find that in several instances the imposed standard is too restrictive relative to a theoretical upper bound.

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

JEL Code: L11, D6, F13.

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1 Introduction

In the presence of heterogeneity in the underlying characteristics of firms, market efficiency depends in large part on the efficient allocation of production across firms. Allocative inefficient markets can lead to losses in terms of aggregate productivity (Basu and Fernald, 2002) and welfare (Edmond et al., 2015). The high degree of firm heterogeneity in productivity (Bernard et al., 2007) and product appeal (Hottman et al., 2016) documented in the empirical literature implies that policies that generate a reallocation of production can have major welfare effects (Hsieh and Klenow, 2009; Dhingra and Morrow, 2016). However, practical policy implications are difficult to find as a way to improve upon the observed misallocation.¹ As a complement to the aforementioned studies, this paper focuses on the set of policies that targets the selection of firms into production or exit. We study the welfare effects of these policies with a theoretical model and quantify their effects by calibrating our model using Chilean firm-level data.

As a representative policy that directly targets the selection of firms into production or exit, we examine regulations on goods' characteristics, namely product standards. Standards directly affect the selection of firms, as more restrictive product standards force the exit of low-quality firms that are unable to comply with them. Such an exit can be rationalized by an increase in the fixed cost of operation, as Fontagné et al. (2015) and Ferro et al. (2015) documented that more restrictive standards mainly affect the number of firms selling to a destination, rather than the sales per firm. The natural implication of these studies is that standards reduce welfare through a reduction in competition and the number of varieties. However, with firm heterogeneity, the subsequent reallocation of production from exiting low-quality firms to surviving high-quality firms makes the overall welfare implications ambiguous. We show that standards can improve welfare by reducing the distortions that arise in allocatively inefficient markets. Such distortions originate from the interaction between consumers' preferences and firms' variable market power.

We motivate our focus on product standards by documenting the effects of one particular type of standard on the reallocation of production across firms. We use a panel data of Chilean firms and the TRAINS database on sanitary and phythosanitary (SPS) standards and compare the sales and survival probability of large firms relative to small ones, when SPS standards become more restrictive in an industry. The specification controls for industry-year shocks and time-invariant firm specific characteristics. The main result is that sales and

¹In the context of international trade, Edmond et al. (2015) and Dhingra and Morrow (2016) show that competition improves allocative efficiency. However, increased competition is the byproduct of reduction in trade costs or increases in market size, and not the target of a specific policy. In fact, Costinot et al. (2016) lament the dearth of analysis for optimal trade policies when firms are heterogeneous.

survival probability of large firms, relative to small firms, are magnified in industries with a larger number of standards. The effects of SPS standards are similar when considering low- and high-quality firms or small and large firms. We interpret this as a reallocation of production from low- towards high-quality/productivity firms.

To study the welfare consequences of such a reallocation, we incorporate regulations on product standards into a closed economy framework of perfect information, monopolistic competition, and firms that are heterogeneous in quality. 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. Finally, we represent the imposition of regulation as a level of quality that a government allows in the market. The latter two assumptions allow us to present our main results in the simplest possible setting. However, we verify that our theoretical results hold in two important extensions that relax these two assumptions. First, we link firm quality to exogenous productivity draws and allow the variable costs of production to be related to quality. Second, we model the imposition of the regulation as the payment of a fixed cost of compliance³, which affects the selection of firms, generalizing our results to all vertical norms and not exclusively to product standards.⁴

Raising the standard or, equivalently, making regulations more stringent, has two opposing effects on welfare. First, the quality standard reduces the total number of varieties available for consumption, as the low-quality varieties exit. In models featuring love for variety ([Krugman, 1980](#)), as ours, fewer varieties reduce welfare. Furthermore, as the standard reduces the number of competitors, it can generate *anti-competitive* effects, whereby welfare is reduced as surviving high-quality firms increase their markups in response to lower competition. Second, the standard causes a reallocation of production from low- to high-quality firms, which we label the *composition effect* of the standard, and is consistent with our mo-

²Standards are crucial in trade policy, so we introduce trade separately in a companion paper ([Macedoni and Weinberger, 2019](#)). We confirm that the results in this paper hold, and in fact product standards work as a complement to lower trade barriers (please contact authors for results). Notice however that standards are imposed on *all firms in the domestic economy*, so trade is not necessary as a rationale for standards.

³Complying to a regulation can increase both variable and fixed costs of production. Both costs affect the selection of firms but, relative to the baseline model, they reallocate workers from production to compliance tasks, which is welfare reducing. This welfare reducing effect always dominates potential welfare benefits of regulations if only variable costs increase. As we show in this paper, such a result does not necessarily happen if regulations affect only the fixed costs.

⁴Vertical 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 2 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](#)).

tivational evidence. The composition effect of the standard improves the average quality in a market and, thus, it raises welfare.

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: indirectly additive (IA), directly additive (DA), and homothetic. In this general demand system, the model predicts a non-monotone, hump-shaped relationship between the quality standard and welfare for all parametric specifications. At low levels of the quality standard, the composition effect improves allocative efficiency and such an effect dominates the welfare loss from diminishing variety and competition. Eventually the standard becomes too restrictive — above its optimal level — when the welfare loss from diminishing the number of firms offsets the welfare enhancing components of the standard.

The interaction between consumers’ preferences and firms’ variable market power impacts the anti-competitive effect of the standard. In fact, the size of the anti-competitive effects depends on the elasticity of a firm’s markup with respect to the number of competitors. The three preferences included in GTP differ in the extent of anti-competitive effects, which are absent in the IA case and are the largest under homothetic preferences. Hence, the model predicts the most restrictive optimal standard under IA, intermediate under DA, and the smallest under homothetic preferences. That the presence of an optimal standard holds for the three classes of preferences is significant because the rationale for the policy is not dependent on parametric assumptions that are difficult to test. Furthermore, comparing the three cases provides useful intuition on the channels that are important for our result.

We clarify the mechanisms through which the standard reduces distortions by comparing the market allocation to the socially optimal allocation. Generally, there are three margins through which the market is inefficient: the selection of firms, the quantity produced by each firm, and the number of firms that attempt to enter the market. We limit the analysis to the allocation of production among entrants (the first two margins) by making an assumption common to the literature with firm heterogeneity, that firms draw their quality from a Pareto distribution ([Chaney, 2008](#); [Arkolakis et al., 2012, 2017](#)).

The distortion reduced by a quality standard is known as “business stealing bias”, where too many low-quality firms are active in a market, relative to an optimal allocation.⁵ In addition, due to the markup distribution, high-quality firms under-produce and low-quality firms over-produce, relative to an efficient allocation. A necessary condition for such a

⁵This intuition is present in [Mankiw and Whinston \(1986\)](#) and [Dhingra and Morrow \(2016\)](#). The business stealing bias dominates another distortion commonly labeled “lack of appropriability”, which generates *too little* production from low-quality firms, and occurs when firms cannot fully seize or appropriate the gains from a new variety.

misallocation is that firms charge variable markups – consumers are willing to purchase low-quality goods provided that those markups are low enough in the laissez faire economy.

To quantify the effects of product standards, we estimate our model across 40 Chilean manufacturing industries.⁶ 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% on average. The restrictiveness of regulations also differs across industries: Chemicals, Motor Vehicles, Food, and Books/Journals are consistently the most regulated industries, while Furniture and Apparel are the least regulated. As a sanity check, we also find that simulating the model with calibrated parameters, varying only the implied estimated standards, generates distributional outcomes consistent with those in Chile in response to changes in the number of SPS regulations.

We conduct a policy-relevant evaluation by comparing the estimated level of restrictiveness with a theoretical upper bound for the restrictiveness of the standard predicted by our model. In 5 out of 38 industries in 2005, we cannot reject the hypothesis that the estimated standard is different than the theoretical upper bound. Hence, in those five industries, the standards are too restrictive in light of our model. Moreover, the number of industries that are too restrictive has declined since 2000. We postulate that an increase in the relative size of the largest firms is consistent with policymakers’ willingness to reduce restrictiveness of standards. Such a reallocation could be the result of trade openness as Chile experienced a boom in trade after 2000.⁷ Trade reduces misallocation ([Edmond et al., 2015](#)), and standards work as a complement as they generate a similar compositional effect.

Relationship with the Literature. Our paper relates to a growing literature within the trade, industrial organization, and macro fields, on the aggregate consequences of misallocation of production across heterogeneous firms.⁸ In this paper, we explore the case where a policy-maker can set a minimum level of quality that is allowed to sell in a market, and generalize the result to the payment of a fixed cost that achieves the same allocation. Under a plausible set of conditions – governed by the demand faced by firms – regulatory measures can raise welfare through an increase in allocative efficiency. The extension of optimality results in [Dhingra and Morrow \(2016\)](#) and [Bertoletti and Etro \(2018\)](#) to a framework with

⁶Our estimates of the implied survival restrictions in Chilean industries is similar to [Behrens et al. \(2018\)](#) who use firm revenues/employment to estimate the distortions present within French industries.

⁷This is exemplified not only by the observed increase in trade flows, but the passage of important free trade agreements with the United States, EU, and China.

⁸Quantitative evidence has been highlighted in [Restuccia and Rogerson \(2008\)](#), [Hsieh and Klenow \(2009\)](#), [Edmond et al. \(2015\)](#), [Behrens et al. \(2018\)](#), and [Weinberger \(2017\)](#).

quality differentiation, is a separate contribution of this paper.

The trade literature has highlighted that an increase in 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). In addition to that, trade induced pro-competitive effects can further improve allocative efficiency (Dhingra and Morrow, 2016). This paper shows that a similar reallocation can be achieved with domestic policies that force the exit of low-quality firms. Furthermore, we show that our results generalize to a framework in which firm quality depends on the underlying distribution of productivity.⁹ 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*.¹⁰

An important contribution is to provide a rationale for product standards that has not been explored in any of the previous literature. Quality standards or regulations could be raised to address negative externalities, such as environmental externalities (Parenti, 2016; Mei, 2017), to reduce oligopolists' market power (Baldwin et al., 2000), to enhance investments in quality upgrading (Gaigne and Larue, 2016), or to reduce distortions due to information frictions (Atkeson et al., 2014). Last but not least, standards could 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 acts as a complement to the existing literature on rationales for regulations as it is the first to explore the role of inefficient markets. The “quality” of the firm in our model encompasses any (single) dimension through which quality is determined for a product, including characteristics that involve a negative externality. However, we do not impose an ad hoc externality because the presence of quality differentiation across firms in itself creates a distortion.

Trade policy makers have traditionally considered regulations on product standards as a form of barriers to trade that primarily impacts the extensive margin of firms. In this vein, studies have relied on export flows to show that exporters, and in particular the smallest ones, from a specific origin (e.g France) are less likely to sell a product to destinations that impose relatively more regulations in those products (Fontagné et al., 2015; Fernandes et al., 2015; Ferro et al., 2015). We separate from this literature and examine the effect on

⁹However, our results could be generalized to policies that force low-productivity firms to exit as well.

¹⁰In the spirit of Djankov et al. (2002), there is a related literature on the anti-competitive consequences of regulations on entry. For example, Mitton (2008) and Fisman and Allende (2010) establish that regulations generate industry concentration.

domestic firms instead, with a focus on the distribution of firm sales. Our approach fits with the emphasis on firm selection and reallocation of production that are integral to gains from trade when firms are heterogeneous and compete monopolistically (Melitz, 2003).

This paper is organized as follows. Section 2 presents the stylized facts that motivate our focus on product standards. Section 3 describes a framework with generalized translated power preferences and quality differentiation, where a policy maker may impose a quality standard. Section 4 shows the results from estimating the model. Section 5 concludes.

2 Motivational Evidence

The theory in Section 3 frames regulations on product characteristics as a quality standard, which selects out of the market the smallest firms. Our baseline model links firm size to exogenous quality draws and hence the standard reallocates production from small, low-quality firms to large, high-quality firms. In this section, we aim to motivate this approach with firm-level data that allows us to observe survival and sales distributions at the finest industry disaggregation available (4-digit ISIC). We take a balanced panel of Chilean firms and provide evidence of a relationship between the imposition of regulations at the industry level and a growing differential of survival and sales across small and large firms.

2.1 Data

Detailed Database of Non-Tariff Measures. In order to map our regulations to the data, we make use of the prevalence of technical measures. Technical measures 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 they are standards imposed by the government with the aim of restricting access to both domestic and foreign firms depending on the characteristics of their products. For example, when Chile imposes a “zero-tolerance” on salmonella in poultry products, the stringency of their standards must be applied equally for domestic and imported products. We view it as reasonable to interpret the risk-factors for salmonella as part of the quality of this product, so that this type of technical measure could 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).¹¹ The 2012 NTM classification separates measures into 16 chapters (labeled A-P), and we make use of the sanitary and phytosanitary (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 quality standard in the theory, although robustness results include TBT as well. These are the type of regulations that Ferro et al. (2015) and Fontagné et al. (2015) have shown to primarily reduce the extensive margin of exporters. Although Fontagné et al. (2015) focus on “specific trade concerns” raised by trade partners, we use all technical measures applied by Chile. Our empirical question differs from theirs: we want to capture the imposition of all possible regulations on the books that act as a quality standard in a particular industry.

The technical measures apply to both imported goods and locally-produced goods and, thus, do not discriminate between domestic and foreign firms.¹² We emphasize that these capture a broad measure of product standards and not just import barriers.

The data is available at the imposing country-product-NTM code-year level. For each SPS regulation, the starting year, products affected, and type of standard are reported.¹³ We construct a frequency index at the industry ISIC(i)-year(t) level as our measure of restrictiveness, labeled TM_{it} , that can be merged to our domestic firm production data (described below). To construct the frequency index, we first count the number of regulations (unique 2-digit NTM codes) in each product-year, where products are 6-digit HS codes. Then, we sum the total number of regulations for each 4-digit ISIC (revision 3) industry. To control for the number of products in each industry, we divide the previous sum by the number of HS6 products in the 4-digit industry. Table 4 in Appendix 6.2 lists the top 25 industries ranked by the restrictiveness in the 1995-2007 period, where just 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.

Chilean Firm Data. 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,

¹¹TRAINS 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.

¹²To safeguard against discriminatory technical measures, in the main specification we drop NTM classification A1 within the SPS chapter (and B1 with the TBT chapter in the robustness). These are most likely to include regulations that only affect imported goods.

¹³See Appendix 6.1 for a detailed description of the data and how we compute our frequency index. We use the starting year for time variation, as we use a flow measure of standards.

National Industrial Survey) and collected by the National Institute of Statistics (INE). Each firm is classified with a 4-digit ISIC industry. There are approximately 5,000 firm level observations per year and firms are tracked across time with a unique identification number. The census includes detailed firm data such as total sales, value/usage of its factors, etc.

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:

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

where y_{fit} is a performance measure for firm f in industry i at year t which includes log domestic sales and a dummy for positive sales (“survival premium”). TM_{it} is the measure of industry restrictiveness based on the imposition of SPS and TBT measures as reported in Table 4. $Char_f$ 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.

As a proxy for the “ $Char_f$ ” characteristic above, we identify firms size by their domestic sales and also rely on three input measures as proxies for quality: the firms’ capital stock, labor costs, and intermediate input costs, each divided each by the number of employees. Higher capital intensity, average wage per worker, and average material input costs all arguably correlate with output quality given the relationship of output quality with input quality (Fan et al., 2018).¹⁴ These have been used in previous studies, for example Hallak and Sivadasan (2013) use the same quality proxies for Chile, although they complement these with Indian product-level data that allows them to also use the adoption of ISO 9000 certification and input/output prices.¹⁵ The three proxies in our paper are likely capturing similar attributes as the more direct quality measures, although they are of course imperfect.¹⁶

¹⁴The three proxies are positively correlated with a ratio of skilled workers to unskilled workers, using a (rough) measure in the Chilean data that labels a category of workers as unskilled (or “no calificados” in Spanish). Not surprisingly, the correlation is strongest with the wages per worker quality proxy.

¹⁵When they investigate the exporter quality premium conditional on size, they find very similar results across all of the quality proxies.

¹⁶Access to product price data would allow us for better proxies of quality. On a related note, we cannot capture single vs. multi-product firms which is a concern since the regulations are on products and not on

We include industry-year (α_{it}) and firm (α_f) fixed effects to control for the variety of 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 with the firm indicator to control for differences in competition introduced by trade, and an interaction of the firm indicator with the level of import tariffs at the industry level.¹⁸

In our main specification, we consider a balanced panel of firms. We keep only firms alive in 1995 and construct a balanced panel where a firm is given a survival dummy equal to 0 if it does not sell in that year. This follows the specification in [Fontagné et al. \(2015\)](#) and allows us to interpret the firms in the first year as the “potential” producers. Firms are assigned an indicator ($Char_f$) based on being above or below the median in 1995.¹⁹ To some degree the results on the “survival” outcome are 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 and the sign on relative survival (β_M) is in the direction that we expect, the censoring of the data likely *understates* the magnitude of the firm churning.

We first rely on a OLS estimation of (1). This 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 by the government, and for this reason one might worry about reverse causality. For example, sales dispersion may reflect Chilean consumers preference for quality in certain industries, and the government responds by imposing standards. Panel B of Table 1 reports an IV specification where TM_{it} is instrumented using the TM_{it} measure in *Peru*, interacted with the same firm indicator. We use the TM_{it} in *Peru* because we find this country to be closest to Chile in terms of regulatory structure across industries (and therefore the F-stat in the first stage is very large).

firms. First, we note that firm fixed effects control for whether an affected firm is single or multi-product (if they are not changing across types). Second, our theoretical results can be extended to include multi-product firms that produce varieties of different quality. A standard may force the exit not only low-quality firms, but also of the low-quality varieties of any firm. 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. For details see [Macedoni and Xu \(2018\)](#).

¹⁷Our specification controls for time-varying industry characteristics, as well as time-invariant firm characteristics, that are correlated with the sales distribution. For example, differences in product differentiation and demand elasticities across firms and industries are controlled for with the fixed effects.

¹⁸As described below, import tariffs declined in this period, although mostly uniformly across industries.

¹⁹For the specification with sales as an outcome, our results are robust to using the unbalanced panel.

