

Competition, Markups, and the Gains from International Trade*

Chris Edmond[†] Virgiliu Midrigan[‡] Daniel Yi Xu[§]

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Abstract

We study the gains from trade in a model with endogenously variable markups. We show that the *pro-competitive* gains from trade are large if the economy is characterized by (i) extensive misallocation, i.e., large inefficiencies associated with markups, and (ii) a weak pattern of cross-country comparative advantage in individual sectors. We find strong evidence for both of these ingredients using producer-level data for Taiwanese manufacturing establishments. Parameterizations of the model consistent with this data thus predict large pro-competitive gains from trade, much larger than those in standard Ricardian models. In stark contrast to standard Ricardian models, data on changes in trade volume are not sufficient for determining the gains from trade.

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[†]University of Melbourne, cedmond@unimelb.edu.au.

[‡]Federal Reserve Bank of Minneapolis, New York University, and NBER, virgiliu.midrigan@nyu.edu.

[§]Duke University and NBER, daniel.xu@duke.edu.

1 Introduction

How large are the welfare gains from international trade? We answer this question using a quantitative model with endogenously variable markups. In such a model, trade can increase productivity and welfare via two channels. First, if opening an economy to trade exposes domestic firms to more competition, then there may be gains due to reduced markups and reduced markup dispersion. We refer to these as *pro-competitive effects*. Second, as in standard models, opening to trade implies welfare and productivity gains due to *Ricardian effects*. Our goal is to measure the strength of these two effects using producer-level data.

One of the oldest ideas in economics is that opening an economy to trade may lead to welfare gains from increased competition. And existing empirical work provides support for this idea.¹ But, perhaps surprisingly, existing trade models with variable markups do not generally predict pro-competitive effects. Indeed, the workhorse trade model with variable markups studied by [Bernard, Eaton, Jensen and Kortum \(2003\)](#), hereafter BEJK) implies exactly zero pro-competitive gains from trade, as does the model of [Arkolakis, Costinot and Rodríguez-Clare \(2010\)](#). Moreover, recent work by [Arkolakis, Costinot, Donaldson and Rodríguez-Clare \(2012b\)](#) shows that pro-competitive effects can be negative.

We study the gains from trade in the model developed by [Atkeson and Burstein \(2008\)](#). In this model, any given sector has a small number of producers who engage in *oligopolistic competition*. The demand elasticity for any given producer, and hence its markup, depends on the producer’s *sectoral sales share*. A reduction in trade barriers reduces the sectoral share of domestic producers, thus reducing their markups.

We focus on the [Atkeson and Burstein \(2008\)](#) model for a number of reasons. First, the model is a parsimonious extension of the BEJK model, widely used in existing work. Unlike in BEJK, however, the *markup distribution* in the [Atkeson and Burstein \(2008\)](#) model may vary over time and in response to changes in trade policy. Moreover, the model nests BEJK as a special case and is sufficiently rich to produce a wide range of implications regarding the size of the pro-competitive gains from trade. Finally, because the model implies a direct link between individual markups and a producer’s sectoral sales share, the model can be straightforwardly parameterized using micro data on sectoral shares.

We show that the pro-competitive gains from trade in the Atkeson-Burstein model can be large, much larger than those implied by standard trade models,² so long as two conditions are satisfied. First, there must be large inefficiencies associated with markups to begin

¹We discuss evidence for pro-competitive effects, including a brief survey of existing work, in [Section 9](#) below. By contrast, see [De Loecker, Goldberg, Khandelwal and Pavcnik \(2012\)](#) for evidence that markups *increase* after a trade liberalization.

²[Eaton and Kortum \(2002\)](#) and [Melitz \(2003\)](#). See also [Arkolakis, Costinot and Rodríguez-Clare \(2012a\)](#), who study the welfare gains from trade in this broad class of trade models.

with, i.e., there must be extensive initial *misallocation*. Second, the pattern of cross-country comparative advantage in individual sectors must be relatively weak, i.e., trade partners must be characterized by relatively similar productivities within a given sector.

The first condition is obvious and intuitive. There simply cannot be large pro-competitive gains from trade if there are only small distortions associated with markups to begin with. The second condition is also intuitive. Trade can only reduce markups if it in fact increases the amount of competition faced by domestic producers in individual sectors. If trade partners are characterized by similar productivities within a given sector, then opening to trade exposes domestic producers to more intense head-to-head competition and forces them to reduce markups. By contrast, if there are large cross-country differences in sectoral productivity, then the pro-competitive gains from trade are small or even negative. In this latter case, most of the increase in trade is on the extensive margin: a country that opens up to trade starts importing goods in new sectors, but trade has little effect on the amount of competition faced by domestic producers in existing sectors.

To quantify the model we use product-level (7-digit) Taiwanese manufacturing data. We use the data to discipline two key factors governing the extent of initial misallocation: (i) the elasticity of substitution across sectors, and (ii) the equilibrium distribution of producer-level sectoral shares. The elasticity of substitution across sectors plays a key role because it determines the extent to which producers that face little competition in their own sector can raise markups. We pin down this elasticity by requiring that our model fits the cross-sectional relationship between measures of markups and sectoral shares that we observe in the Taiwanese data. We pin down the parameters governing the producer-level productivity distribution and fixed costs of operating and exporting by requiring that our model reproduces the distribution of sectoral shares and concentration statistics in the Taiwanese data.