Results. In order 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 and described above, is the lack of an explicit measure of quality. It is important to note however 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. Furthermore, we have extended the model to the case where firms are heterogeneous in productivity, and the same welfare-improve reallocation is possible. Therefore, we believe that an agnostic interpretation of the empirical analysis, where reallocation across firms can be interpreted as either being across firm quality or firm size, is consistent with the theoretical model. The interpretation of β_M highlights this reallocation.

Table 1 reports the main motivational results using OLS (Panel A) and IV (Panel B) estimations. The results on domestic sales suggest that the ratio of sales between small and large firms is magnified when industries become more regulated. The coefficient in the first row of column (1) implies that imposing one standard that affects every product in an industry results in a 1% larger sales difference between an average large firm relative to the average small firm (Panel A). The three proxies for quality yield similar results, although they are the most precise when using capital intensity. In column (2), imposing a regulation for every product in an industry results in a 1.5% difference between a firm with above-median capital intensity relative to below-median capital intensity. Our interpretation is that imposing new product standards in an industry generates reallocation from small to large firms, and suggests this reallocation is also across low to high quality firms.

The last four columns in Panel A suggest that the survival of large firms relative to small firms is also higher in more regulated industries. In this case, the standard errors increase due to the limited variation in exit rates. Still, we find that exit rates increase significantly for smaller firms relative to large firms as product standards increase. The higher relative exit rates show up across the three firm indicators as well.

The coefficient on the interaction between industry tariffs and firm characteristics is generally negative and statistically significant. In line with the empirical trade literature, reducing tariff reallocates production from small to large firms. Industry openness has mostly an insignificant effect on the distribution of firm sales while it reduces the difference in the survival probability of large relative to small firms. This result might reflect the positive effect of increased access to foreign markets on the extensive margin of firms, or it might be correlated with the tariff measure. However, we find that eliminating the openness interaction has no effect on our coefficient of interest (results omitted).

In the IV specification, the standard errors and coefficients are both larger, likely indicat-

ing that the IV estimator provides an upper bound, but the qualitative results are consistent with the OLS estimation. There is a reallocation across small and large firms as industries as product standards increase, and this also shows up in the average wage proxy.

Table 1: Firm Sales and Survival Heterogeneity: Effect of Technical Measures

Panel A: OLS

	Log Domestic Sales				Survival			
	(Sales)	(K/L)	(W/L)	(M/L)	(Sales)	(K/L)	(W/L)	(M/L)
TM*Char	0.010** (0.005)	0.015*** (0.005)	0.009* (0.006)	0.007 (0.006)	0.011** (0.004)	0.008* (0.004)	0.011 (0.007)	0.009** (0.003)
Openness*Char	0.028 (1.291)	0.964 (0.787)	0.146 (1.095)	-0.262 (0.827)	-0.521** (0.245)	-0.523*** (0.100)	-0.406 (0.269)	-0.427*** (0.185)
Tariff*Char	-0.010*** (0.004)	-0.011*** (0.004)	-0.013*** (0.004)	-0.009** (0.004)	-0.003** (0.002)	-0.008*** (0.002)	0.000 (0.001)	-0.002* (0.001)
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
R^2	0.955	0.955	0.955	0.955	0.644	0.645	0.644	0.644
# Observations	44220	44220	44220	44220	69679	69679	69679	69679

Panel B: IV Results

	Domestic Sales				Survival			
	(IV-Sales)	(IV-K/L)	(IV-W/L)	(IV-M/L)	(IV-Sales)	(IV-K/L)	(IV-W/L)	(IV-M/L)
TM*Char	0.028** (0.014)	0.032** (0.014)	0.034** (0.014)	0.003 (0.014)	0.022** (0.010)	0.006 (0.010)	0.022** (0.010)	0.011 (0.010)
Openness*Char	0.010 (0.716)	0.949 (0.831)	0.125 (0.884)	-0.258 (0.901)	-0.526*** (0.117)	-0.522*** (0.113)	-0.411*** (0.120)	-0.428*** (0.118)
Tariff*Char	-0.011*** (0.002)	-0.012*** (0.002)	-0.013*** (0.002)	-0.009*** (0.002)	-0.004*** (0.001)	-0.008*** (0.001)	-0.000 (0.001)	-0.002*** (0.001)
F-stat (first stage)	1708.0	1733.0	1718.9	1727.4	1842.3	1842.3	1842.3	1842.3
# Observations	44220	44220	44220	44220	69679	69679	69679	69679
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

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 technical measures (bottom). 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 input 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

In the appendix, we show that there is a strong correlation in the data between all the quality proxies and firm sales, which allows us to interpret a quality standard as essentially eliminating firms in the left tail of the sales distribution. Furthermore, we document a strong relationship between all the quality proxies and a measure of TFP. This result is important because our theoretical implications with quality heterogeneity can be translated

to productivity heterogeneity. These relationships are also consistent with [Hottman et al. \(2016\)](#), which find that product “appeal” is the most important component of sales heterogeneity. In summary, the empirical findings motivate our theoretical framework, with firms differentiated by quality, and a standard that eliminates the lowest quality firms.

Next, we briefly describe several robustness results to the above empirical specification that are reported in Appendix 6.2.

Robustness. 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 6 in the Appendix we replace the set of technical measures used in specification (1) with a more general definition, using TBT measures as well. Either type of technical measure could be associated with a widening of sales dispersion and lower survival for low-quality firms. The results are almost identical, which suggests that neither SPS or TBT are driven by horizontal norms, although they are arguably more likely to come in technical regulations under TBT.²⁰

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, the specification is a repeated cross-section, with sales as the outcome within industry-year, and ran on an unbalanced panel. The main drawback in this case is that we cannot control for firm fixed effects. 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. 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. We 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 (Table 7).²¹

The results rely on the implicit assumption that technical measures are non-discriminatory. In fact, regulations must fit this criteria to be legal under WTO rules, and we attempt to omit technical measures that might be more heavily weighted towards importers. To test this

²⁰The presence of measures based on horizontal norms likely biases our results towards zero. These measures do not discriminate on any attributes related to quality, which means that “treated” industries will receive no distributional impact.

²¹On a related note, we checked whether 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).

assumption, we create our TM variable using only a subset of technical measures dropped from the main analysis that might be aimed at importers – those classified by UNCTAD as “Prohibitions/restrictions of imports for SPS reasons” and “Prohibitions/restrictions of imports for objectives set out in the TBT agreement”, and “Pre-Shipment Inspections”. Since these are the measures least likely to affect domestic firms, we expect to not find the same type of evidence for reallocation. In fact, we find the opposite result of our baseline specification: in 7 of the 8 interactions the coefficients are negative (Table 8). We caution however that these results have large standard errors as there are few technical measures that fit this definition.²²

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. Then, we proceed by allowing a policy maker the option of imposing a quality standard, 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 find that a standard more restrictive than the market allocation is always optimal. We discuss the sources of market distortions that a minimum quality standard reduces, and identify the features of each type of preferences that cause shifts in the magnitude of the optimal standard in an economy. Given the generality of this demand system, our welfare results provide a strong motivation for the rationale of a quality standard or other policies that target the selection of firms.

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.²³

²²One coefficient is positive and large (though insignificant), but overall the results do not point to the same reallocation effects present with the other measures.

²³Papers on regulations often introduce an *ad hoc* externality, usually pollution or public health, to justify the imposition of a standard (Parenti, 2016; Mei, 2017). In this spirit, we can also think of our quality measure as a proxy for how healthy a product is. Despite consumers knowing and appreciating the healthiness of a good, our model features a market allocation that generates over-production of unhealthy products.

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 6.3.5).²⁴

3.2 Consumer and Firm Problems

3.2.1 Consumer Problem

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

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

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 is implicitly defined as:

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

The GTP utility follows the generalized Gorman-Pollak demand system²⁵, 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 $\eta \rightarrow \infty$, preferences become directly additive (DA), and generalize the preferences used by [Melitz and Ottaviano \(2008\)](#).²⁶ [Fally](#)

²⁴[Feenstra and Romalis \(2014\)](#) provide the microfoundation for such an assumption. Our results would also hold in a standard framework with productivity heterogeneity.

²⁵[Gorman \(1972\)](#), [Pollack \(1972\)](#).

²⁶The case where $\gamma = 1$ generates linear demand as in the separable case of [Melitz and Ottaviano \(2008\)](#).

(2018) describes the regularity conditions for these preferences.²⁷

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. Consumer's inverse demand is:

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

3.2.2 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:

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

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

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

and setting $q(z^*) = 0$ yields the market determined quality cutoff:

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

For a quality level below the cutoff $z < z^*$, a firm has zero demand.²⁸ The relationship between the cutoff and η will be key in comparing our results across the types of preferences because the demand faced by each firm is governed by the firms' quality relative to the market cutoff. The quality cutoff in the IA case ($\eta = -1$) only depends on income (normalized to one): $z_{IA}^* = \frac{c}{a}$. The cutoff for homothetic preferences ($\eta = 0$) depends only on the number of competitors and is independent of income: $z_H^* = \frac{c}{a} \xi^{-1}$. In the DA case, the

²⁷In Web Appendices we make available interesting non-GTP cases such as CES demand with a variety externality, and several variable elasticity demand systems (e.g. [Simonovska \(2015\)](#)).

²⁸In terms of cutoff (6) our model is isomorphic to one with productivity heterogeneity. In fact, heterogeneity in c or z generate the same vertical shift of the marginal cost curve or the marginal revenue curve. To generate a model with quality heterogeneity that is fully isomorphic to one with productivity heterogeneity, the utility function should be written as: $U = \int_{\Omega} \left(az(\omega)\xi q(\omega) - \frac{z(\omega)(\xi q(\omega))^{1+\frac{1}{\gamma}}}{1+\frac{1}{\gamma}} \right) d\omega + \frac{\xi^{-\eta-1}}{\eta}$. With these preferences, the results of our paper would still hold, but it would be more difficult for the model to match the distribution of sales for the largest firms.

market determined cutoff depends on *both* income and the number of competitors. Given the relationship between ξ and the marginal utility of income λ^{29} , for $\eta \rightarrow \infty$, $z_{\text{DA}}^* = \frac{\lambda c}{a}$.

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

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

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:

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

Markups are increasing in z : higher quality firms charge higher prices. Such prediction receives empirical support from [Bastos and Silva \(2010\)](#), [Martin \(2012\)](#), [Dingel \(2015\)](#), and [Manova and Zhang \(2017\)](#).

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

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

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

3.3 Quality Standard and Welfare

The government of the closed economy sets a minimum quality standard $\bar{z} \geq z^*$, such that a firm with quality $z < \bar{z}$ is not allowed to sell in the economy. The quality standard is a vertical norm ([Baldwin et al., 2000](#)): \bar{z} can be easily interpreted as more or less restrictive. Since firms' quality is exogenously determined, the policy only affects the selection of firms into the domestic market. In particular, the larger \bar{z} becomes, the more low-quality firms are forced out of the market. The model is consistent with the evidence of Section 2.

Our results generalize to all vertical norms that require the payment of a fixed cost of compliance by all firms. This is an important generalization because it allows for a separate way to impose the standard: a policy-maker can impose a fixed production cost that generates the same exit of low-quality firms as \bar{z} . In appendix 6.3.4, we investigate the case where the standard is imposed as a fixed cost, which merely generates a downward shift in the level of the optimal standard. We choose to model \bar{z} as a direct policy tool because,

²⁹ $\lambda = \frac{1}{y} \int \left(az\xi q(\omega) - (\xi q(\omega))^{1+\frac{1}{\gamma}} \right) d\omega = \frac{\xi^{-\eta}}{y}$, where λ is the multiplier on the resource constraint.

in Section 4, we will be able to estimate its restrictiveness regardless of the level of the fixed cost. We abstract from any costs associated with enforcing the standard by the government, which would be hard to quantify, and would reduce the welfare benefits of standards. If the standard or other policies only increase the marginal cost of production c , their welfare effect would be unambiguously negative.

We abstract from firms paying a fixed cost to improve their quality à la [Gaigne and Larue \(2016\)](#) because such an assumption would not generate any additional sources of distortions.³⁰ Furthermore, in the presence of quality upgrading there would be a set of low-quality firms selling products with a quality equal to the standard. Raising the standard would raise the quality of the smallest surviving firms to the new level of the standard, which would raise their revenues and thus reduce the sales difference between high-quality and low-quality firms, contrary to the evidence of Section 2.

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 one determined by 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: $\frac{P(z \geq \bar{g} | g > 1)}{P(z \geq \bar{g} | g = 1)} = g^{-\kappa}$.

3.3.1 Market Aggregates

We start with the market aggregates necessary to compute welfare. Details on the derivations are relegated to the appendix. The equilibrium quality cutoff z^* can be represented as a function of the restrictiveness of the standard g and parameters:

$$z^* = \left[\frac{Lc^{\frac{\eta}{1+\eta}} \gamma^\gamma b^\kappa a^{\gamma + \frac{1}{1+\eta}}}{f_E(1+\gamma)^{1+\gamma}} g^{-\kappa} G_1(g) \right]^{\frac{1}{\kappa - \gamma - \frac{1}{1+\eta}}} \quad (11)$$

where $g^{-\kappa} G_1(g)$ is decreasing in g .³¹ 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

³⁰[Gaigne and Larue \(2016\)](#) find that in such framework, a standard can improve welfare only under unusual parametrical assumptions.

³¹ $G_1(g) = \kappa g^{1+\gamma} \left[\frac{F_1(g)}{\kappa - \gamma - 1} - g^{-1} \frac{F_2(g)}{\kappa - \gamma} \right]$. $F_1(g) = {}_2F_1[\kappa - \gamma - 1, -\gamma; \kappa - \gamma, g^{-1}]$ and $F_2(g) = {}_2F_1[\kappa - \gamma, -\gamma; \kappa - \gamma + 1, g^{-1}]$, where ${}_2F_1[a, b; c, d]$ is the hypergeometric function. We restrict the parameter space such that $\kappa - \gamma - 1 > 0$.

($\eta = \infty$). However, under IA preferences ($\eta = -1$), where the cutoff is only dependent on income, there are no selection effects due to market size.³²

Substituting (11) into (6) yields the aggregator ξ :

$$\xi = \left[\frac{Lb^\kappa a^\kappa \gamma^\gamma}{f_E(1+\gamma)^{1+\gamma} c^{\kappa-\gamma-1}} g^{-\kappa} G_1(g) \right]^{-\frac{1}{(1+\eta)(\kappa-\gamma)-1}} \quad (12)$$

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. Hence, the quality standard has a partial negative effect on the volumes produced under IA preferences, and a partial positive effect under homothetic preferences.

Finally, the mass of entrants J is independent of η :

$$J = \frac{L}{f_E} \frac{G_1(g)}{G_2(g)} \quad (13)$$

and is increasing in the restrictiveness of the standard.³³ 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.

3.3.2 Welfare

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

$$U = \frac{az^*\xi}{c} \left[(1+\gamma) \frac{G_3(g)}{G_2(g)} - \frac{\gamma^2}{1+\gamma} \frac{G_1(g)}{G_2(g)} + \frac{1}{\eta} \right] - \frac{1}{\eta} \quad (14)$$

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 .³⁴ On the other hand, the product of the quality cutoff z^* and the aggregator ξ is declining in g . Using the cutoff condition (6) and the equilibrium value of ξ (12) yields

³²The elasticity of the cutoff with respect to marginal costs c , similar to the income effects of [Bertoletti and Etro \(2018\)](#), is $\frac{\partial \ln z^*}{\partial \ln c} = \frac{\eta}{(1+\eta)(\kappa-\gamma)-1} \cdot \frac{\partial \ln z^*}{\partial \ln c} = 0$ for homothetic preferences, as in [Melitz \(2003\)](#), $\frac{\partial \ln z^*}{\partial \ln c} = 1$ for IA preferences ($\eta = -1$), and $\frac{\partial \ln z^*}{\partial \ln c} = \frac{1}{\kappa-\gamma} < 1$ for DA preferences.

³³ $G_2(g) = \kappa g^{1+\gamma} \left[\frac{F_1(g)}{\kappa-\gamma-1} + \gamma g^{-1} \frac{F_2(g)}{\kappa-\gamma} \right]$

³⁴ $G_3(g) = \kappa g^{1+\gamma} \left[\frac{F_1(g)}{\kappa-\gamma-1} \right]$. Notice that, as U declines in c , policies that would only increase the marginal cost of production c would be welfare reducing.

the utility of consumers as a function of g :

$$U = \left[\frac{Lb^\kappa a^\kappa \gamma^\gamma g^{-\kappa} G_1(g)}{f_E(1+\gamma)^{1+\gamma} c^{\kappa-\gamma-1}} \right]^{\frac{\eta}{(1+\eta)(\kappa-\gamma)-1}} \left[(1+\gamma) \frac{G_3(g)}{G_2(g)} - \frac{\gamma^2}{1+\gamma} \frac{G_1(g)}{G_2(g)} + \frac{1}{\eta} \right] - \frac{1}{\eta} \quad (15)$$

As shown in Figure 1, a minimum quality standard can improve welfare across the three preferences nested into GTP. In fact, the relationship between welfare and the standard is hump-shaped. There are two opposing welfare effects that generate such a relationship. First, in the presence of a quality standard, the selection of firms is determined by the government imposed \bar{z} , and not by the market cutoff z^* . We call this the *composition effect* of the standard: regardless of the preferences, the exit of low-quality firms reallocates production towards the surviving high-quality firms. Such a reallocation is welfare improving.

Second, the quality standard reduces the number of varieties available for consumption, which is welfare reducing under the assumption of love for variety. Furthermore, the reduction in the number of varieties may cause a change in the markups of surviving firms, through a change in z^* (8). The effects of the standard on markups of surviving firms depend on the preferences used and, in particular, on the elasticity of the market cutoff with respect to L . Under IA preferences, in which such an elasticity is zero, the standard leaves the markups of surviving firms unchanged. Under DA and homothetic preferences, the standard increases the markups of surviving firms. We call this the *anti-competitive* effect of the standard: it operates under homothetic and DA preferences, but is silent under IA preferences. Finally, the increase in markups, or anti-competitive effect, is largest under homothetic preferences.³⁵

For “small” levels of restrictiveness, the composition effect dominates the reduction in the number of varieties and the anti-competitive effects. Increasing the standard over its optimal value causes the variety reduction to dominate, and welfare starts falling.

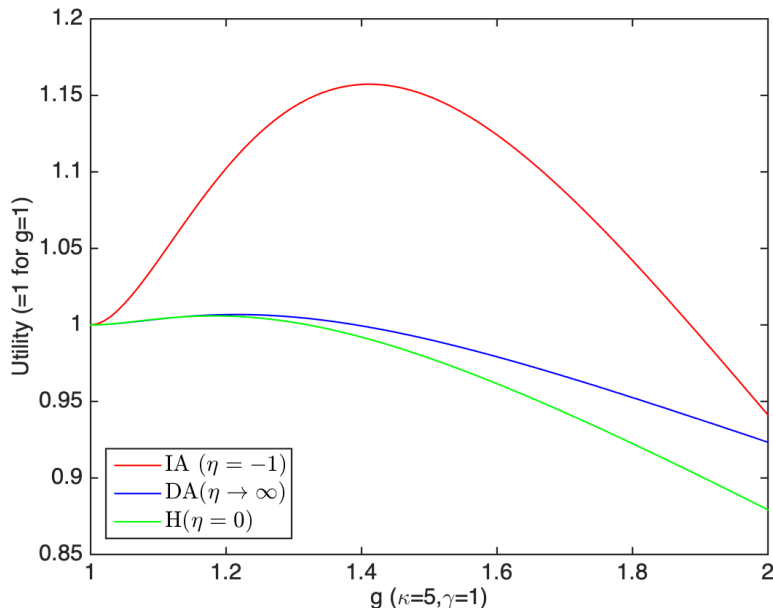
The optimal level of the measure of the restrictiveness of the standard $g^{opt}(\kappa, \gamma, \eta)$ only depends on the parameters κ , γ , and η . The optimal level of the standard \bar{z}^{opt} is then proportional to the market-determined cutoff:

$$\bar{z}^{opt} = g^{opt}(\kappa, \gamma, \eta) z^* \quad (16)$$

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 $\kappa = 5$ and $\gamma = 1$, welfare

³⁵In fact, one can relate this result to [Arkolakis et al. \(2017\)](#), who show that the effect of *trade costs* on the choke price can be ranked across the same types of preferences.

Figure 1: Minimum Quality Standard and Welfare



is maximized at $g = 1.41$: the government sets a standard which reduces the probability of a firm being active by $|1.41^{-5} - 1| = 82\%$ relative to the market allocation.³⁶

3.4 Discussion

The most direct way to interpret how the quality standard alters welfare is through the two channels described above. A higher standard lowers the number of varieties available, which lowers welfare, but it raises allocative efficiency. The latter channel raises the measure of average markups in the market allocation closer to the average social markups. 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 \(2017\)](#), and [Weinberger \(2017\)](#).

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

³⁶Under 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 $\tilde{g} = \frac{\bar{z}}{z^*(1)} = g \left[\frac{g^{-\kappa} G_1(g)}{G_1(1)} \right]^{\frac{1}{\kappa - \gamma - 1 + \eta}}$. We can prove analytically that $g > 1$ improves welfare under the assumption of linear demand ($\gamma = 1$). Details are available upon request.

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).³⁷

To understand these two margins, we recap the two biases identified in [Dhingra and Morrow \(2016\)](#) (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 bias” causes an excessive degree of firms’ selection, whereby $z^* > z_p^*$ 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. $z^* < z_p^*$, because it allows low-quality firms to steal business from high-quality firms.³⁸ 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 in (15), 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.³⁹ 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 .⁴⁰

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.

³⁷The mass of entrants J is always efficient in the market allocation ([Arkolakis et al., 2017](#)).

³⁸The [Dhingra and Morrow \(2016\)](#) results are in fact applicable to our framework with firms differentiated in quality instead of productivity.

³⁹The social planner chooses to equalize markups across firms at $m = \frac{\kappa - \gamma}{\kappa - \gamma - 1}$.

⁴⁰We 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.

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.

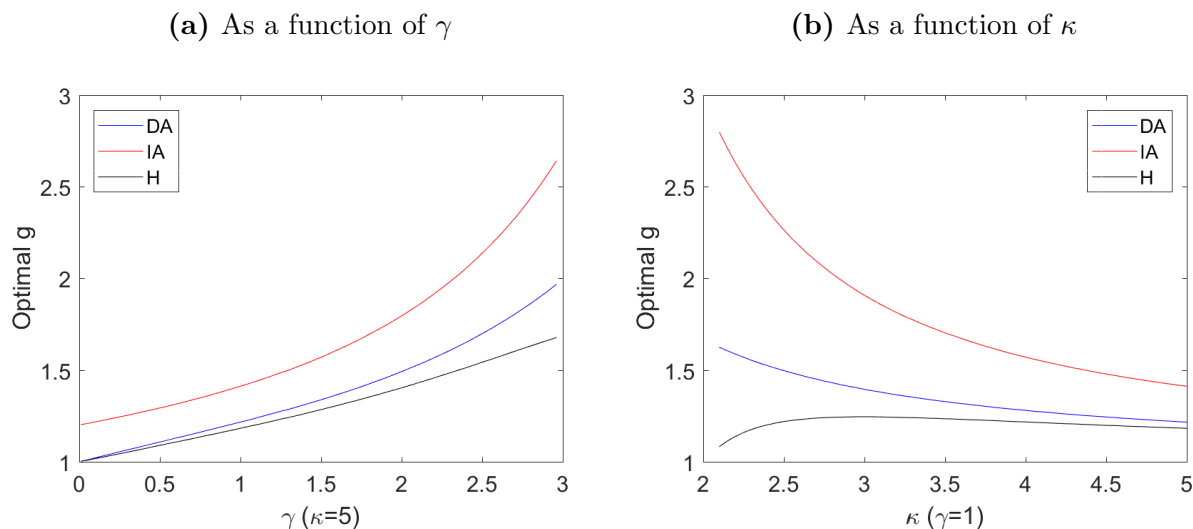
DA Preferences. Under DA preferences ($\eta \rightarrow \infty$), the market allocation generates business stealing bias, provided that $\gamma > 0$ and, thus, demand is not fully rigid. The ratio of the planner's cutoff to the market cutoff is $\left(\frac{z_P^*}{z^*(1)}\right)_{DA} = \left(1 + \frac{1}{\gamma}\right)^{\frac{\gamma}{\kappa-\gamma}} \geq 1$. 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.⁴¹ 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.

⁴¹The 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 empirical section we verified that it only occurs in one industry.

Figure 2: Optimal g Across Preferences



Optimal Standard Across Preferences. Figure 2 shows a ranking of the optimal degree of restrictiveness of the standard g across preferences. In particular, $g_{IA}^{opt} > g_{DA}^{opt} > g_H^{opt}$. The ranking follows the extent of the anti-competitive effects of the standard, which depends on the elasticity of the market cutoff with respect to market size $\frac{\partial \ln z^*}{\partial \ln L}$. Under IA preferences, such an elasticity is zero and the anti-competitive effects are absent. Thus, the optimal standard is the most restrictive. Under DA and homothetic preferences, the reduction in the number of firms generates increases in markups. Such increases are the largest under homothetic preferences. Hence, the optimal standard is the smallest under homothetic preferences, and it is at an intermediate level under DA preferences.⁴²

4 Model Estimation

In the theoretical framework, we incorporate regulations that affect firm selection into an economy with firm heterogeneity, so that the measure of producing firms and the sales of these firms depend on the level of regulatory restrictiveness in the industry plus demand and supply parameters. Next, we use the model to estimate the regulatory restrictiveness of Chilean industries by matching 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

⁴²The 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 variety externality in the Benassy-CES preferences (Benassy, 1996)

between percentiles of the model and data sales distribution. 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.⁴³

We run this procedure for a cross-section of industries and repeat it across multiple years. 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 industry level given the supply and demand parameters. Hence, we provide a meaningful interpretation of how many industries appear to be *too restrictive* as characterized by the structure of the model, even allowing for large optimal standards.

4.1 Strategy

Our goal is to estimate the parameter set (g, κ, γ) for each industry, as these are enough to characterize the “restrictiveness” of an industry as given by g/g^{opt} . 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 from 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 500,000 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 the market quality cutoff (z^*) is a constant in the IA case, we normalize this to one. By construction, $z \in [1, \infty]$, and hence all draws have positive demand in the case where there is no government imposed quality standard. 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 99 moments from the empirical domestic sales distribution. Given a set of potential producers in the simulation, namely those with $z > g$, we compute firm revenues normalized by mean revenues:

$$\tilde{r}(z|z > g) = \frac{r}{\bar{r}} = (G_2(g))^{-1} \left(\frac{z}{z^*} - 1 \right)^\gamma \left(\frac{z}{z^*} + \gamma \right) \quad (17)$$

⁴³Below, we report an exercise that confirms that the model generates similar results as in the data if we run specification 1 on simulated firms.

where $G_2(g)$ is a function that depends on the targeted parameters and is described in footnote 33. After conditioning on active firms, relative sales are independent of η .⁴⁴

The theoretical relative sales are matched to their counterpart in the data in order to identify the model parameters in an approach that follows [Sager and Timoshenko \(2017\)](#). 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 of the log sales distribution. Our identification consists of choosing the parameter set that minimizes the sum of the squared errors between empirical and theoretical quantiles:

$$\min_{g, \kappa, \gamma} \sum_{q=1}^{99} (F_q^d - F_q^m(g, \kappa, \gamma))^2. \quad (18)$$

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. We employ the strategy above for each 4-digit ISIC (revision 3) industry by year. Although there are about 100 industries in this level of classification, we only keep those with at least 35 firms in 1995, which allows us to estimate restrictiveness for 40 industries.

The strategy to estimate the parameter set $(\hat{g}, \hat{\kappa}, \hat{\gamma})$ is based on the separate ways that each parameter is 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., 2017](#)), which do not apply to our GTP specification. The 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 .⁴⁵ 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.

⁴⁴In general, z^* depends on η (11). In the non-IA cases, we compute the new z^* for any given guess of the standard. The predicted optimal standard depends on η , and for this reason in the appendix we compare the results between the IA and DA cases (see footnote 36). The estimated parameters across the types of preferences are almost identical. We implicitly ignore cross-industry interactions, as it would be the case if consumer's utility was a Cobb-Douglas aggregation of the industry specific utility shown in (2). Furthermore, our algorithm does not require the estimation of the mass of entrants per industry.

⁴⁵As is not the case, for example, if preferences were CES and the distribution of quality is Pareto.

4.2 Estimation Results

For expositional purposes, we employ the procedure outlined in the previous section to estimate $(\hat{g}, \hat{\kappa}, \hat{\gamma})$ for the universe of Chilean manufacturing firms in each year. The estimated level of the quality standard \hat{g} had 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 (standard error .002).

Panel A of Table 2 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.⁴⁶ 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%, 12%, and 31% in the three displayed years. These are very much in line with the empirical average markup estimates, which are not targeted in the estimation.⁴⁷

The empirical sales distribution exhibits structural changes captured by the variation of $\hat{\kappa}$ and $\hat{\gamma}$ over time. Although $\hat{\kappa}$ is roughly constant between 1995 and 2000, the subsequent reduction in $\hat{\kappa}$ highlights an increase in the underlying quality dispersion. There are several moments of the sales distribution that help explain the observed movement in the parameters of the model. For example, we find that the ratio of sales between exporters and non-exporters gets larger⁴⁸, differences in sales between firms at certain percentiles become larger, skewness decreases (longer left tail), and average markups increase (as reported above). This could reflect an expansion of the largest firms, or smaller firms at the bottom of the distribution. We find that the former is more apparent in the sales data, and point to the effect of trade in the industry analysis below.

The estimated restrictiveness of the standard \hat{g} is highly heterogeneous across industries. Consider the reduction in the survival probability due to the standard, which is calculated as $(1 - \hat{g}^{-\hat{\kappa}})$. Table 3 reports the reduced probability for each industry in 1995, 2000 and 2005. The most restrictive industries across the years – Motor Vehicles, Books/Journals, Machinery and Other Metals, Pharmaceutical, and various food industries – averaged over

⁴⁶In 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.

⁴⁷These are based on the De Loecker and Warzynski (2012) procedure and using material inputs as the variable input. We take a weighted average using the firms' share of total employment in the economy.

⁴⁸This holds with average sales of firms above the median in domestic sales versus below the median, which are reported in Table 2.

Table 2: Estimation Results: Manufacturing-wide in 1995, 2000, and 2005

Panel A: Parameter Estimates						
Year	Data Targets	\hat{g}	$\hat{\kappa}$	$\hat{\gamma}$		
1995	Sales Percentiles (1-99)	1.1 (.01)	4.49 (.57)	1.92 (.15)		
2000	Sales Percentiles (1-99)	1.13 (.01)	4.94 (.69)	2.40 (.18)		
2005	Sales Percentiles (1-99)	1.02 (.004)	2.45 (.17)	1.30 (.06)		

Panel B: Moments: Data versus Model						
Moment	1995		2000		2005	
	Data	Model	Data	Model	Data	Model
Sales Advantage	2.41	2.42	2.57	2.59	2.88	2.87
90-10 Sales	3.89	3.88	4.15	4.15	4.71	4.65
99-90 Sales	2.02	2.04	2.25	2.28	2.26	2.35
Skewness	.67	.69	0.78	.79	.43	.33
Average Markup	22%	14%	20%	12%	38%	31%

Panel A reports the parameter estimates when estimating the model for all manufacturing firms in each year (results also available per industry, but are not reported as they would contain 40 estimates for each parameter per year). 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 top 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.

50% lower survival probability. On the other hand, there are industries such as Apparel and Furniture that hover around 10% in reduced probability across all years.⁴⁹ On average, the reduction in probability is 37% in 1995, 43% in 2000, and drops to 29% in 2005. This is consistent with the previous results, where the restrictiveness at the economy wide-level seems to decrease in 2005.

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. As a robustness check, we have applied 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” firms⁵⁰; ii) the skewness of the distribution which captures the composition effect of the standard; and two

⁴⁹In the analysis of time variation below, we eliminate “Other Publishing” and “Bakery” which have massive decreases in restrictiveness. There are also a few industry-year pairs we drop from the table as the estimated $\hat{\kappa}$ is imprecise.

⁵⁰This moment is related to that used to identify the elasticity of substitution in [Bernard et al. \(2003\)](#). Instead of comparing exporters and non-exporters, we compare firms above and below the median in sales.

differences: iii) $\log(\tilde{r})_{99} - \log(\tilde{r})_{90}$, and iv) $\log(\tilde{r})_{90} - \log(\tilde{r})_{10}$.⁵¹ We plot the simulated sales distribution in Appendix 6.4 and report the estimated parameters. We do not find large discrepancies with our benchmark strategy: \hat{g} is very similar and has the same time series patterns, as do the other two parameters. However, in the alternative calibration, the fit with the data distribution is clearly not as close.

As an alternative approach, we consider fixing some parameters to estimate restrictiveness, with full results in Appendix 6.4. First, we set $\gamma = 1$ and estimate the remaining two parameters, in case there is collinearity with the shape of the quality distribution. A graphical analysis shows that this specification is not able to match the dispersion in sales in the data. Moreover, the implied average markups, which are 39%, 46%, and 51%, are larger than reasonable markup estimates. However, the time series pattern of \hat{g} uncovered in the baseline estimation holds.⁵² Second, we estimate *only* the restrictiveness parameter, and set $\kappa = 4$ and $\gamma = 1.8$ as deep parameters constant over time. Still, \hat{g} ranges between 1.04 and 1.1 with similar time-series movements.⁵³

We also tie our model to the empirical exercise in Section 2. The industry-standards parameter is interpreted slightly differently than TM_{it} , but a rise in TM_{it} should be reflected in \hat{g}_{it} . As in the previous exercise, we fix κ and γ , but use the industry-year estimated standards parameter to construct variation in $(1 - \hat{g}_{it}^{-\kappa})$. As a link to (1), we regress firm outcomes on an interaction of standards with the simulated quality draw (z). Firm quality is held constant and we include the same fixed effects.⁵⁴ Table 9 confirms that in fact, as an industry experiences a reduction in survival probability, firms with a higher quality draw have a relatively higher survival rate, and they raise their relative sales share and markups. Therefore, our model generates results that are consistent with distributional outcomes experienced in Chile in response to changes in the number of SPS regulations.

⁵¹We do not use moments from other distributions, such as markups and value added, because the data does not allow us to differentiate between exported and domestic components.

⁵²There is a shift downwards of $\hat{\kappa}$ and \hat{g} , as the restriction on the demand curvature requires a larger dispersion in quality to match the dispersion in sales. The result supports the findings of [Jung et al. \(2019\)](#), who estimate the [Melitz and Ottaviano \(2008\)](#) model and argue that linear demand predicts a sales distribution with too little dispersion (given their preferred estimate of κ). A larger γ raises the sales of the largest firms as demand is more elastic.

⁵³As a further robustness check, we have estimated the addilog model of [Bertoletti and Etro \(2017\)](#) and the linear, separable [Melitz and Ottaviano \(2008\)](#) model. The former is very similar to the IA case in our GTP framework, while the latter is nested in our DA case with $\gamma = 1$. We found the results are almost identical to those two estimations, and we make the results available upon request.

⁵⁴We cannot compare the magnitude of the coefficients because our calibrated parameter, which we used to estimate “reduction in survival probability”, is not comparable to the standards measure in the data. This specification allows us to compare the signs, while holding “everything else constant” except \hat{g} (and the aggregate competitiveness that follows).

4.3 Restrictiveness of Standards and Optimal Standard

We compare the estimated level of restrictiveness with the optimal standard predicted by our model. We construct a restrictiveness index (RI) using the estimated parameters:

$$RI_{it} = \frac{\hat{g}_{it}}{\hat{g}_{it}^{opt}(\hat{\kappa}_{it}, \hat{\gamma}_{it})}. \quad (19)$$

where i denotes an industry, and t a year. 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. We choose the IA model in a closed economy as the benchmark because it yields the most conservative estimate of whether an industry is *too* restrictive. We interpret g_{IA}^{opt} as an *upper bound* for which policymakers can view an industry as overly regulated. For each industry-year, we compute (19) and find that there are several industries that appear too restrictive but that number has changed over the years. As in the estimation for the universe of firms, the level of restrictiveness increases from 1995 to 2000, but drops significantly in 2005.