The Taiwanese data feature a large amount of dispersion and concentration in producer-level sectoral shares, as well as a very strong relationship between sectoral shares and markups. Interpreted through the lens of the model, this implies a great deal of misallocation, due to a high level and dispersion of markups.

Given this initial misallocation, our model predicts large pro-competitive gains from trade if, in addition, there is a relatively weak pattern of comparative advantage so that increased trade in fact confronts producers with increased competition. To measure the pattern of comparative advantage across Taiwan and its trading partners, we observe that the degree of dispersion in productivity across countries is strongly related to the pattern of intra-industry trade implied by the model. If the pattern of comparative advantage is weak, productivity is relatively similar within a given sector and most trade is primarily intra-industry. If the pattern of comparative advantage is strong, however, so that domestic firms are highly-

productive in some sectors while foreign firms are highly-productive in an entirely different set of sectors, then most trade is across industries.

We measure the amount of intra-industry trade using measures of dispersion in sectoral import shares and find that most Taiwanese trade is intra-industry (as is most US trade). Interpreted through the model, this implies a weak pattern of comparative advantage and hence implies that most of the gains from trade are indeed due to pro-competitive effects.

Our work is related to a number of recent papers. [Arkolakis, Costinot and Rodríguez-Clare \(2012a\)](#) show that the welfare gains from trade are identical in a large class of trade models.³ These models differ in their micro details, but their aggregate welfare implications are solely determined by the effect a reduction in trade barriers has on the volume of trade. In our model with variable markups, this aggregation result no longer holds. Even in versions of our model in which Ricardian effects dominate and markups move little in response to changes in trade barriers, data on trade volumes alone are no longer sufficient for determining the welfare gains from trade.

Several recent theoretical papers highlight the connection between endogenously variable markups and the gains from trade.⁴ In particular, an important recent contribution by [De Blas and Russ \(2010\)](#) extends BEJK to allow for a finite number of producers in a given sector. In their model, as in [Atkeson and Burstein \(2008\)](#), the distribution of markups varies in response to changes in trade costs. [Holmes, Hsu and Lee \(2011\)](#) study that model's implications for the impact of trade on productivity and misallocation. Relative to these theoretical papers, as well as to earlier studies by [Devereux and Lee \(2001\)](#) and [Melitz and Ottaviano \(2008\)](#), our main contribution is to *quantify* the pro-competitive mechanism using micro data. In addition, we relax the assumption, commonly made in this literature, that productivity draws are independent across countries. As discussed above, the pro-competitive effects in our model depend crucially on the extent to which productivities within a given sector are correlated across countries.

Increasing total factor productivity (TFP) by reducing markup dispersion is an effect familiar from the work on misallocation of factors of production by [Restuccia and Rogerson \(2008\)](#), [Hsieh and Klenow \(2009\)](#) and others. We find that international trade can play a powerful role in reducing misallocation and increasing productivity. From a policy viewpoint, our model suggests that obtaining large welfare gains from an improved allocation may not require the detailed, perhaps impractical, scheme of subsidies and taxes that implement the first-best. Instead, simply opening an economy to trade may provide an excellent practical

³These include the models of [Armington \(1969\)](#), [Krugman \(1980\)](#), [Eaton and Kortum \(2002\)](#), [Melitz \(2003\)](#), and [Bernard et al. \(2003\)](#).

⁴See also [Epifani and Gancia \(2011\)](#) who consider a trade model with exogenous markup dispersion and [Peters \(2011\)](#) who considers a model with endogenously variable markups but in a closed economy setting.

alternative that substantially improves welfare.

We conclude our analysis by presenting evidence of pro-competitive effects. Versions of our model that imply strong pro-competitive effects predict that sectors with higher import shares face more competition from abroad and thus have lower levels and dispersion of markups. We find strong evidence of these pro-competitive effects in Taiwanese and US data.

The remainder of the paper proceeds as follows. [Section 2](#) presents the model. [Section 3](#) gives an overview of the data, and [Section 4](#) explains how we use that data to quantify the model. [Section 5](#) studies the welfare gains from trade for two extreme parameterizations of the pattern of comparative advantage while [Section 6](#) studies the gains from trade more generally. [Section 7](#) compares the welfare gains in our model to those implied by standard Ricardian models. [Section 8](#) conducts a number of robustness checks. [Section 9](#) provides evidence of strong pro-competitive effects in Taiwanese and US data. [Section 10](#) concludes.

2 Model

The world consists of two symmetric countries, Home and Foreign. We focus on describing the problem of Home agents in detail. We indicate Foreign variables with an asterisk.

2.1 Consumers and final good producers

Each country is inhabited by a continuum of identical consumers. Perfectly competitive firms in each country produce a homogeneous final good that is used for consumption and investment. Final good firms produce using inputs derived from a continuum of sectors. Importantly, each sector consists of a *finite* number of domestic and foreign intermediate goods producers.

Consumers. The problem of Home consumers is to choose aggregate consumption C_t , labor supply L_t , and investment X_t in physical capital to maximize

$$\sum_{t=0}^{\infty} \beta^t U(C_t, L_t)$$

subject to

$$P_t(C_t + X_t) \leq W_t L_t + \Pi_t - T_t + R_t K_t,$$

where P_t is the price of the final good, W_t is the wage rate, Π_t is firm profits, T_t is lump-sum net taxes, and R_t is the rental rate of physical capital K_t , which satisfies

$$K_{t+1} = (1 - \delta)K_t + X_t.$$

We assume identical initial capital stocks and technologies in the two countries and that trade is balanced in each period.

Final good producers. The producers of the final good are perfectly competitive. The technology with which they operate is

$$Y_t = \left(\int_0^1 y_{j,t}^{\frac{\theta-1}{\theta}} dj \right)^{\frac{\theta}{\theta-1}},$$

where $\theta > 1$ is the elasticity of substitution *across* sectors $j \in [0, 1]$ and where sectoral output is produced using N domestic and N imported intermediate inputs,

$$y_{j,t} = \left(\frac{1}{N} \sum_{i=1}^N (y_{ij,t}^H)^{\frac{\gamma-1}{\gamma}} + \frac{1}{N} \sum_{i=1}^N (y_{ij,t}^F)^{\frac{\gamma-1}{\gamma}} \right)^{\frac{\gamma}{\gamma-1}}, \quad (1)$$

where $\gamma > \theta$ is the elasticity of substitution across goods i *within* a particular sector j .

2.2 Intermediate inputs

Intermediate goods producer i in sector j uses the technology

$$y_{ij,t} = a_{ij} k_{ij,t}^\alpha l_{ij,t}^{1-\alpha},$$

where a_{ij} is the producer's idiosyncratic productivity (which for simplicity we assume is *time-invariant*), $k_{ij,t}$ is the amount of capital hired by the producer, and $l_{ij,t}$ is the amount of labor hired. We discuss the assumptions we make on the distribution of firm-level productivity in [Section 4](#) below. To conserve notation, for the remainder of the paper we suppress time subscripts whenever there is no possibility of confusion.

Trade costs. An intermediate goods producer sells output to final goods producers located in both countries. Let y_{ij}^H be the amount sold to Home final goods producers, and similarly let y_{ij}^{*H} be the amount sold to Foreign final goods producers. The resource constraint for Home intermediates is

$$y_{ij} = y_{ij}^H + (1 + \tau) y_{ij}^{*H},$$

where $\tau > 0$ is an iceberg trade cost, i.e., $(1 + \tau) y_{ij}^{*H}$ must be shipped for y_{ij}^{*H} to arrive abroad.

We describe an intermediate producer's problem below, after describing the demand for their good. Due to fixed costs, intermediate producers may decide not to operate. Let the indicator function $\phi_{ij}^H \in \{0, 1\}$ denote the decision to operate or not in the Home market, and let $\phi_{ij}^{*H} \in \{0, 1\}$ denote the decision to operate or not in the Foreign market.

Foreign intermediate goods producers face an identical problem. We let y_{ij}^* denote their output and note that the resource constraint for Foreign intermediates is

$$y_{ij}^* = (1 + \tau)y_{ij}^F + y_{ij}^{*F},$$

where y_{ij}^{*F} is the amount sold by Foreign intermediates to Foreign final goods producers and y_{ij}^F is the amount shipped to Home final goods producers.

Demand for intermediate inputs. Final good producers buy intermediate goods from Home producers at prices p_{ij}^H and from Foreign producers at prices p_{ij}^F . Consumers buy the final good at price P . The problem of a final good producer is to choose intermediate inputs y_{ij}^H and y_{ij}^F to maximize profits:

$$PY - \int_0^1 \left(\frac{1}{N} \sum_{i=1}^N p_{ij}^H y_{ij}^H + (1 + \tau) \frac{1}{N} \sum_{i=1}^N p_{ij}^F y_{ij}^F \right) dj.$$

The solution to this problem gives the demand functions

$$y_{ij}^H = \left(\frac{p_{ij}^H}{p_j} \right)^{-\gamma} \left(\frac{p_j}{P} \right)^{-\theta} Y, \quad (2)$$

and

$$y_{ij}^F = \left(\frac{(1 + \tau) p_{ij}^F}{p_j} \right)^{-\gamma} \left(\frac{p_j}{P} \right)^{-\theta} Y, \quad (3)$$

where the aggregate and sectoral price indexes are

$$P = \left(\int_0^1 p_j^{1-\theta} dj \right)^{\frac{1}{1-\theta}}, \quad (4)$$

and

$$p_j = \left(\frac{1}{N} \sum_{i=1}^N \phi_{ij}^H (p_{ij}^H)^{1-\gamma} + (1 + \tau)^{1-\gamma} \frac{1}{N} \sum_{i=1}^N \phi_{ij}^F (p_{ij}^F)^{1-\gamma} \right)^{\frac{1}{1-\gamma}}. \quad (5)$$

Market structure. An intermediate good producer faces the demand system given by (2)-(5) and engages in *Cournot competition* within its sector.⁵ That is, each individual producer chooses a given quantity y_{ij}^H or y_{ij}^{*H} , taking as given the quantity decisions of its competitors in sector j . Due to constant returns, the problem of a firm in its domestic market and its export market can be considered separately.

⁵In Section 8 below we solve our model under the alternative assumption of *Bertrand competition*.

Fixed costs. A fixed cost F_d , denominated in units of labor, must be paid in order to operate in the domestic market, and a fixed cost F_f must be paid in order to export. The firm may choose to produce zero units of output for the domestic market to avoid paying the fixed cost F_d . Similarly, the firm may choose to produce zero units of output for the export market to avoid paying the fixed cost F_f .