Figure 3 plots the RI in 1995, 2000, and 2005 for each industry, sorted from largest to smallest. For each industry-year, we derive the 95% confidence interval using the estimated standard error for g in the calibration. We define industries with a confidence interval for RI that includes a ratio of one or above as too restrictive. In 1995, 11 out of 38 industries are too restrictive, although there are several industries that hover around 1.⁵⁵ In 2000, there are 12 too-restrictive industries, though a similar number are clustered around an RI index of 1. Therefore, even with the conservative measure of the optimal standard, 32% of industries are within the confidence interval of being too restrictive. We take this as evidence that Chilean manufacturing industries appear to be overly regulated – either through protectionism or other types of regulations – at the start of the century. However, this restrictiveness drops precipitously over the next few years. In 2005 only 5 out of 38 industries (13%) were overly regulated, and many more industries drop far below the cutoff.⁵⁶

Recall that the welfare-enhancing properties of standards are a reallocation to large high-quality firms. For example, take the meat industry (ISIC 1511). The ratio of average domestic sales of the top 50% of firms relative to the smallest 50% is 2.82 in 2000, and increases to 3.44 in 2005 (reflected by the “Sales Advantage” in Panel B of Table 2). The

⁵⁵The noise in the estimation can affect whether an industry fits within our definition of too restrictive. However, this is only obvious in the “Other Manufacturing” and “Journals” industries.

⁵⁶Plots that result from the estimation of DA preferences and assuming a fixed cost for the standard are in the appendix – in both cases the optimal standard is merely shifted downwards.

results suggest that the expansion of the large firms is concurrent with a lower estimated restrictiveness of industries.

It is likely that a greater openness to trade contributed to the reallocation and is related to drop in observed restrictiveness. [Edmond et al. \(2015\)](#) argue that trade reduces misallocation through competition, and in fact we confirm that the standard in our paper works as a complement to lower trade costs in an open economy setting (results available upon request). In the appendix we report suggestive evidence. First, a plot of the total value of exports and imports relative to GDP (Figure 18), suggests that the economy becomes more open after 2000. Furthermore, Chile signed free trade agreements with the EU in 2002, with the United States and Korea in 2004, and with China in 2005. It also lowered its across-the-board tariffs to 6% for all countries with which it did not have an agreement. In the bottom panel of Figure 18, we plot average applied tariff rates (weighted by industry import flows) and the terms of trade (provided by the World Development Indicators). Tariffs begin their decline in 1999, dropping from 11% to 2% in 2007. There is a large terms of trade appreciation after 2001 – due to the price of copper – which creates opportunities for importers to enter the Chilean market. Finally, there is a negative correlation between the changes in restrictiveness and openness of the industry. In a plot of the log difference in RI between 2000 and 2005 against an openness measure, the correlation is -0.20 (Figure 19).

5 Conclusion

We have provided a policy that can improve allocative efficiency without relying on international economic integration and merely affecting the selection of firms. An example of such policy are product standards, which force low-quality firms out of the market and improve welfare. In order 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 firm sales across industries that differ in their level of regulation. Our findings that technical measures skew domestic sales towards high-quality firms complements the findings in the trade literature that has found these measures to reduce the extensive margin of export flows.

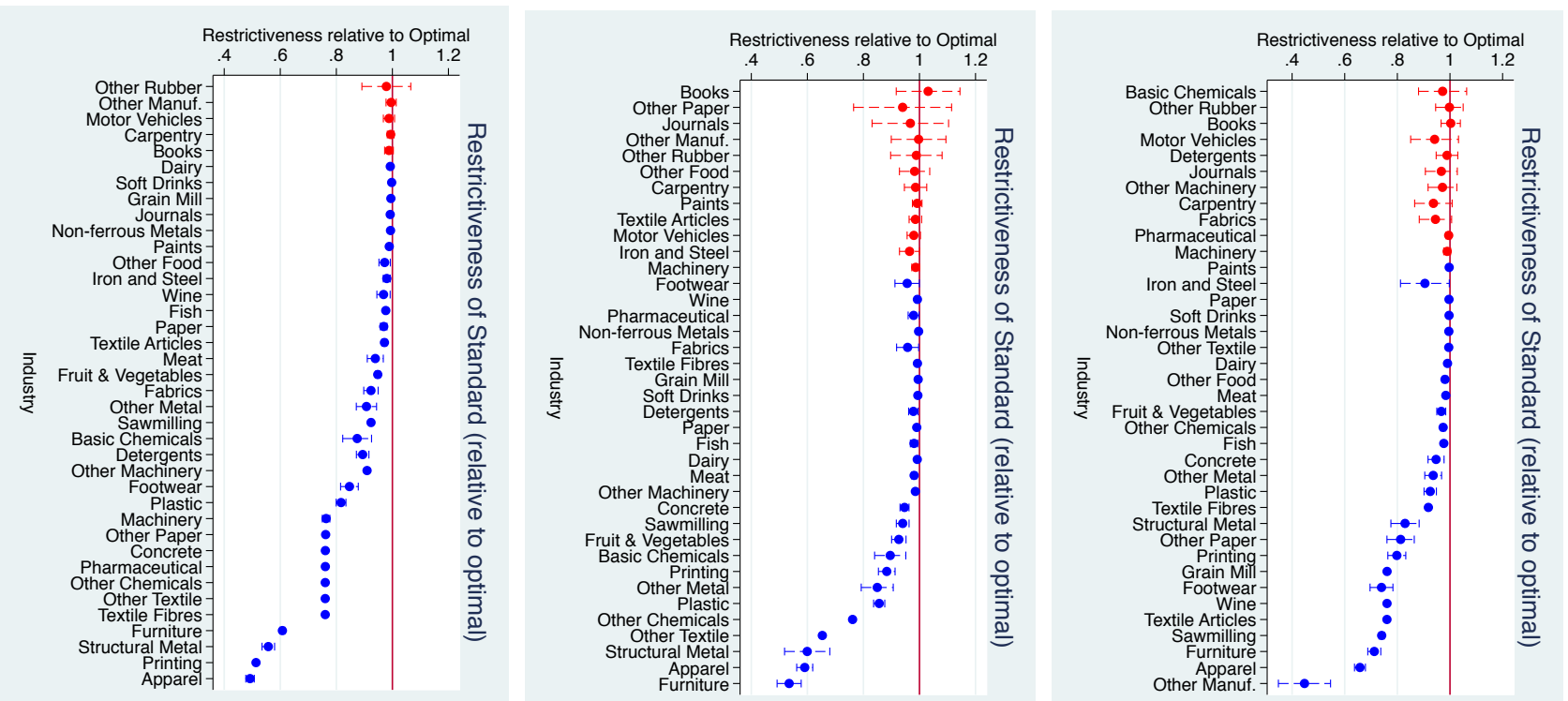
We estimate the model to fit the observed distribution of domestic sales and conduct a policy-relevant evaluation that compares the estimated level of restrictiveness with the optimal standard as predicted by our model. Although industries appear heavily regulated up until 2000, this is not the case in 2005 and there is suggestive evidence that it is driven by more open industries.

Table 3: Reduction in Probability of Survival Due to Restrictions by Industry-Year

ISIC	Industry name	1995	2000	2005
1511	Meat	0.4	0.45	0.47
1512	Fish	0.16	0.38	0.2
1513	Fruit & Vegetables	0.35	0.33	0.13
1520	Dairy	0.32	0.22	0.3
1531	Grain Mill	-	0.06	0.08
1549	Other Food	0.55	0.72	0.41
1552	Wine	-	0.3	0.42
1554	Soft Drinks	0.12	0.33	0.1
1711	Textile Fibres	0.04	0.25	-
1721	Textile Articles	-	0.49	0.13
1729	Other Textile	0	0	0.8
1730	Fabrics	0.59	0.57	0.25
1810	Apparel	0.12	0.15	0.02
1920	Footwear	0.32	0.61	0.17
2010	Sawmilling	0.06	0.38	0.14
2022	Carpentry	0.31	0.71	0.48
2102	Paper	0.23	0.35	0.31
2109	Other Paper	0.22	0.84	0
2211	Books	0.87	0.98	0.45
2212	Journals	0.71	0.81	0.45
2221	Printing	0.2	0.27	0
2411	Basic Chemicals	0.8	0.43	0.21
2422	Paints	0.09	0.49	0.22
2423	Pharmaceutical	0.48	0.42	-
2424	Detergents	0.75	0.65	0.11
2429	Other Chemicals	0.19	-	-
2519	Other Rubber	0.79	0.78	0.58
2520	Plastic	0.37	0.26	0.19
2695	Concrete	0.5	0.26	-
2710	Iron and Steel	0.47	0.72	0.39
2720	Non-ferrous Metals	0.2	0.13	0.11
2811	Structural Metal	0.46	0.22	0.04
2899	Other Metal	0.49	0.48	0.48
2919	Other Machinery	0.62	0	0
2924	Machinery	0.43	0.53	-
3430	Motor Vehicles	0.6	0.61	0.56
3610	Furniture	0.15	0.13	0.03
3699	Other Manuf.	0.16	0.84	0.6
	Average	0.37	0.43	0.29

This table reports the reduced probability of producing in each industry given the estimated restrictiveness of the industry. The probability is calculated as $(1 - \hat{g}^{-\hat{\kappa}})$. It is based on the simulated method of moments estimation for year industry by year. For certain industry-year pairs, the data was insufficient to estimate stable parameter values, which is why certain entries above are missing.

Figure 3: Restrictiveness Index with IA Preferences: 1995, 2000, and 2005.



In red are the industries where we cannot reject the null hypothesis that the restrictiveness index is different from one.

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6 Appendix

6.1 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 “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.⁵⁷ We construct a Frequency Index in industry i which can be written as:

$$F_i = \frac{\sum_{p \in i} D_p M_p}{\sum_{p \in i} M_p} \quad (20)$$

where D_p is equal to the number of unique 2-digit NTM codes imposed in product p , within

⁵⁷A 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).

industry i . M_p is a dummy for a product produced within the industry. The trade literature 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 .

6.2 Motivational Evidence

Table 4: Top 25 Most Regulated Industries

Rank	SPS and TBT Rank		SPS 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.

Table 5: Correlation of Quality with TFP (top) and Size (bottom) across Firms

	Quality Proxy					
	log(K/L)	log(W/L)	log(M/L)	log(K/L)	log(W/L)	log(M/L)
Log TFP	0.532*** (0.110)	0.436*** (0.036)	1.323*** (0.068)			
Log Labor Productivity				0.646*** (0.030)	0.349*** (0.012)	0.606*** (0.030)
Fixed Effects	Industry-Year	Industry-Year	Industry-Year	Industry-Year	Industry-Year	Industry-Year
# Observations	63790	63785	63790	61779	65483	65441

	Quality Proxy		
	(K/L)	(W/L)	(M/L)
Log Size	0.464*** (0.015)	0.227*** (0.005)	0.473*** (0.014)
Fixed Effects	Industry-Year	Industry-Year	Industry-Year
# Observations	64894	68864	67993

This table regresses the quality proxy on measures of productivity and size. The top table displays results for two different measures of productivity: log TFP estimated from a Translog production function using the procedure outlined in [Weinberger \(2017\)](#), and a simple measure of logged value added per worker. The bottom panel displays results for the relationship between quality and log sales. Quality is proxied by (logged) capital per worker, total wages per worker, and input expenditure per worker respectively. In all specifications we use the full panel of firm-year observations and include industry-year fixed effects so that we are only capturing within industry-year relationships. Standard errors – clustered by 4-digit industry – are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 6: Firm Sales and Survival Heterogeneity: Effects of Technical Measures including TBT

Panel A: OLS

	Log Domestic Sales				Survival			
	(Sales)	(K/L)	(W/L)	(M/L)	(Sales)	(K/L)	(W/L)	(M/L)
TM*Char	0.013** (0.005)	0.015** (0.006)	0.012** (0.006)	0.008 (0.006)	0.016*** (0.004)	0.012** (0.005)	0.009 (0.006)	0.006 (0.004)
Openness*Char	0.022 (1.294)	0.965 (0.787)	0.144 (1.094)	-1.998** (0.769)	-0.525** (0.249)	-0.526*** (0.099)	-0.406 (0.271)	-0.206 (0.129)
Tariff*Char	-0.010*** (0.004)	-0.011*** (0.004)	-0.012*** (0.004)	-0.006 (0.005)	-0.003** (0.002)	-0.008*** (0.002)	0.000 (0.001)	-0.001 (0.001)
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
R^2	0.955	0.955	0.955	0.955	0.644	0.645	0.644	0.643
# Observations	44220	44220	44220	43789	69679	69679	69679	68924

Panel B: IV Results

	Log Domestic Sales				Survival			
	(IV-Sales)	(IV-K/L)	(IV-W/L)	(IV-M/L)	(IV-Sales)	(IV-K/L)	(IV-W/L)	(IV-M/L)
TM*Char	0.028* (0.016)	0.034** (0.016)	0.046*** (0.016)	0.006 (0.016)	0.027** (0.011)	0.002 (0.011)	0.031*** (0.011)	0.002 (0.011)
Openness*Char	0.003 (0.717)	0.949 (0.831)	0.114 (0.882)	-1.995** (0.825)	-0.532*** (0.118)	-0.520*** (0.113)	-0.420*** (0.120)	-0.204 (0.161)
Tariff*Char	-0.010*** (0.002)	-0.011*** (0.002)	-0.013*** (0.002)	-0.006*** (0.002)	-0.003*** (0.001)	-0.008*** (0.001)	0.000 (0.001)	-0.001 (0.001)
F-stat (first stage)	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
# Observations	44220	44220	44220	43789	69679	69679	69679	68924
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

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 technical measures (bottom). 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 input 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 7: Firm Sales Heterogeneity - Repeated Cross-Sections

Panel A: OLS

	Log Domestic Sales			
	(Sales)	(K/L)	(W/L)	(M/L)
TM*Char	0.150*** (0.032)	0.113*** (0.030)	0.094*** (0.033)	0.139*** (0.032)
Openness*Char	4.833 (5.175)	3.236 (2.533)	3.557 (3.172)	1.640 (2.913)
Tariff*Char	0.184*** (0.010)	0.090*** (0.009)	0.125*** (0.009)	0.113*** (0.009)
DemandElast*Char	-0.002 (0.030)	-0.010 (0.027)	-0.005 (0.027)	-0.016 (0.025)
Fixed Effects	I-Y	I-Y	I-Y	I-Y
R^2	0.589	0.364	0.415	0.406
# Observations	41557	41557	41557	41118

Panel B: IV Results

	Log Domestic Sales			
	(IV-Sales)	(IV-K/L)	(IV-W/L)	(IV-M/L)
TM*Char	0.095*** (0.007)	0.058*** (0.008)	0.044*** (0.008)	0.092*** (0.008)
Openness*Char	5.003*** (1.044)	3.398*** (0.888)	3.714*** (1.181)	1.804 (1.123)
Tariff*Char	0.194*** (0.002)	0.099*** (0.002)	0.133*** (0.002)	0.121*** (0.002)
DemandElast*Char	0.005*** (0.002)	-0.002 (0.002)	0.003 (0.002)	-0.009*** (0.002)
F-stat (first stage)	1.0	1.0	1.0	1.0
# Observations	41557	41557	41557	41118
Fixed Effects	I-Y	I-Y	I-Y	I-Y

This Table is a repeated cross-section analysis of specification (1). Regulations are aggregated by industry across all years, so variation is only at the industry level. 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.) 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 input 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 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 8: Firm Sales and Survival Heterogeneity: Effects of Technical Measures that include only Pre-Shipment Inspections and Prohibitions of Imports for SPS and TBT reasons

Panel A: OLS

	Log Domestic Sales				Survival			
	(Sales)	(K/L)	(W/L)	(M/L)	(Sales)	(K/L)	(W/L)	(M/L)
TM*Char	-0.013 (0.023)	0.042 (0.026)	-0.007 (0.030)	-0.019 (0.019)	-0.012 (0.014)	-0.004 (0.012)	-0.000 (0.015)	-0.019 (0.015)
Openness*Char	0.037 (1.290)	0.980 (0.788)	0.154 (1.096)	-0.257 (0.827)	-0.516** (0.246)	-0.519*** (0.101)	-0.401 (0.269)	-0.424** (0.186)
Tariff*Char	-0.010** (0.004)	-0.011*** (0.004)	-0.012*** (0.004)	-0.009** (0.004)	-0.003* (0.002)	-0.008*** (0.002)	0.000 (0.001)	-0.002 (0.001)
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
R^2	0.955	0.955	0.955	0.954	0.644	0.645	0.644	0.644
# Observations	44220	44220	44220	44220	69679	69679	69679	69679

Panel B: IV Results

	Log Domestic Sales				Survival			
	(IV-Sales)	(IV-K/L)	(IV-W/L)	(IV-M/L)	(IV-Sales)	(IV-K/L)	(IV-W/L)	(IV-M/L)
TM*Char	-1.325 (1.664)	-0.453 (1.673)	-2.227 (1.759)	1.795 (1.685)	-0.511 (2.454)	2.284 (3.079)	-3.422 (3.726)	-1.770 (2.815)
Openness*Char	-0.041 (0.723)	0.946 (0.833)	0.017 (0.888)	-0.142 (0.902)	-0.540*** (0.163)	-0.410** (0.187)	-0.565*** (0.214)	-0.508*** (0.176)
Tariff*Char	-0.014*** (0.006)	-0.013** (0.005)	-0.019*** (0.006)	-0.003 (0.006)	-0.005 (0.008)	-0.001 (0.010)	-0.010 (0.012)	-0.007 (0.009)
F-stat (first stage)	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
# Observations	44220	44220	44220	44220	69679	69679	69679	69679
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

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 technical measures (bottom). Compared to the Table in the main text, here we construct the frequency index of technical measures allowing technical measure to be only pre-shipment inspections plus the NTM codes with SPS and TBT that seem more likely to apply to importers (A1 and B1). 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 input 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

6.3 Model's Derivations

6.3.1 Consumers' Problem

Recall the Generalized Translated Power (GTP) preferences:

$$U = \int_{\Omega} \left(az\xi q(\omega) - \frac{(\xi q(\omega))^{1+\frac{1}{\gamma}}}{1+\frac{1}{\gamma}} \right) d\omega + \frac{\xi^{-\eta} - 1}{\eta} \quad (21)$$