Domestic market. The problem of a Home firm in its domestic market is given by:

$$\pi_{ij}^H \equiv \max_{y_{ij}^H, k_{ij}^H, l_{ij}^H, \phi_{ij}^H} [p_{ij}^H y_{ij}^H - R k_{ij}^H - W l_{ij}^H - W F_d] \phi_{ij}^H.$$

Conditional on selling, $\phi_{ij}^H = 1$, the demand for labor and capital satisfy

$$\alpha v_{ij} \frac{y_{ij}^H}{k_{ij}^H} = R, \quad (6)$$

$$(1 - \alpha) v_{ij} \frac{y_{ij}^H}{l_{ij}^H} = W, \quad (7)$$

where v_{ij} is the intermediate's marginal cost (which, by symmetry, is common to both the domestic and the export market), and is given by:

$$v_{ij} = \frac{V}{a_{ij}}, \quad \text{where} \quad V \equiv \alpha^{-\alpha} (1 - \alpha)^{-(1-\alpha)} R^\alpha W^{1-\alpha}. \quad (8)$$

Using this notation, we can rewrite the profits of the intermediate producer as

$$\pi_{ij}^H = \max_{y_{ij}^H, \phi_{ij}^H} [(p_{ij}^H - v_{ij}) y_{ij}^H - W F_d] \phi_{ij}^H,$$

subject to the demand system above. The solution to this problem is characterized by a price that is a markup over marginal cost:

$$p_{ij}^H = \frac{\varepsilon_{ij}^H}{\varepsilon_{ij}^H - 1} v_{ij}. \quad (9)$$

Here ε_{ij}^H is the demand elasticity in the domestic market, which satisfies

$$\varepsilon_{ij}^H = \left(\omega_{ij}^H \frac{1}{\theta} + (1 - \omega_{ij}^H) \frac{1}{\gamma} \right)^{-1}, \quad (10)$$

where ω_{ij}^H is the sectoral share in the domestic market:

$$\omega_{ij}^H = \frac{p_{ij}^H y_{ij}^H}{\sum_{i=1}^N p_{ij}^H y_{ij}^H + (1 + \tau) \sum_{i=1}^N p_{ij}^F y_{ij}^F} = \frac{1}{N} \left(\frac{p_{ij}^H}{p_j} \right)^{1-\gamma}. \quad (11)$$

Sectoral shares and demand elasticity. The demand elasticity faced by any producer is endogenous and given by a weighted harmonic average of the across-sector elasticity θ and the within-sector elasticity $\gamma > \theta$. Firms with a large share of a sector's revenue face a lower demand elasticity and charge a higher markup. These firms compete more with producers in other sectors and so face a demand elasticity closer to θ . Similarly, firms with a low share in any individual sector compete mostly with producers in that particular sector and face a demand elasticity closer to γ . Clearly, the extent of markup dispersion across firms depends both on the degree of dispersion in sectoral shares within sectors and on the size of the *gap* between γ and θ . If γ and θ are equal, the demand elasticity is constant as in a standard trade model. Alternatively, if γ is substantially larger than θ , then a modest change in sectoral shares can have a large effect on the demand elasticity.

Sectoral shares and labor shares. The model implies a negative *linear* relationship between a firm's sectoral share and its labor share. To see this, observe from (7) and (9) that a firm's revenue productivity is proportional to its markup:

$$\frac{p_{ij}^H y_{ij}^H}{W l_{ij}^H} = \frac{1}{1 - \alpha} \frac{\varepsilon_{ij}^H}{\varepsilon_{ij}^H - 1}. \quad (12)$$

Now using (10) to substitute out the elasticity ε_{ij}^H in terms of the sectoral share ω_{ij}^H gives:

$$\frac{W l_{ij}^H}{p_{ij}^H y_{ij}^H} = (1 - \alpha) \left(1 - \frac{1}{\gamma} \right) - (1 - \alpha) \left(\frac{1}{\theta} - \frac{1}{\gamma} \right) \omega_{ij}^H. \quad (13)$$

Since $\gamma > \theta$, the coefficient on the sectoral share ω_{ij}^H is negative. Section 4 below uses the linear relationship in equation (13) and micro data on sectoral shares and labor shares to identify these key elasticity parameters.

Export market and tariffs. The problem of a Home firm in its export market is essentially identical except that (i) to export, it pays a fixed cost F_f rather than F_d , and (ii) the sales of their good abroad are subject to an *ad valorem* tariff $\xi \in [0, 1]$. This problem can be written

$$\pi_{ij}^{*H} = \max_{y_{ij}^{*H}, \phi_{ij}^{*H}} \left[((1 - \xi)p_{ij}^{*H} - v_{ij}) y_{ij}^{*H} - W F_f \right] \phi_{ij}^{*H},$$

subject to the demand system in the Foreign market, analogous to (2) above. We assume that the revenue from tariffs is redistributed lump-sum to consumers in the importing country.

Prices are then given by

$$p_{ij}^{*H} = \frac{1}{1 - \xi} \frac{\varepsilon_{ij}^{*H}}{\varepsilon_{ij}^{*H} - 1} v_{ij},$$

where ε_{ij}^{*H} is the demand elasticity in the export market:

$$\varepsilon_{ij}^{*H} = \left(\omega_{ij}^{*H} \frac{1}{\theta} + (1 - \omega_{ij}^{*H}) \frac{1}{\gamma} \right)^{-1}, \quad (14)$$

and where ω_{ij}^{*H} is the sectoral share in the export market:

$$\omega_{ij}^{*H} = \frac{(1 + \tau) p_{ij}^{*H} y_{ij}^{*H}}{\sum_{i=1}^N p_{ij}^{*F} y_{ij}^{*F} + (1 + \tau) \sum_{i=1}^N p_{ij}^{*H} y_{ij}^{*H}}. \quad (15)$$

Entry and exit. Each period a Home firm must pay a fixed cost F_d to sell in its domestic market. The firm sells in the domestic market as long as

$$(p_{ij}^H - v_{ij}) y_{ij}^H \geq W F_d.$$

Similarly, the Home firm must pay another fixed cost F_f to operate in its export market. The firm exports as long as

$$((1 - \xi) p_{ij}^{*H} - v_{ij}) y_{ij}^{*H} \geq W F_f.$$

There are multiple equilibria in any given sector. Different combinations of intermediate firms may choose to operate, given that the others do not. As [Atkeson and Burstein \(2008\)](#) do, we place intermediate firms in the order of their productivity a_{ij} and focus on equilibria in which firms sequentially decide on whether to operate or not: the most productive decides first (given that no other firm enters), the second most productive decides second (given that no other less productive firm enters), etc.⁶

2.3 Equilibrium

In equilibrium, consumers and firms optimize and the markets for labor and physical capital clear:

$$\begin{aligned} L_t &= \int_0^1 \frac{1}{N} \sum_{i=1}^N [(l_{ij,t}^H + F_d) \phi_{ij,t}^H + (l_{ij,t}^{*H} + F_f) \phi_{ij,t}^{*H}] dj \\ K_{t-1} &= \int_0^1 \frac{1}{N} \sum_{i=1}^N [k_{ij,t}^H \phi_{ij,t}^H + k_{ij,t}^{*H} \phi_{ij,t}^{*H}] dj. \end{aligned}$$

The market clearing condition for the final good in each country is:

$$Y_t = C_t + X_t.$$

⁶The exact ordering we choose makes little difference quantitatively when we calibrate the model to match the strong concentration in the data. Productive producers always enter and unproductive ones always stay out; the multiplicity of equilibria only affects the entry decisions of small marginal producers that have a negligible effect on the aggregates. Moreover, as we show in [Section 8](#) below, our model's implications for the gains from trade are essentially unchanged when we set $F_d = F_f = 0$ so that all producers enter and the equilibrium is unique.

2.4 Aggregation

The model aggregates to a two-country representative agent economy, which is standard except that TFP, the aggregate markup, and the Armington elasticity are all endogenous. Each of these key objects is determined by underlying productivity differences a_{ij} , the elasticity of substitution parameters θ and γ , as well as the trade cost and tariff parameters τ , ξ that govern the amount of trade.

Aggregate productivity. The quantity of final output in each economy can be written

$$Y = AK^\alpha \tilde{L}^{1-\alpha},$$

where A is the endogenous level of TFP, K is the aggregate stock of physical capital, and $\tilde{L}$ is the aggregate amount of labor used *net of fixed costs*. Using the firms' optimality conditions for input choices and the market clearing conditions for capital and labor, it is straightforward to show that aggregate productivity is a *quantity-weighted* harmonic mean of producer-level productivities:

$$A = \left(\int_0^1 \frac{1}{N} \sum_{i=1}^N \frac{1}{a_{ij}} \frac{y_{ij}^H}{Y} dj + (1 + \tau) \int_0^1 \frac{1}{N} \sum_{i=1}^N \frac{1}{a_{ij}} \frac{y_{ij}^{*H}}{Y} dj \right)^{-1}. \quad (16)$$

Aggregate markup. Define the aggregate (economy-wide) markup by

$$M \equiv \frac{P}{V/A},$$

that is, aggregate price divided by aggregate marginal cost. Using the firms' optimality conditions and the market clearing condition for labor, we can write:

$$\frac{W\tilde{L}}{PY} = (1 - \alpha) \frac{1}{M}.$$

The aggregate labor share is reduced in proportion to the aggregate markup. Once again, it is straightforward to show that

$$M = \left(\int_0^1 \frac{1}{N} \sum_{i=1}^N \frac{1}{m_{ij}^H} \frac{p_{ij}^H y_{ij}^H}{PY} dj + (1 + \tau) \int_0^1 \frac{1}{N} \sum_{i=1}^N \frac{(1 - \xi) p_{ij}^{*H} y_{ij}^{*H}}{m_{ij}^{*H} PY} dj \right)^{-1}. \quad (17)$$

That is, the aggregate markup is a *revenue-weighted* harmonic mean of firm-level markups. Observe that revenues from abroad are reduced in proportion to the tariff rate ξ .

Two sources of distortions due to markups. The presence of market power provides two channels that distort equilibrium allocations relative to the efficient level. First, the level of the aggregate markup distorts aggregate labor and investment decisions. From the first-order conditions for the consumers' problem and the expressions for labor and capital demand, we have

$$-\frac{U_{l,t}}{U_{c,t}} = \frac{W_t}{P_t} = \frac{1}{M_t}(1-\alpha)\frac{Y_t}{\tilde{L}_t},$$

and

$$U_{c,t} = \beta U_{c,t+1} \left(\frac{R_{t+1}}{P_{t+1}} + (1-\delta) \right) = \beta U_{c,t+1} \left(\frac{1}{M_{t+1}} \alpha \frac{Y_{t+1}}{K_{t+1}} + (1-\delta) \right).$$

High aggregate markups thus act like distortionary labor and capital income taxes and reduce output relative to its efficient level.