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

$$\xi^{-\eta} = \int \left(az\xi q(\omega) - (\xi q(\omega))^{1+\frac{1}{\gamma}} \right) d\omega \quad (22)$$

The first order conditions of the consumers' problem are:

$$az\xi - \xi^{1+\frac{1}{\gamma}} q(\omega)^{\frac{1}{\gamma}} + \left[\underbrace{\int \left(azq(\omega) - \xi^{\frac{1}{\gamma}} (q(\omega))^{1+\frac{1}{\gamma}} \right) d\omega - \xi^{-\eta-1}}_{=0 \text{ by (22)}} \right] \frac{\partial \xi}{\partial q(\omega)} = \lambda p(\omega)$$

$$az\xi - \xi^{1+\frac{1}{\gamma}} q(\omega)^{\frac{1}{\gamma}} = \lambda p(\omega) \quad (23)$$

By multiplying both sides of (23) by $q(\omega)$ and integrating across all varieties $\omega \in \Omega$, we obtain the marginal utility of income λ .

$$\lambda = \frac{1}{y} \int \left(az\xi q(\omega) - (\xi q(\omega))^{1+\frac{1}{\gamma}} \right) d\omega = \frac{\xi^{-\eta}}{y} \quad (24)$$

Using (24) in (23) yields the inverse demand:

$$p(\omega) = \frac{\xi}{\lambda} \left[az(\omega) - (\xi q(\omega))^{\frac{1}{\gamma}} \right] = y\xi^{1+\eta} \left[az - (\xi q(\omega))^{\frac{1}{\gamma}} \right] \quad (25)$$

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

6.3.2 Quality Standard and Aggregate Variables

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

$$\begin{aligned} \bar{\pi} &= \int_{\bar{z}}^{\infty} \pi(z) \frac{\kappa \bar{z}^{\kappa}}{z^{\kappa+1}} dz = \\ &= \frac{Lc}{1+\gamma} \left(\frac{a\gamma}{1+\gamma} \right)^{\gamma} \frac{(z^*)^{\gamma}}{\xi} \int_{\bar{z}}^{\infty} \left(\frac{z}{z^*} - 1 \right)^{1+\gamma} \frac{\kappa \bar{z}^{\kappa}}{z^{\kappa+1}} dz = \\ &= \frac{Lc}{1+\gamma} \left(\frac{a\gamma}{1+\gamma} \right)^{\gamma} \frac{(z^*)^{\gamma}}{\xi} G_1(g) \end{aligned} \quad (26)$$

where $G_1(g)$ is a function of κ , γ , and of the restrictiveness of the standard g :

$$\begin{aligned}
G_1(g) &= \int_{\bar{z}}^{\infty} \kappa \left(\frac{z}{z^*} - 1 \right)^{1+\gamma} \frac{\bar{z}^\kappa}{z^{\kappa+1}} dz = \\
&= \int_{\bar{z}}^{\infty} \kappa \left(1 - \frac{z^*}{z} \right)^{1+\gamma} \frac{\bar{z}^\kappa}{(z^*)^{1+\gamma} z^{\kappa-\gamma}} dz = \\
&= \kappa g^{1+\gamma} \left[\frac{F_1(g)}{\kappa - \gamma - 1} - g^{-1} \frac{F_2(g)}{\kappa - \gamma} \right]
\end{aligned} \tag{27}$$

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

$$\begin{aligned}
F_1(g) &= {}_2F_1 [\kappa - \gamma - 1, -\gamma; \kappa - \gamma, g^{-1}] \\
F_2(g) &= {}_2F_1 [\kappa - \gamma, -\gamma; \kappa - \gamma + 1, g^{-1}].
\end{aligned}$$

The probability of a firm being active is:

$$P(z \geq \bar{z}) = \frac{b^\kappa}{\bar{z}^\kappa} = \frac{b^\kappa}{(z^*g)^\kappa} \tag{28}$$

The zero expected profit condition is:

$$\begin{aligned}
P(z \geq \bar{z})\bar{\pi} &= f_E \\
\frac{Lc}{1+\gamma} \left(\frac{a\gamma}{1+\gamma} \right)^\gamma \frac{b^\kappa}{(z^*)^{\kappa-\gamma} g^\kappa \xi} G_1(g) &= f_E
\end{aligned} \tag{29}$$

from which we obtain:

$$(z^*)^{\kappa-\gamma} \xi = \frac{Lcb^\kappa}{f_E(1+\gamma)} \left(\frac{a\gamma}{1+\gamma} \right)^\gamma g^{-\kappa} G_1(g) \tag{30}$$

Substituting the quality cutoff $z^* = \frac{c}{a} \xi^{-(1+\eta)}$ into (30) yields the quality cutoff z^* and market aggregator ξ as a function of g and model's parameters:

$$z^* = \left[\frac{Lc^{\frac{\eta}{1+\eta}} \gamma^\gamma b^\kappa a^{\gamma+\frac{1}{1+\eta}}}{f_E(1+\gamma)^{1+\gamma}} g^{-\kappa} G_1(g) \right]^{\frac{1}{\kappa-\gamma-\frac{1}{1+\eta}}} \tag{31}$$

$$\xi = \left[\frac{Lb^\kappa a^\kappa \gamma^\gamma}{f_E(1+\gamma)^{1+\gamma} c^{\kappa-\gamma-1}} g^{-\kappa} G_1(g) \right]^{-\frac{1}{(1+\eta)(\kappa-\gamma)-1}} \tag{32}$$

Firms' average revenues are:

$$\bar{r} = \int_{\bar{z}}^{\infty} r(z) \kappa \frac{\bar{z}^\kappa}{z^{\kappa+1}} dz = \frac{Lc}{1+\gamma} \left(\frac{a\gamma}{1+\gamma} \right)^\gamma \frac{(z^*)^\gamma}{\xi} G_2(g) \tag{33}$$

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

$$\begin{aligned}
G_2(g) &= \int_{\bar{z}}^{\infty} \kappa \left(\frac{z}{z^*} - 1 \right)^\gamma \left(\frac{z}{z^*} + \gamma \right) \frac{\bar{z}^\kappa}{z^{\kappa+1}} dz = \\
&= \int_{\bar{z}}^{\infty} \kappa \left(1 - \frac{z^*}{z} \right)^\gamma \left(1 + \gamma \frac{z^*}{z} \right) \frac{\bar{z}^\kappa}{(z^*)^{1+\gamma} z^{\kappa-\gamma}} dz = \\
&= \kappa g^{1+\gamma} \left[\frac{F_1(g)}{\kappa - \gamma - 1} + \gamma g^{-1} \frac{F_2(g)}{\kappa - \gamma} \right]
\end{aligned} \tag{34}$$

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

$$\frac{r(z)}{\bar{r}} = (G_2(g))^{-1} \left(\frac{z}{z^*} - 1 \right)^\gamma \left(\frac{z}{z^*} + \gamma \right) \tag{35}$$

By market clearing:

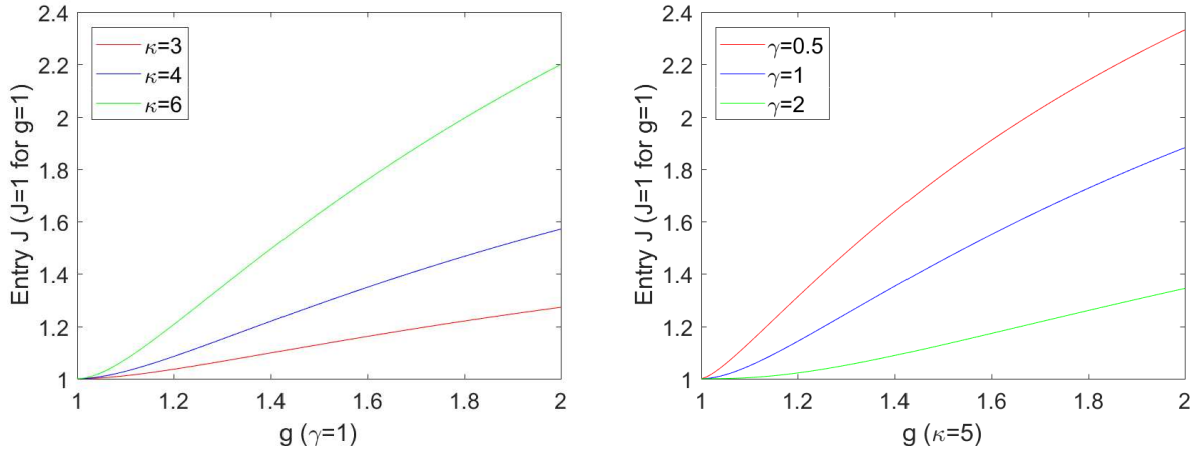
$$\frac{c}{1 + \gamma} \left(\frac{a\gamma}{1 + \gamma} \right)^\gamma \frac{Jb^\kappa}{(z^*)^{\kappa-\gamma} g^\kappa \xi} G_2(g) = 1 \tag{36}$$

Dividing (36) by (29) yields the equilibrium mass of entrants, which is independent of η :

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

As shown in figure 4, market entry J is increasing in the restrictiveness of the standard.

Figure 4: Effects of a Standard on Entry



6.3.3 Welfare

To derive the utility, we need to derive the two integrals in (21) and (22). First, we obtain:

$$\int_{\bar{z}}^{\infty} a \xi z q(z) = a \left(\frac{a\gamma}{1 + \gamma} \right)^\gamma \frac{Jb^\kappa}{(z^*)^{\kappa-\gamma} g^\kappa} z^* G_3(g) \tag{37}$$

where $G_3(g)$ is given by:

$$\begin{aligned}
G_3(g) &= \int_{\bar{z}}^{\infty} \kappa \frac{z}{z^*} \left(\frac{z}{z^*} - 1 \right)^\gamma \frac{\bar{z}^\kappa}{z^{\kappa+1}} dz = \\
&= \int_{\bar{z}}^{\infty} \kappa \left(1 - \frac{z^*}{z} \right)^\gamma \frac{\bar{z}^\kappa}{(z^*)^{1+\gamma} z^{\kappa-\gamma}} dz = \\
&= \kappa g^{1+\gamma} \left[\frac{F_1(g)}{\kappa - \gamma - 1} \right]
\end{aligned} \tag{38}$$

Rearranging the market clearing condition,

$$\left(\frac{a\gamma}{1+\gamma} \right)^\gamma \frac{Jb^\kappa}{(z^*)^{\kappa-\gamma} g^\kappa \xi} = \frac{(1+\gamma)\xi}{cG_2(g)} \tag{39}$$

Using (39) into (37) yields:

$$\int_{\bar{z}}^{\infty} a\xi zq(z) = (1+\gamma) \frac{az^*\xi}{c} \left(\frac{G_3(g)}{G_2(g)} \right) \tag{40}$$

Following the same steps, we obtain the second integral:

$$\begin{aligned}
\int_{\bar{z}}^{\infty} (\xi q(z))^{1+\frac{1}{\gamma}} &= \left(\frac{a\gamma}{1+\gamma} \right)^{1+\gamma} \frac{Jb^\kappa}{(z^*)^{\kappa-\gamma} g^\kappa} z^* G_1(g) \\
&= \frac{az^*\xi}{c} \gamma \left(\frac{G_1(g)}{G_2(g)} \right)
\end{aligned} \tag{41}$$

Substituting (40) and (41) into the utility function 21 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:

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

Finally, by the cutoff condition, $z^* = \frac{c}{a}\xi^{-1-\eta}$. Thus, the utility becomes:

$$U = \xi^{-\eta} \left[(1+\gamma) \frac{G_3(g)}{G_2(g)} - \frac{\gamma^2}{1+\gamma} \frac{G_1(g)}{G_2(g)} + \frac{1}{\eta} \right] - \frac{1}{\eta} \tag{42}$$

Substituting (32) into (42) yields:

$$U = \left[\frac{Lb^\kappa a^\kappa \gamma^\gamma}{f_E(1+\gamma)^{1+\gamma} c^{\kappa-\gamma-1}} g^{-\kappa} G_1(g) \right]^{\frac{\eta}{(1+\eta)(\kappa-\gamma)-1}} \left[(1+\gamma) \frac{G_3(g)}{G_2(g)} - \frac{\gamma^2}{1+\gamma} \frac{G_1(g)}{G_2(g)} + \frac{1}{\eta} \right] - \frac{1}{\eta} \quad (43)$$

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:

$$\tilde{g} = \frac{\bar{z}}{z^*(1)} = \frac{\bar{z}}{z^*(g)} \frac{z^*(g)}{z^*(1)} = g \left[\frac{g^{-\kappa} G_1(g)}{G_1(1)} \right]^{\frac{1}{\kappa-\gamma-\frac{1}{1+\eta}}} \quad (44)$$

and exactly equals g under IA preferences $\eta = -1$.

Directly Additive Preferences

The case of DA preferences is obtained by setting $\eta \rightarrow \infty$. The utility, market cutoff, and aggregator become:

$$U_{DA} = \left[\frac{Lb^\kappa a^\kappa \gamma^\gamma}{f_E(1+\gamma)^{1+\gamma} c^{\kappa-\gamma-1}} g^{-\kappa} G_1(g) \right]^{\frac{1}{\kappa-\gamma}} \left[(1+\gamma) \frac{G_3(g)}{G_2(g)} - \frac{\gamma^2}{1+\gamma} \frac{G_1(g)}{G_2(g)} \right] \quad (45)$$

$$z_{DA}^*(g) = \left[\frac{Lc\gamma^\gamma b^\kappa a^\gamma}{f_E(1+\gamma)^{1+\gamma}} g^{-\kappa} G_1(g) \right]^{\frac{1}{\kappa-\gamma}} \quad (46)$$

$$\xi_{DA} = 1 \quad (47)$$

Indirectly Additive Preferences

The case of IA preferences is obtained by setting $\eta = -1$. The utility becomes:

$$U_{IA} = \left[\frac{Lb^\kappa a^\kappa \gamma^\gamma}{f_E(1+\gamma)^{1+\gamma} c^{\kappa-\gamma-1}} g^{-\kappa} G_1(g) \right] \left[(1+\gamma) \frac{G_3(g)}{G_2(g)} - \frac{\gamma^2}{1+\gamma} \frac{G_1(g)}{G_2(g)} - 1 \right] + 1 \quad (48)$$

$$z_{IA}^* = \frac{c}{a} \quad (49)$$

$$\xi_{IA} = \frac{Lb^\kappa a^\kappa \gamma^\gamma}{f_E(1+\gamma)^{1+\gamma} c^{\kappa-\gamma-1}} g^{-\kappa} G_1(g) \quad (50)$$

Homothetic Preferences

The case of homothetic preferences is obtained by setting $\eta = 0$. The market determined cutoff and aggregator become:

$$z_H^* = \left[\frac{L\gamma^\gamma b^\kappa a^{\gamma+1}}{f_E(1+\gamma)^{1+\gamma}} g^{-\kappa} G_1(g) \right]^{\frac{1}{\kappa-\gamma-1}} \quad (51)$$

$$\xi_H = \left[\frac{Lb^\kappa a^\kappa \gamma^\gamma}{f_E(1+\gamma)^{1+\gamma}} g^{-\kappa} G_1(g) c^{\kappa-\gamma-1} \right]^{-\frac{1}{\kappa-\gamma-1}} \quad (52)$$

The utility becomes:

$$\begin{aligned} U_H &= \lim_{\eta \rightarrow 0} \left\{ \left(\frac{az^*}{c} \right)^{\frac{\eta}{1+\eta}} \left[(1+\gamma) \frac{G_3(g)}{G_2(g)} - \frac{\gamma^2}{1+\gamma} \frac{G_1(g)}{G_2(g)} \right] + \frac{\left(\frac{az^*}{c} \right)^{\frac{\eta}{1+\eta}} - 1}{\eta} \right\} = \\ &= \left[(1+\gamma) \frac{G_3(g)}{G_2(g)} - \frac{\gamma^2}{1+\gamma} \frac{G_1(g)}{G_2(g)} \right] + \ln \left(\frac{az^*}{c} \right) = \\ &= \frac{\ln \left[\frac{L\gamma^\gamma b^\kappa a^{\gamma+1}}{f_E(1+\gamma)^{1+\gamma}} \right]}{\kappa - \gamma - 1} + \ln \left(\frac{a}{c} \right) + (1+\gamma) \frac{G_3(g)}{G_2(g)} - \frac{\gamma^2}{1+\gamma} \frac{G_1(g)}{G_2(g)} - \frac{\kappa \ln g}{\kappa - \gamma - 1} + \frac{\ln G_1(g)}{\kappa - \gamma - 1} \end{aligned} \quad (53)$$

Figure 5 shows the hump-shaped relationship between the utility of the consumers and the restrictiveness of the standard g . Figure 6 presents the negative relationship between the mass of active firms N and the standard g . Figure 7 presents the negative relationship between the market determined quality cutoff z^* and the standard g , under DA and homothetic preferences, since under IA, the cutoff is a constant. Finally, figure 8 presents the relationship between the aggregator ξ and the standard g , under IA and homothetic preferences, since under DA, the aggregator equals one. The standard reduces the aggregator under IA preferences while it increases the aggregator under homothetic preferences.