Second, dispersion in markups also reduces the level of aggregate TFP, as in the work of [Restuccia and Rogerson \(2008\)](#) and [Hsieh and Klenow \(2009\)](#). To understand this second effect, notice that the expression for aggregate productivity reduces to

$$A = \left(\int_0^1 \left(\frac{m_j}{M} \right)^{-\theta} a_j^{\theta-1} dj \right)^{\frac{1}{\theta-1}},$$

where $m_j = p_j/(V/a_j)$ is the sector-level markup and where sector-level productivity, a_j , is

$$a_j = \left(\frac{1}{N} \sum_{i=1}^N \phi_{ij}^H \left(\frac{m_{ij}^H}{m_j} \right)^{-\gamma} a_{ij}^{\gamma-1} + (1+\tau)^{1-\gamma} \frac{1}{N} \sum_{i=1}^N \phi_{ij}^F \left(\frac{m_{ij}^F}{(1-\xi)m_j} \right)^{-\gamma} a_{ij}^{*\gamma-1} \right)^{\frac{1}{\gamma-1}}.$$

The first-best TFP level (attainable by a planner given a particular tariff ξ) is equal to:

$$A = \left(\int_0^1 a_j^{\theta-1} dj \right)^{\frac{1}{\theta-1}}, \quad (18)$$

where

$$a_j = \left(\frac{1}{N} \sum_{i=1}^N \phi_{ij}^H a_{ij}^{\gamma-1} + (1+\tau)^{1-\gamma} \frac{1}{N} \sum_{i=1}^N \left(\frac{1}{1-\xi} \right)^{-\gamma} \phi_{ij}^F a_{ij}^{*\gamma-1} \right)^{\frac{1}{\gamma-1}}. \quad (19)$$

Absent markup dispersion, TFP is at its first-best level. With markup dispersion, the most productive producers employ a smaller share of the economy's capital and labor than efficiency dictates, since markups and productivity are positively related. Markup dispersion thus lowers TFP by inducing a suboptimal allocation of capital and labor across producers.

Armington elasticity. The Armington elasticity is a key statistic governing the gains from trade in standard trade models. In those models, a high Armington elasticity, of the size inferred from micro trade data, implies small gains from trade since Home and Foreign

goods are closely substitutable. We show below that with endogenously varying markups, the gains from trade can be large *despite a high Armington elasticity*. Here we briefly describe how we compute the Armington elasticity in our model.

The Armington elasticity is defined as the *partial* elasticity of trade flows to changes in trade costs, and in particular,

$$1 - \sigma = -\frac{\partial \log \frac{1-\lambda}{\lambda}}{\partial \tau},$$

where λ is the share of spending on domestically produced goods. In our model λ is equal to

$$\lambda = \frac{\int_0^1 \sum_{i=1}^N p_{ij}^H y_{ij}^H dj}{\int_0^1 \left(\sum_{i=1}^N p_{ij}^H y_{ij}^H + (1 + \tau) \sum_{i=1}^N p_{ij}^F y_{ij}^F \right) dj} = \int_0^1 \lambda_j s_j dj,$$

where λ_j denotes the sector-level share of spending on domestically produced goods and where $s_j \equiv (p_j/P)^{1-\theta}$ is each sector's share in total spending.

Some algebra shows that the Armington elasticity is related to the two key underlying elasticity of substitution parameters γ and θ , according to the weighted average

$$\sigma = \gamma \left(\int_0^1 s_j \frac{\lambda_j}{\lambda} \frac{1 - \lambda_j}{1 - \lambda} dj \right) + \theta \left(1 - \int_0^1 s_j \frac{\lambda_j}{\lambda} \frac{1 - \lambda_j}{1 - \lambda} dj \right). \quad (20)$$

To understand this expression, note that a reduction in trade costs changes the aggregate import share through two channels: (i) by increasing the import shares in each sector j , an effect governed by the within-sector elasticity γ , and (ii) by reallocating expenditure toward sectors with lower import shares, an effect governed by the between-sector elasticity θ . The weight on the within-sector elasticity γ is a measure of the dispersion in sectoral import shares. For example, if all sectors have identical import shares, $\lambda_j = \lambda$ for all j , then changes in trade costs imply no between-industry reallocation of resources and $\sigma = \gamma$. At the other extreme, if a subset of sectors have import shares of $\lambda_j = 0$, while the others have import shares of $\lambda_j = 1$, then changes in trade costs imply that all reallocation is between sectors and $\sigma = \theta$. More generally, the Armington elasticity depends on the dispersion in import shares across sectors.

3 Data

We use the Taiwan Annual Manufacturing Survey. This survey reports data for the universe of establishments⁷ engaged in production activities. Our sample covers the years 2000 and 2002–2004. The year 2001 is missing because in that year a separate census was conducted.

⁷Unfortunately firm-level identifiers are not available in our data. Notice however that our focus on plants, rather than firms, understates the extent of concentration among firms, a key feature that determines the gains from trade in the model.

3.1 Measurement

Product classification. The dataset we use has two components. First, a *plant*-level component collects detailed information on operations, such as employment, expenditure on labor, materials and energy, and total revenue. Second, a *product*-level component reports information on revenues for each of the products produced at a given plant. Each product is categorized into a 7-digit Standard Industrial Classification created by the Taiwanese Statistical Bureau. This classification at 7 digits is comparable to the detailed 5-digit SIC product definition collected for US manufacturing plants as described by [Bernard, Redding and Schott \(2010\)](#). Panel A of Table A1 in the Appendix gives an example of this classification, while Panel B reports the distribution of 7-digit sectors within 4- and 2-digit industries. Most of the products are concentrated in the Chemical Materials, Industrial Machinery, Computer/Electronics and Electrical Machinery industries.

Import shares. We supplement the survey with detailed import data at the harmonized HS-6 product level. We obtain the import data from the WTO and then match HS-6 codes with the 7-digit product codes used in the Annual Manufacturing Survey. This match gives us disaggregated import penetration ratios for each product category.

3.2 Key facts

Two key facts from the Taiwanese manufacturing data are crucial for our model’s quantitative implications: (i) there is very strong concentration among producers, and (ii) there is a pronounced negative correlation between producer cost shares and their sectoral shares.

Strong concentration within sectors. Panel A of [Table 1](#) shows that there is a high degree of concentration among domestic producers in individual 7-digit sectors. The average share of the largest seller in any given industry is equal to 0.45, only slightly greater than the median share of 0.39.⁸ The mean (median) inverse Herfindhals measures of concentration are equal to 7.3 (4.0), much lower than the average number of producers in any given sector.

Panel A of [Table 1](#) also reports moments of the overall distribution of sectoral shares of domestic producers. These sectoral shares, unlike those discussed above, reflect sales by both domestic producers and imports. The average sectoral share of a domestic producer is 2.9%, whereas the median producer has a share of slightly below 0.4%. The distribution of shares is heavily *fat-tailed*: the 95th percentile of this distribution is equal to about 14% and the 99th percentile is equal to about 46%. The pattern that emerges is thus one of very strong

⁸The sectoral statistics weigh each sector by its sales share.

concentration. Although many producers operate in any given 7-digit sector, most of these producers are small; a few large producers account for the bulk of any sector’s sales.

Strong unconditional concentration. Panel A of [Table 1](#) also reports several statistics that capture the degree of concentration across all establishments. As documented in many other studies, employment and value added are strongly concentrated in the few large establishments. The share of value added and wage bill accounted for by the largest 1% of producers is equal to 48% and 32%, respectively. Similarly, the largest 5% of all producers account for almost two-thirds of all value added and about one-half of all labor spending in Taiwanese manufacturing.

The labor share is negatively correlated with the sectoral share. We measure the labor share of producer i as $w_i l_i / p_i y_i$, where $w_i l_i$ is the producer’s wage bill and $p_i y_i$ their *value added*: revenue net of intermediate inputs. To see the strong correlation between labor and sectoral shares, we find it useful to compare the aggregate labor share in Taiwan manufacturing (the sales-weighted average of individual producer labor shares) with the simple unweighted average.

The *unweighted average* labor share in the Taiwanese data is equal to 0.61. However, the *aggregate* labor share

$$\frac{WL}{PY} = \sum_i \frac{w_i l_i}{p_i y_i} \frac{p_i y_i}{\sum_{i'} p_{i'} y_{i'}},$$

is much lower, equal to only 0.43. This pronounced difference between the average and aggregate labor share emerges because, just as in the model, firms in the data that have high sectoral shares are also firms with low labor shares.

Another way to confirm this pattern is to regress producer labor shares on their sectoral shares. The point estimates imply that the labor share of a producer with a sectoral share of zero — essentially the median producer — is equal to 64%. By contrast, the labor share of a producer with a sectoral share of one-half is equal to 41%, i.e., 50% lower.

Is this correlation due to differences in capital intensities? One concern with our focus on labor shares is that differences in labor shares might really be due to firm-level differences in capital intensity rather than markups. To examine this, we suppose that firms have the technology $y_i = a_i k_i^{\alpha_i} l_i^{1-\alpha_i}$ and use data on plant capital stocks to calculate the sum of the labor and capital share. In the model, the sum of the labor and capital share is inversely related to markups but, unlike the labor share, is independent of the producer’s

capital intensity, α_i :

$$\frac{w_i l_i + r k_i}{p_i y_i} = \frac{1}{m_i}.$$

To compute this object, we assume a user cost of capital, r , equal to 0.15 which implies that the median producer has a capital intensity, α_i , equal to 0.33.⁹ Using the sum of the capital and labor shares we find, once again, that the implied aggregate markup is 40% larger than the average markup. Thus, differences in capital intensities alone do not account for the relationship between labor shares and sectoral shares.

4 Quantifying the model

We now discuss how we use the Taiwanese data to pin down the key parameters of our model.

4.1 Overview

In the model, two key factors determine the size of the gains from trade: (i) the extent of initial *misallocation*, and (ii) the pattern of *comparative advantage*. These factors are governed by the amount of dispersion in productivity within and across countries, and by the elasticity parameters γ and θ . We discipline our model along these dimensions as follows.

We choose a distribution of productivities that allows the model to reproduce the amount of concentration within individual sectors as well as the size distribution of establishments in Taiwan. We choose the elasticity parameters γ and θ so that the model reproduces standard estimates of the Armington elasticity used in the trade literature and the relationship between producers' cost shares and sectoral shares in the data. Together, the productivity distribution and the elasticities γ, θ largely determine the amount of misallocation. Finally, the pattern of comparative advantage is largely determined by the cross-country *correlation* in producer-level productivity in individual sectors, which we pin down using data on the amount of *intra-industry* trade.