Figure 5: Effects of a Standard on Welfare

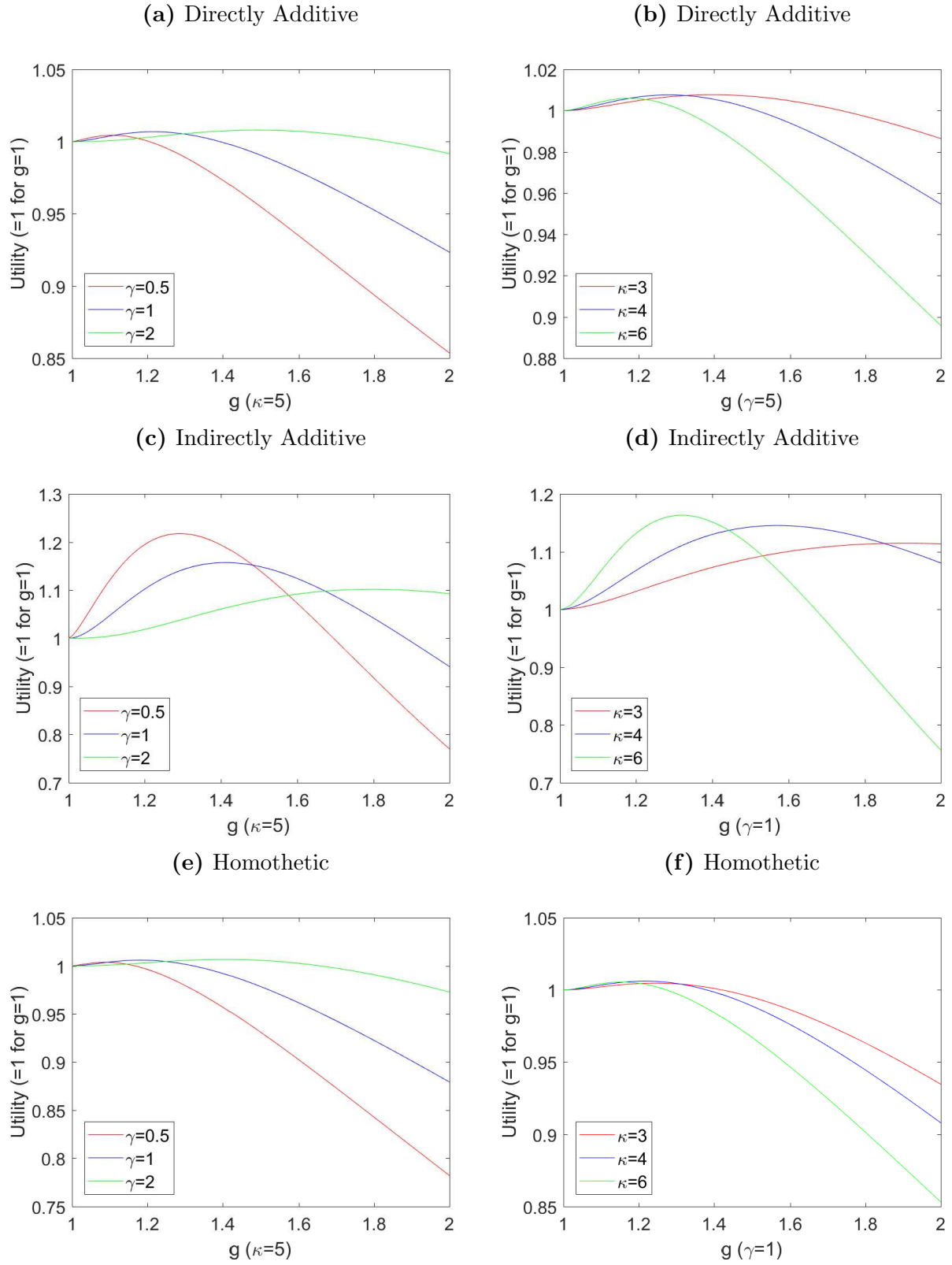


Figure 6: Effects of a Standard on the Mass of Active Firms N

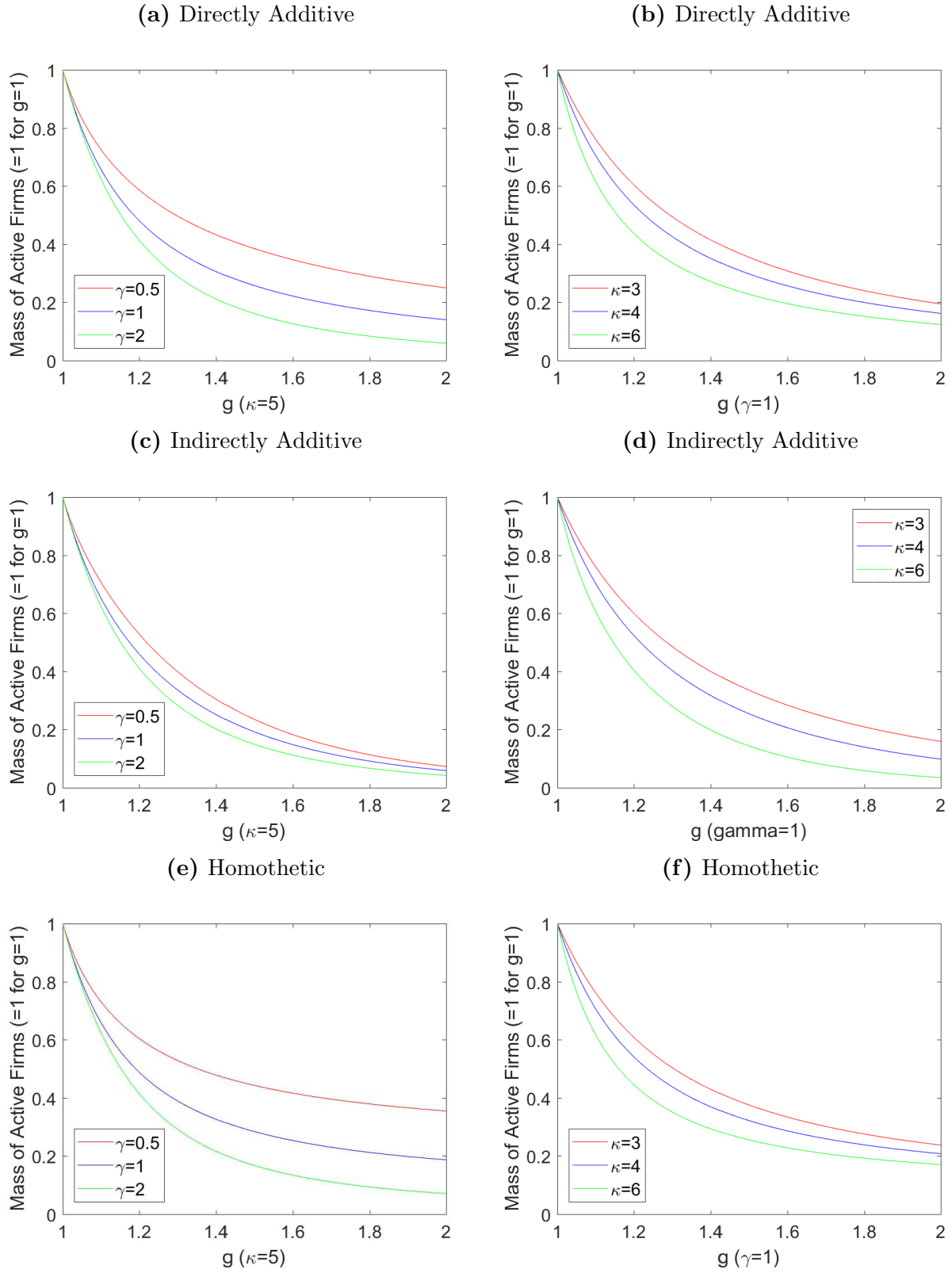


Figure 7: Effects of a Standard on the Market Quality Cutoff z^*

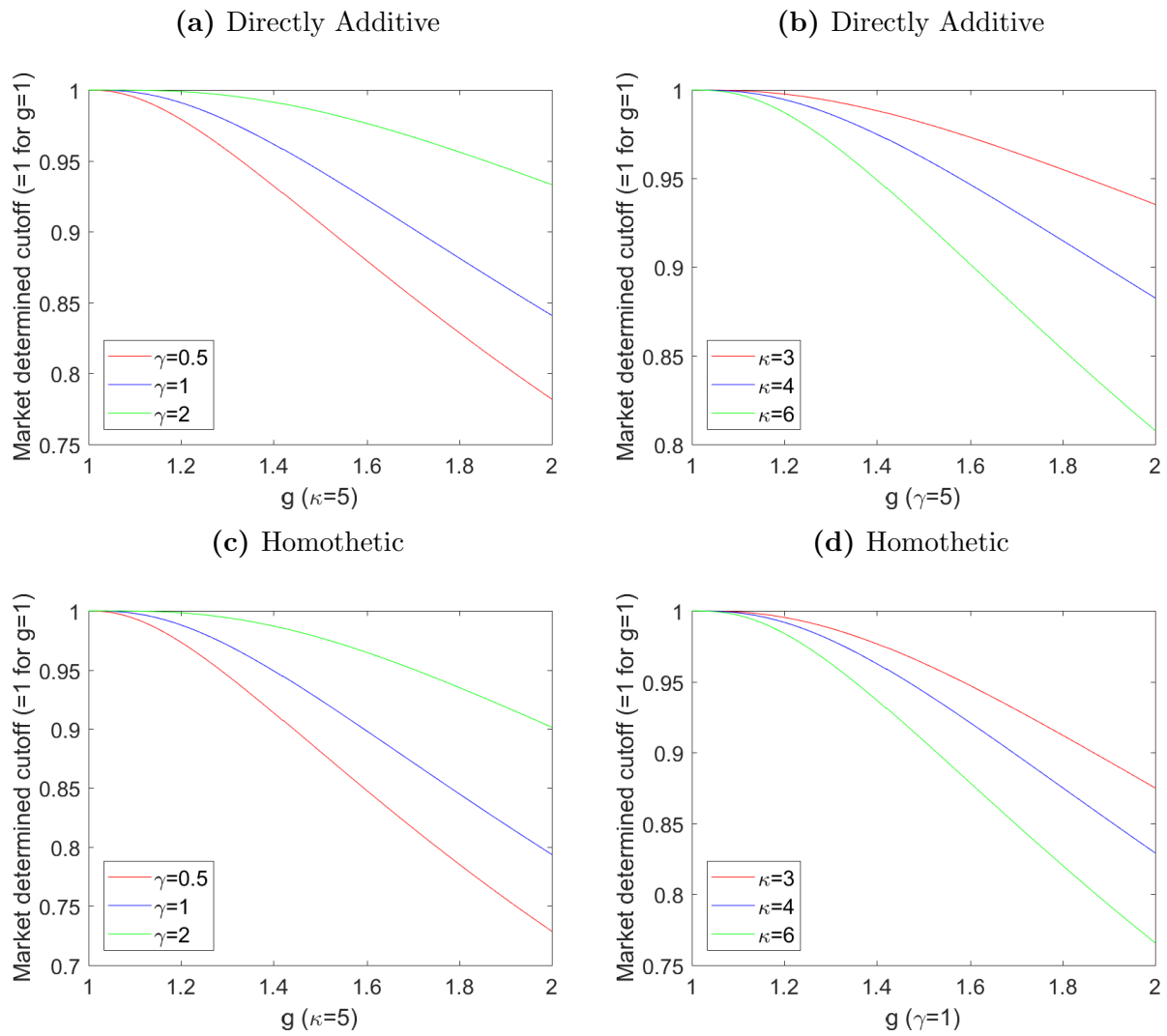
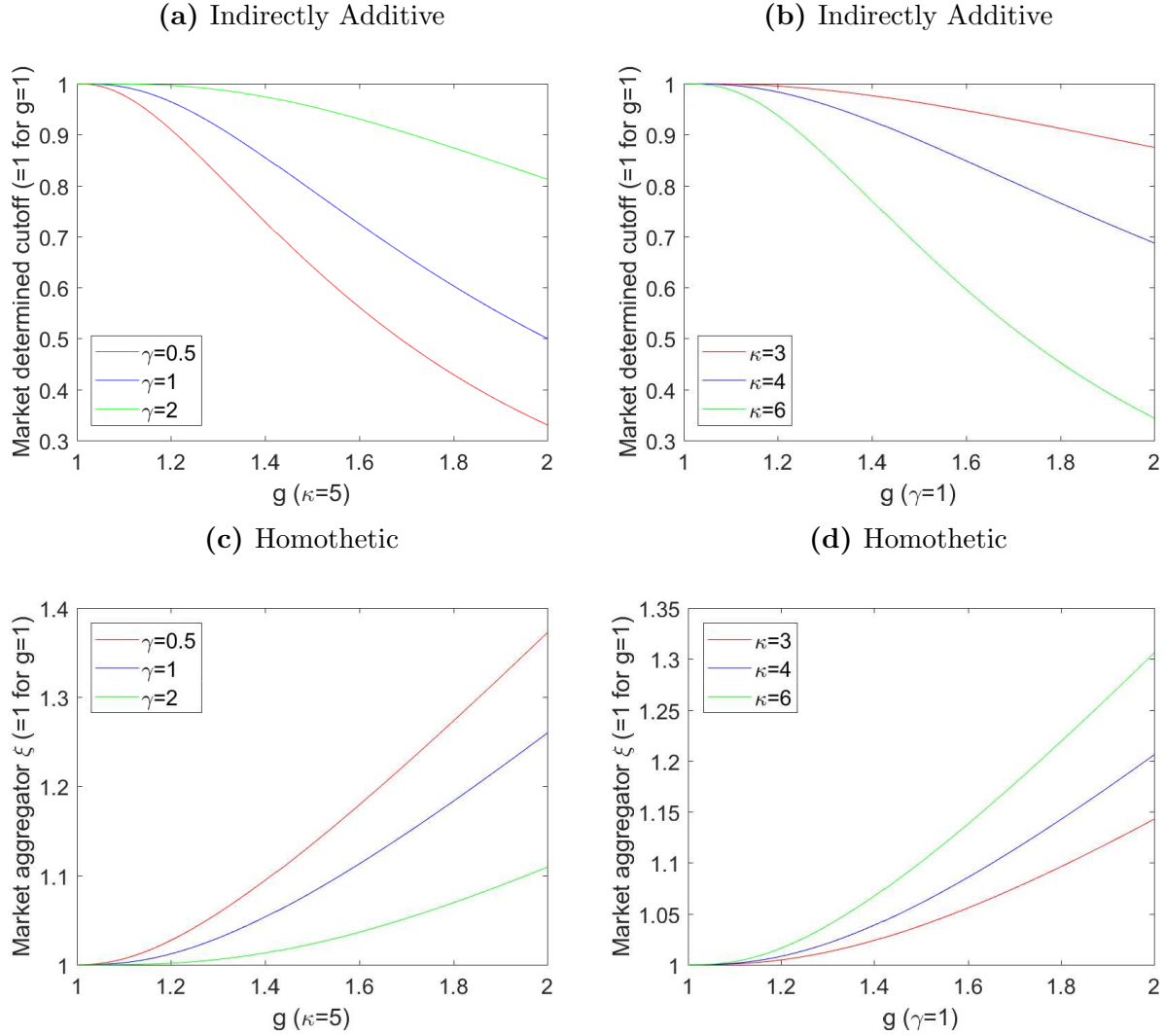


Figure 8: Effects of a Standard on the Aggregator ξ



6.3.4 Fixed Cost

This section briefly outlines the case in which the government imposes a quality standard in the market \bar{z} , through a fixed cost of production f . The fixed cost f rationalizes the compliance costs that firms must incur due to the standard, or the costs associated with inspections for quality levels. The presence of a fixed cost f leaves the solution to the firms' problem (quantities and prices) and, thus, the revenues, unchanged. However, the profits of a firm with quality z become:

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

There exists a firm with quality \bar{z} , such that $\pi(\bar{z}) = 0$. The mapping between the fixed cost f and the cutoff-firm \bar{z} , equivalent to the quality standard imposed in the baseline model,

is:

$$\begin{aligned}\frac{Lc}{1+\gamma} \left(\frac{a\gamma}{1+\gamma} \right)^\gamma \frac{(z^*)^\gamma}{\xi} \left(\frac{\bar{z}}{z^*} - 1 \right)^{1+\gamma} &= f \\ \frac{Lc}{1+\gamma} \left(\frac{a\gamma}{1+\gamma} \right)^\gamma \frac{(z^*)^\gamma}{\xi} (g-1)^{1+\gamma} &= f\end{aligned}\tag{54}$$

Using (54), average profits become:

$$\begin{aligned}\bar{\pi} &= \frac{Lc}{1+\gamma} \left(\frac{a\gamma}{1+\gamma} \right)^\gamma \frac{(z^*)^\gamma}{\xi} G_1(g) - f \\ &= \frac{Lc}{1+\gamma} \left(\frac{a\gamma}{1+\gamma} \right)^\gamma \frac{(z^*)^\gamma}{\xi} (G_1(g) - (g-1)^{1+\gamma})\end{aligned}$$

The zero expected profit condition is then

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

Relative to the baseline model, the fixed cost affects both z^* and ξ . Using the market quality cutoff condition $z^* = \frac{c}{a} \xi^{-(1+\eta)}$ into the zero expected profit condition yields the solutions for z^* and ξ . The fixed cost affect the utility of the representative consumer (42) only through ξ . Following the same steps of the baseline model, the utility becomes:

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

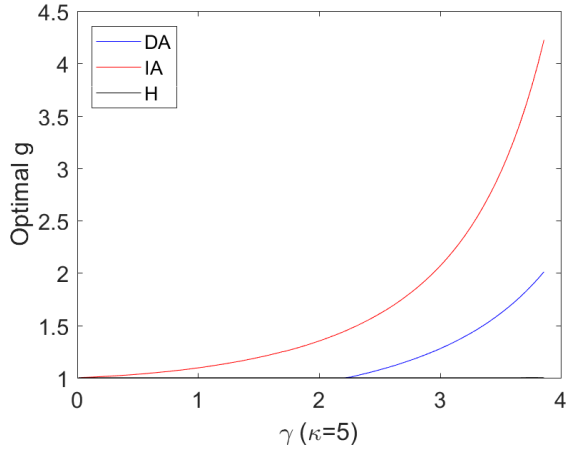
and deriving the closed form expressions for the IA, DA, and homothetic case follows from the baseline model. In particular,

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

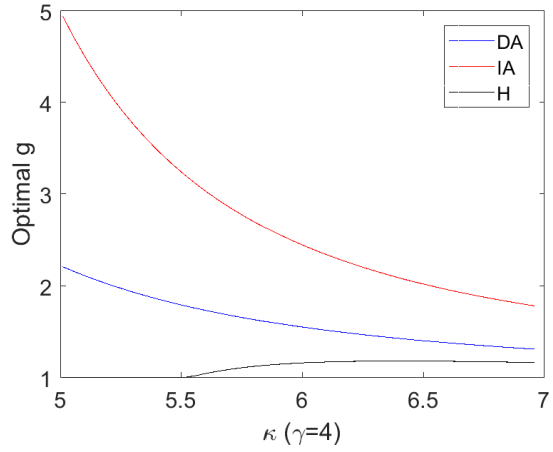
While the standard in the baseline model directly affect the selection of firms, the fixed cost also reallocates resources from production to the activities required to comply to the regulation. As a result, the welfare benefits of the standard examined in the baseline case are diminished by the fixed cost. In fact, the optimal standard is smaller in this extension that it is in the baseline case: the fixed cost acts as a downward shift in the optimal g across preferences. As shown in figure 9, for the DA and homothetic case the optimal policy is no standard under certain parameters.

Figure 9: Optimal g Across Preferences - Standard as Fixed Cost

(a) As a function of γ



(b) As a function of κ



6.3.5 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, 2016). 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.

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: $1 - \left(\frac{b}{\phi}\right)^{\tilde{\kappa}}$. 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.⁵⁸ 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

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

Profit maximization yields the following optimal quantity:

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

⁵⁸Modeling an endogenous quality choice as (Gaigne and Larue, 2016), in which firms must also pay a fixed cost is highly untractable under GTP preferences. We verified that such a technological assumption does not generate additional distortions in a model with standard CES preferences.

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:

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

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

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

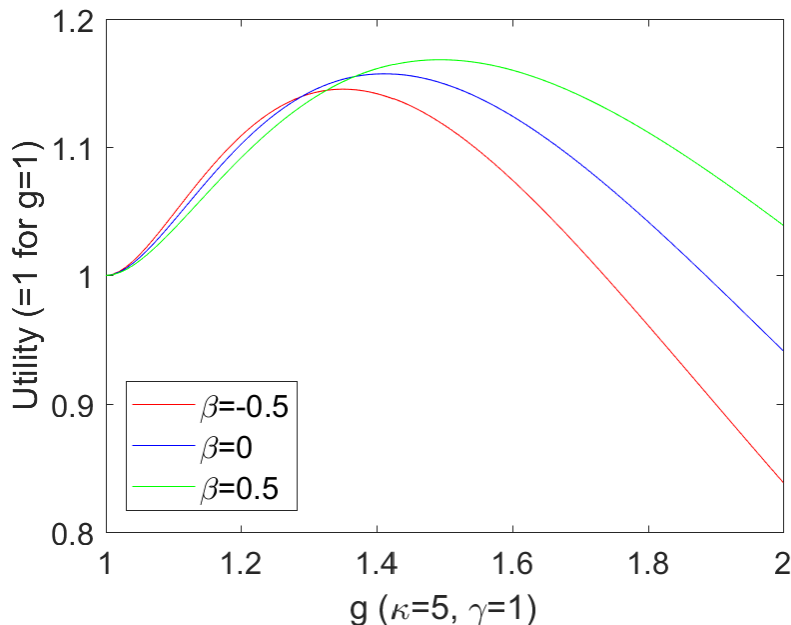
Figure 10 shows the relationship between welfare and the restrictiveness of the standard for different values of β , under IA preferences. For $\beta = 0$, this extension becomes identical to the baseline model. This implies that our baseline model with firms heterogeneous in quality is equivalent to 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 10: Minimum Quality Standard and Welfare ($\eta = -1$)

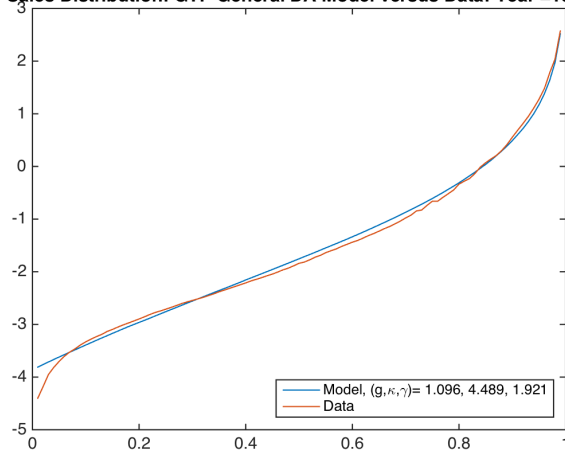


6.4 Estimation

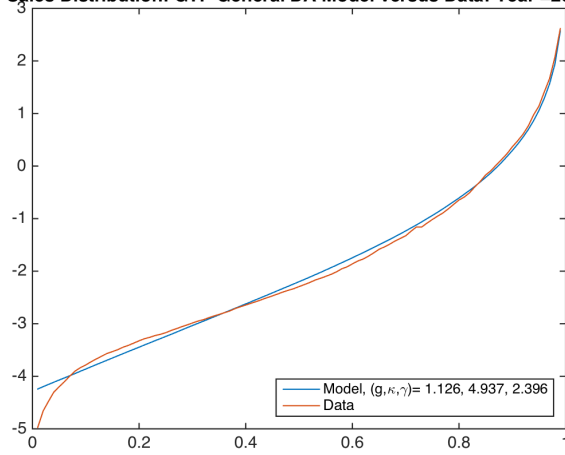
Figure 11 displays the results for the benchmark manufacturing-wide estimation for each year. We show results for the years 1995, 2000, 2005. Figure 12 displays the result under the alternative calibration in which we target only 4 moments: the sales advantage of “high-quality” relative to “low-quality” 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 with a fixed linear demand: $\gamma = 1$. Figure 14 plots the simulated sales distribution when we set $\kappa = 4$ and $\gamma = 1.8$.

Figure 11: Log Domestic Sales Distribution: Model VS Data

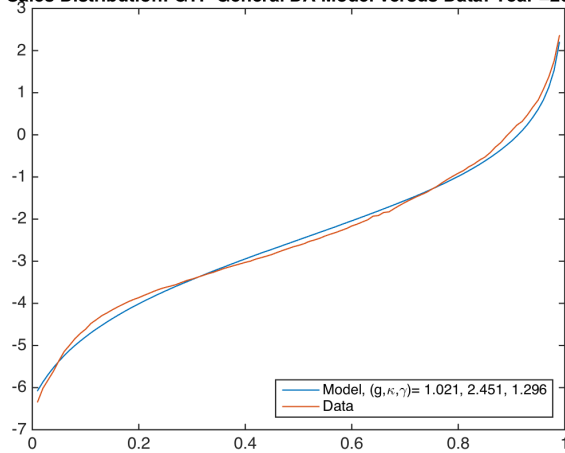
Sales Distribution: GTP General DA Model versus Data: Year =1995



Sales Distribution: GTP General DA Model versus Data: Year =2000

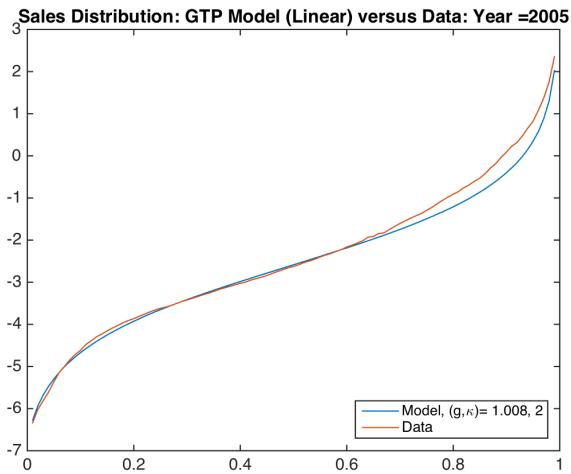
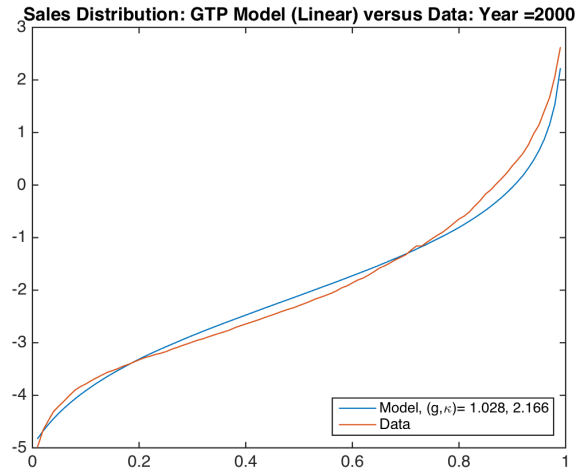
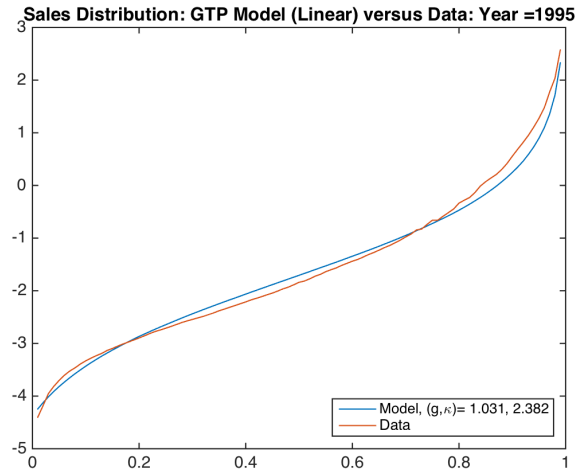


Sales Distribution: GTP General DA Model versus Data: Year =2005



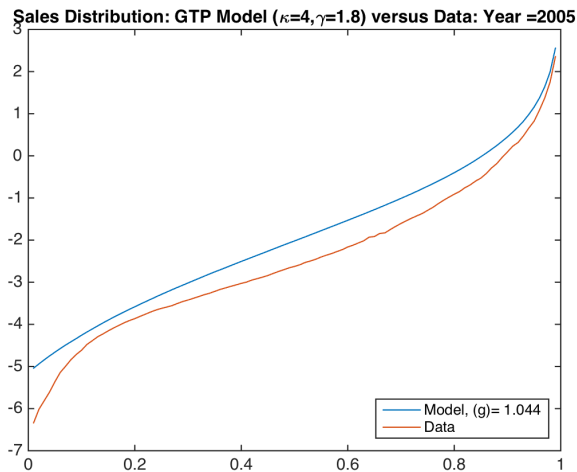
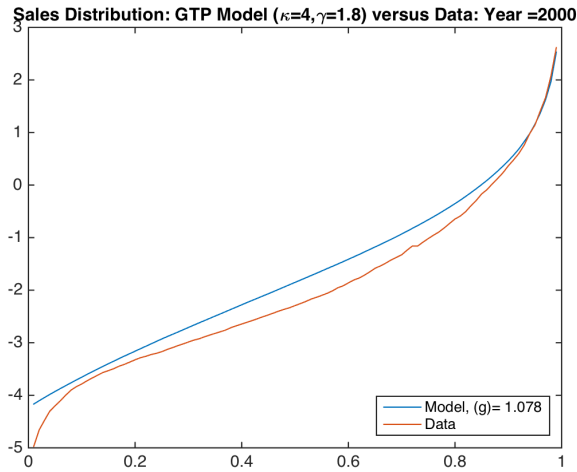
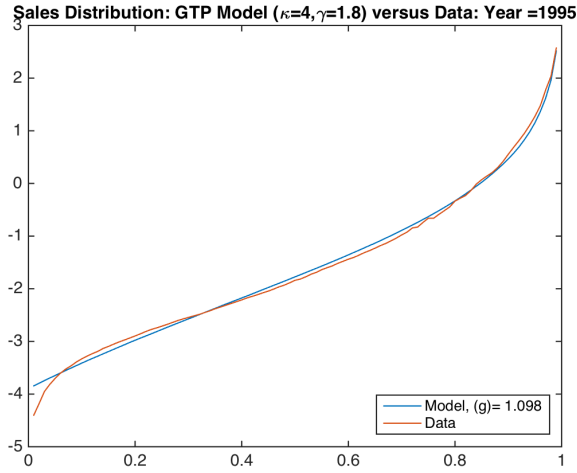
Each figure plots the CDF of the log sales distribution in the data (red) versus the simulated distribution given the estimated parameters. The model is estimated using the universe of manufacturing firms in each year. Although we estimate parameters for all years, we report only 1995, 2000, and 2005. The 95% confidence intervals for the parameters in each of the three years are: $\hat{g} = (1.08, 1.11), (1.1, 1.15), (1.01, 1.03)$; $\hat{\kappa} = (3.37, 5.6), (3.59, 6.29), (2.12, 2.78)$; $\hat{\gamma} = (1.63, 2.21), (2.04, 2.75), (1.17, 1.42)$.

Figure 13: Log Domestic Sales Distribution: Model ($\gamma = 1$) 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 $\gamma = 1$. The model is estimated using the universe of manufacturing firms in each year. The 95% confidence intervals for the parameters in each of the three years are: $\hat{g} = (1.02, 1.04), (1.02, 1.03), (1.00, 1.02)$; $\hat{\kappa} = (0.94, 2.51), (1.26, 2.29), (2, 2)$.

Figure 14: Log Domestic Sales Distribution: Model ($\gamma = 1.8, \kappa = 4$) VS Data



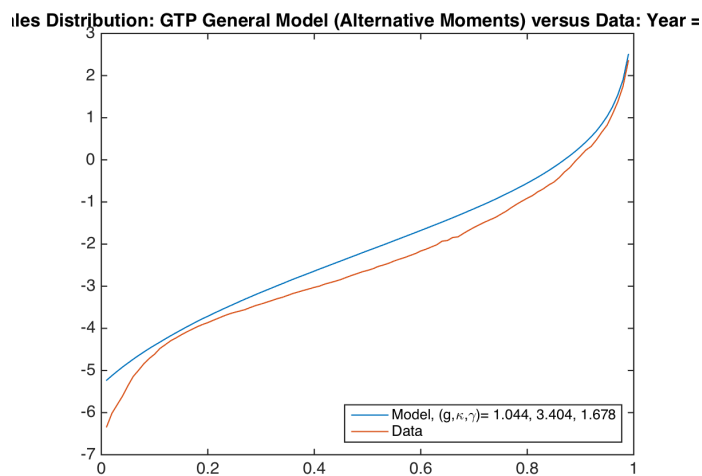
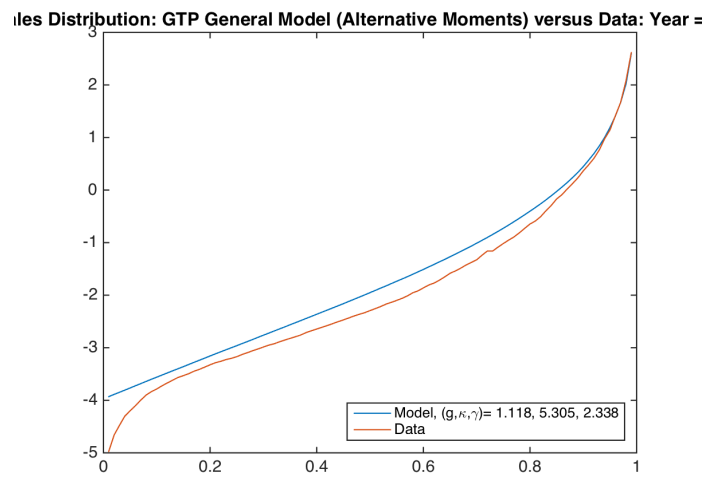
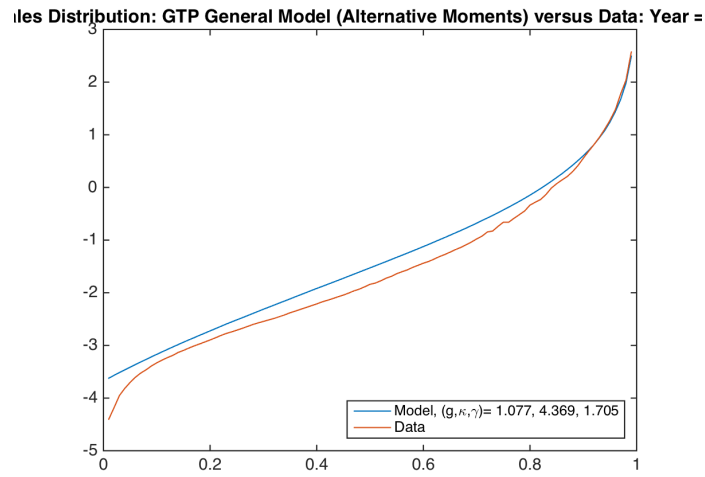
Each figure plots the CDF of the log sales distribution in the data (red) versus the simulated distribution given the estimated parameters. The parameters of the model are estimated using the main specification, but a fixed $\gamma = 1.8$ and $\kappa = 4$. The model is estimated using the universe of manufacturing firms in each year. The 95% confidence intervals for the parameters in each of the three years are: $\hat{g} = (1.09, 1.1), (1.07, 1.08), (1.04, 1.05)$.

Table 9: Firm Heterogeneity as a Response to Restrictiveness: Simulated Data

	Survival	Relative Sales	Log Markup
	(1)	(2)	(3)
\hat{g}^* Quality	2.549***	0.001***	0.002*
	(0.437)	(0.000)	(0.001)
Fixed Effects	Firm, I-Y	Firm, I-Y	Firm, I-Y
# Observations	120000	106406	106406

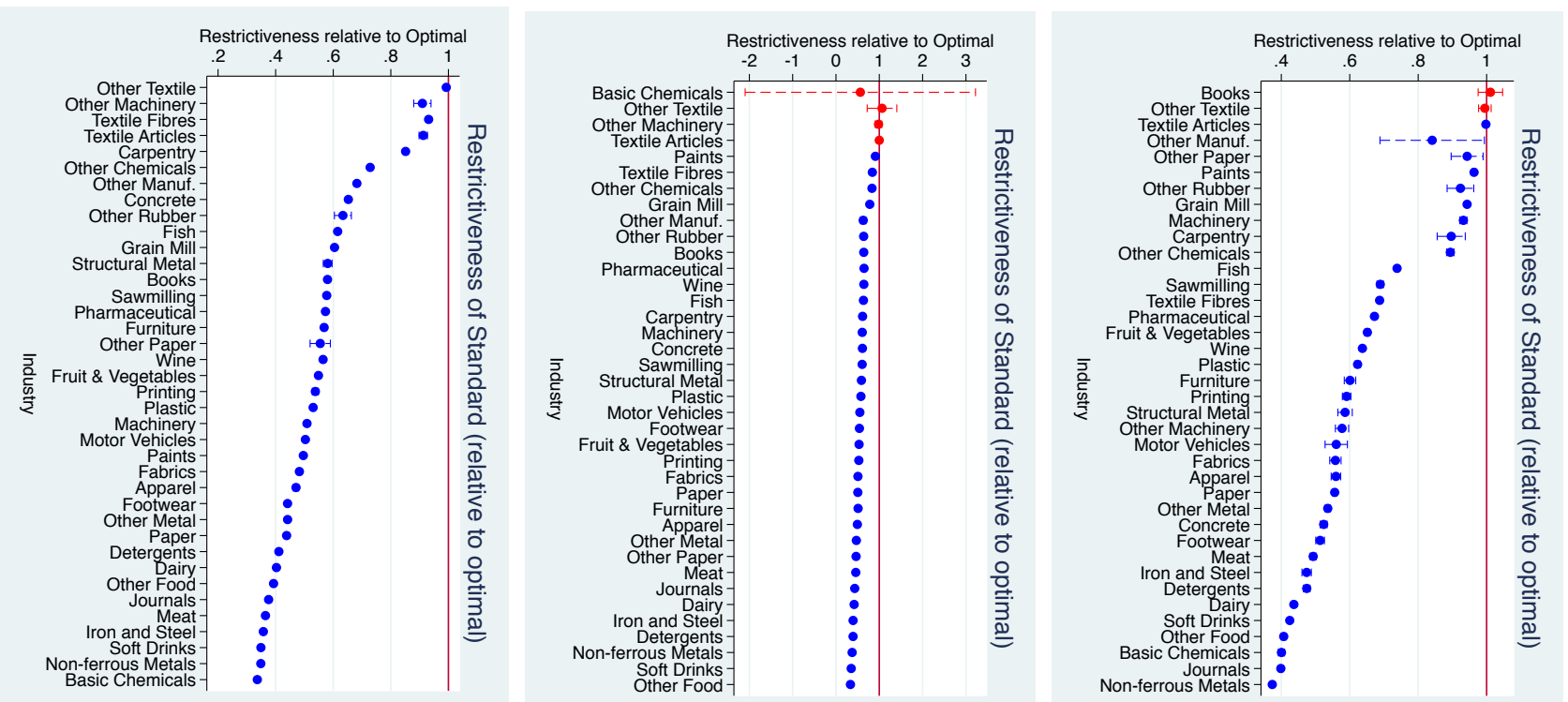
This table regresses simulated firm outcomes on the interaction of the calibrated standards parameter and the firm quality draw. We simulate 1000 firms per industry in 1995, 2000, and 2005 using $\kappa = 4$, $\gamma = 1$, and the estimated \hat{g}_{it} . In all, 40,000 firms are simulated across 40 industries. The restrictiveness parameter is allowed to vary across time, but firm quality draws and other parameters are held fixed. We re-simulate the economy in each year and produce 3 firm outcomes: (i) a survival dummy (column 1), (ii) firm sales (relative to total industry sales) (column 2), and (iii) the firm log markup (column 3). In the first specification we use the full panel of firm-year simulations, where survival is equal to one if the firm produces given the estimated \bar{z}_{it} . In the latter two specifications we include all *producing* firms. As in (1), each specification includes firm and industry-year fixed effects so that we are only capturing within industry-year distributions. Standard errors – clustered by 4-digit industry – are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Figure 12: Log Domestic Sales Distribution: Model (Alternative Calibration) VS Data



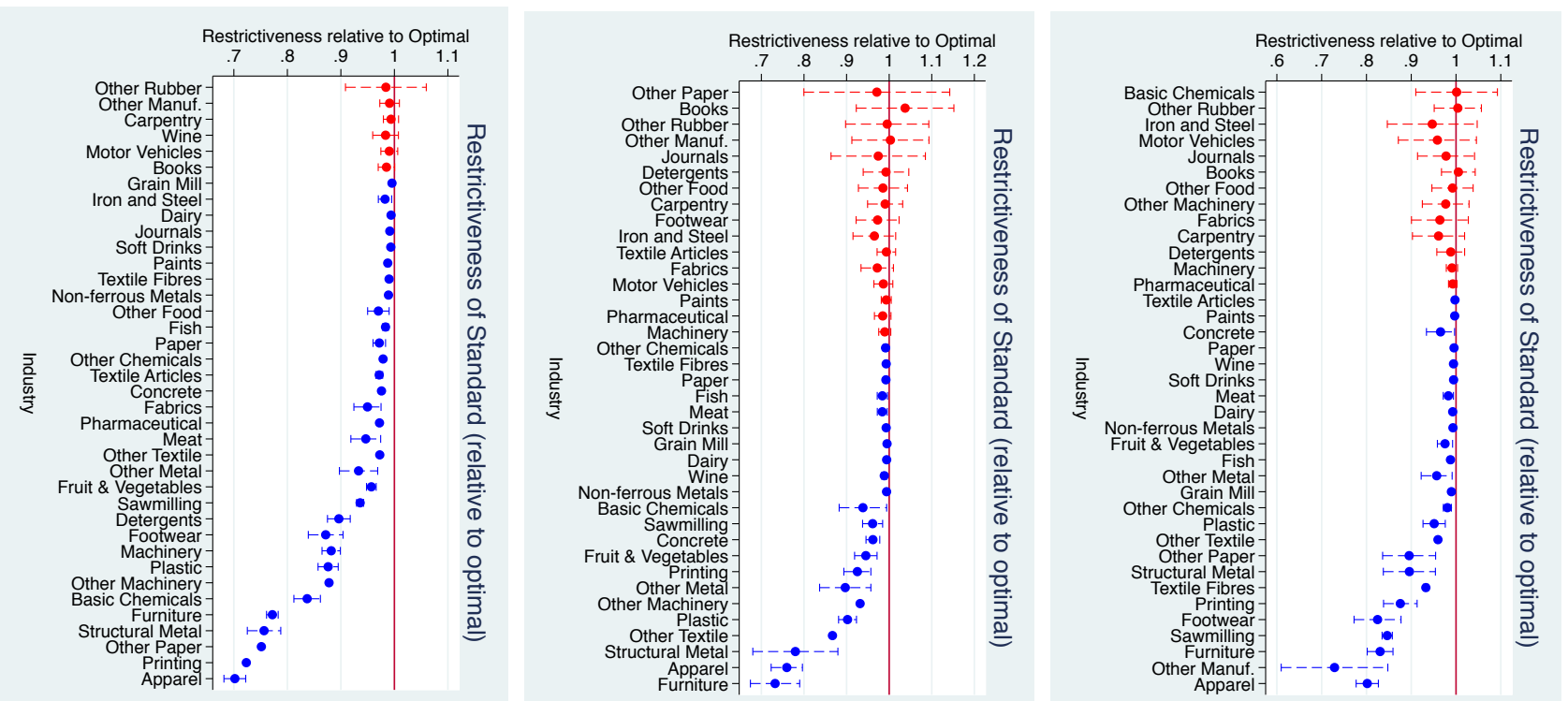
Each Figure plots the CDF of the log sales distribution in the data (red) versus the simulated distribution given the estimated parameters. The parameters of the model are estimated using *only the 4 moments described in the "alternative calibration"*. The model is estimated using the universe of manufacturing firms in each year. The 95% confidence intervals for the parameters in each of the three years are: $\hat{g} = (1.05, 1.11), (1.08, 1.14), (1.03, 1.06)$; $\hat{\kappa} = (0.94, 8.23), (1.26, 8), (2.08, 4.6)$; $\hat{\gamma} = (1.11, 2.50), (1.42, 2.87), (1.27, 2.06)$.

Figure 15: Restrictiveness Index in IA with $\gamma = 1$ Model: 1995, 2000, and 2005.



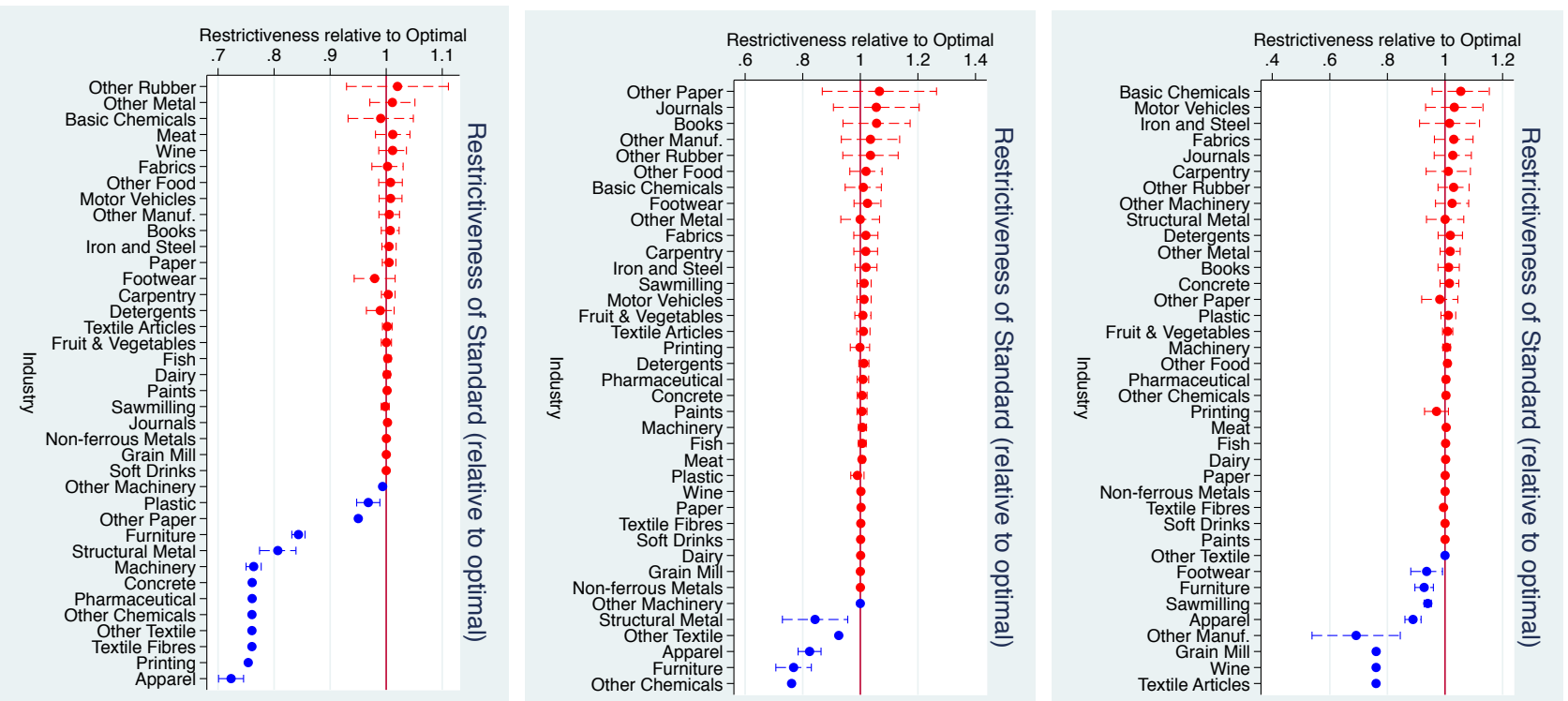
In red are the industries where we cannot reject the null hypothesis that the restrictiveness index is different from one.

Figure 16: Restrictiveness Index in DA with general γ Model: 1995, 2000, and 2005.



In red are the industries where we cannot reject the null hypothesis that the restrictiveness index is different from one.

Figure 17: Restrictiveness Index in IA with Fixed Costs: 1995, 2000, and 2005.



In red are the industries where we cannot reject the null hypothesis that the restrictiveness index is different from one.

Figure 18: Chilean Trade Flows, Tariffs, Terms of Trade

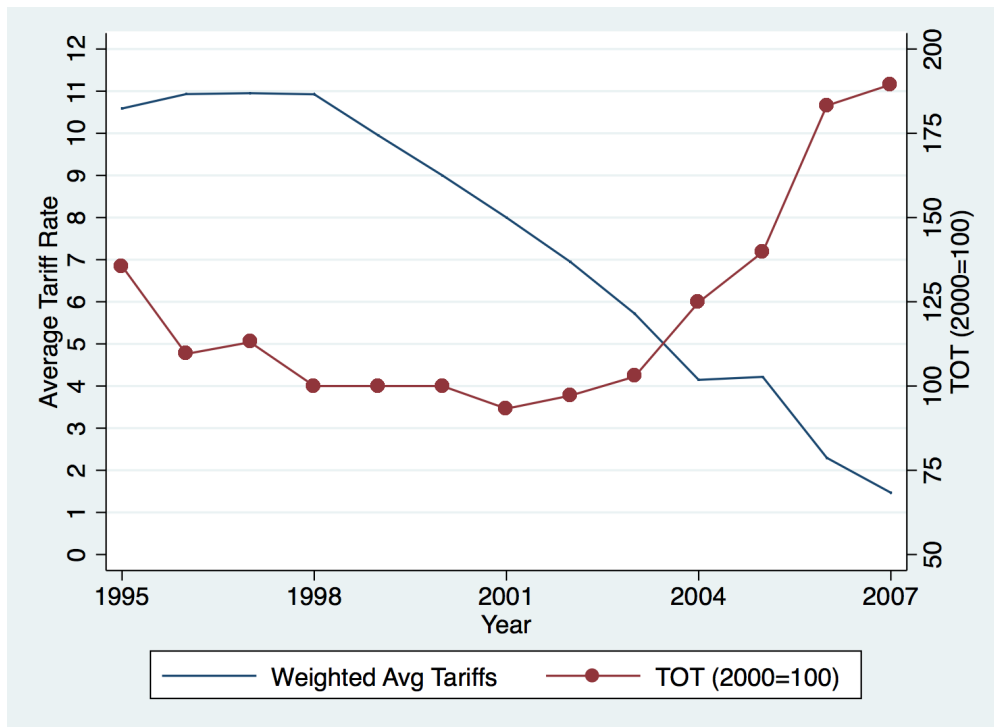
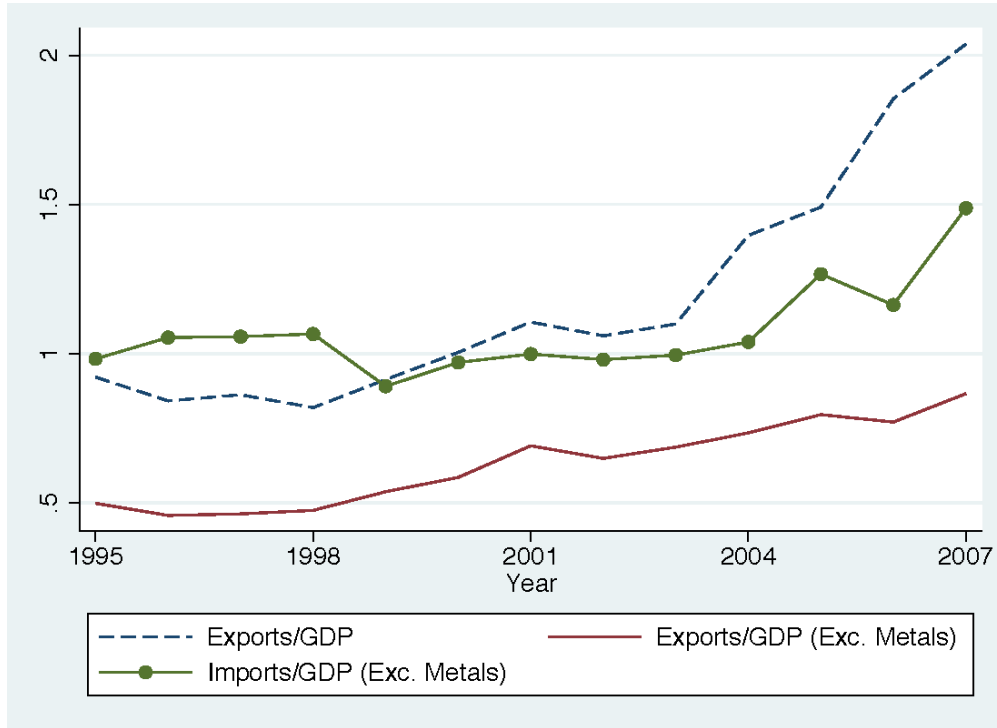
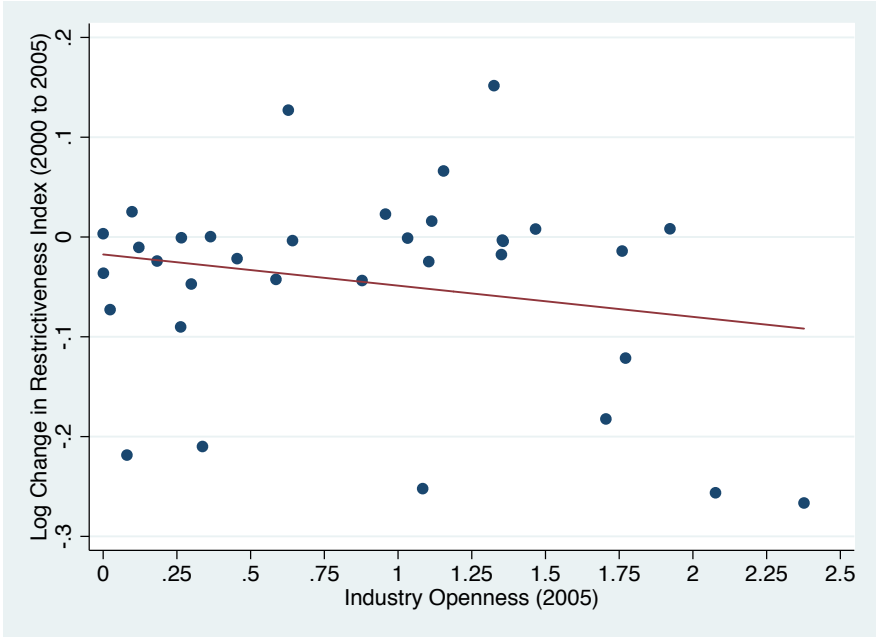


Figure 19: Industry Openness vs Log Difference in Industry Restrictiveness (2000 to 2005)



This figure plots Industry Openness versus the log change in the restrictiveness index between 2000 and 2005. Openness (x-axis) is defined as the sum of imports and exports over total sales. The y-axis is the log change in the restrictiveness index between 2000 and 2005. There are a total of 34 industries in the plot, as we drop industries with openness above a ratio of 4. The result is robust to allowing for industries with an even larger ratio, but we believe a cutoff is necessary because, for example, the “Other Manufacturing” industry has an openness ratio more than 60 times larger than the median industry. The slope of the best fit line is -0.2.