4.2 Productivity distribution

The distribution of producer-level productivities plays a key role in our analysis. Within a given country, the distribution of a_{ij} determines the pattern of concentration in individual sectors and the size distribution of producers. This, in turn, determines the degree of misallocation in the economy. Across countries, the correlation between a_{ij} and a_{ij}^* determines the extent to which opening up to trade exposes highly productive domestic producers to competition from foreign producers. If Home and Foreign productivities are strongly correlated

⁹Our numbers are, however, very robust to reasonable perturbations of r .

in any given sector, opening up to trade implies that even the largest domestic producers are exposed to strong foreign competition and are forced to reduce markups. In contrast, if Home and Foreign productivities are weakly correlated, trade does not much affect the amount of competition and thus has little effect on markups.

In standard trade models,¹⁰ productivity draws are assumed independent across countries. Since the pattern of comparative advantage plays a key role in determining the pro-competitive gains from trade, we allow for dependence between Home and Foreign productivities and study its effect on the gains from trade.

Joint distribution. Let $H(a, a^*)$ denote the joint distribution of productivities and let $F(a)$ and $F(a^*)$ denote the (common) marginal distributions. We write the joint distribution:

$$H(a, a^*) = \mathcal{C}(F(a), F(a^*)), \quad (21)$$

where the *copula* $\mathcal{C}$ is the joint distribution of a pair of uniform random variables u, u^* on $[0, 1]$ and can be written:

$$\mathcal{C}(u, u^*) = H(F^{-1}(u), F^{-1}(u^*)). \quad (22)$$

In short, the copula governs the pattern of dependence between a and a^* leaving the marginal distribution $F(a)$ free to match within-country productivity statistics.

Marginal distribution. Given draws u_{ij} and u_{ij}^* from $\mathcal{C}(u_{ij}, u_{ij}^*)$, we set $a_{ij} = F^{-1}(u_{ij})$ and $a_{ij}^* = F^{-1}(u_{ij}^*)$ and choose the (inverse) marginal distribution $F^{-1}(u)$ to match the pattern of concentration in the Taiwanese data. In particular, we assume:

$$F^{-1}(u) = \begin{cases} (1 - u)^{-\frac{1}{\mu_L}} & \text{if } u < 1 - p_H \\ (1 - u)^{-\frac{1}{\mu_H}} & \text{if } u \geq 1 - p_H \end{cases}. \quad (23)$$

This distribution, which we refer to as the *double Pareto*, allows us to simultaneously match the fat-tailed size distribution of producers in the data and the amount of concentration in individual sectors. A small fraction p_H of producers draw their productivity from a fat-tailed Pareto with shape parameter $\mu_H < \mu_L$, while the rest of producers draw from a thin-tailed Pareto, thus allowing us to capture the size distribution at both the upper and lower tails.¹¹ The robustness section below studies an economy with a single Pareto marginal and illustrates the failure of that distribution to account for the data.

¹⁰For example, [Eaton and Kortum \(2002\)](#) or [Bernard, Eaton, Jensen and Kortum \(2003\)](#).

¹¹We have also redone our analysis with a marginal distribution $F(a)$ that is a binomial mixture of Paretos and obtained essentially identical results. We prefer the specification above since it can match the data with one fewer parameter than the binomial mixture and also because an inverse is available in closed form.

Copula. We use a *Gumbel copula* to control the cross-country dependence in productivity draws. This is a widely used copula that allows for dependence even in the right tails of the distribution:

$$\mathcal{C}(u, u^*) = \exp \left(- [(-\log u)^\rho + (-\log u^*)^\rho]^\frac{1}{\rho} \right), \quad \rho \geq 1. \quad (24)$$

The parameter ρ controls the amount of dependence, which, as usual when working with fat-tailed distributions, we summarize using *Kendall's* τ .¹² As with a conventional linear correlation coefficient, Kendall's τ is scaled so that $\tau = 0$ corresponds to independent random variables while $\tau = 1$ corresponds to perfect dependence.

To highlight the role of dependence between Home and Foreign productivity draws, our analysis below starts by reporting the welfare gains from trade for two extreme parameterizations: $\tau(\rho) = 1$ and $\tau(\rho) = 0$. It turns out that the choice of the other parameters of the model is not very sensitive to the value of ρ . We therefore calibrate all the model's parameters assuming $\tau(\rho) = 1$, and then keep those parameters fixed as we vary the amount of dependence in our experiments.¹³

4.3 Calibration

Assigned parameters. We assume the utility function:

$$U(C, L) = \log C + \psi \log(1 - L).$$

We choose a value for ψ to ensure $L = 0.3$ in the steady-state, implying a Frisch elasticity of labor supply equal to 2.33, in line with the findings of [Rogerson and Wallenius \(2009\)](#).

The period length is one year. We assume a time discount factor of $\beta = 0.96$ and a capital depreciation rate of $\delta = 0.10$. The elasticity of output with respect to physical capital is $\alpha = 1/3$.¹⁴ We set the tariff rate ξ to 6.4%, which is the OECD estimate for Taiwanese manufacturing.

Productivity parameters and fixed costs. We choose the parameters μ_L, μ_H, p_H of the double Pareto distribution, the fixed costs of selling in the domestic and foreign markets,

¹²Defined by:

$$\tau \equiv 4 \int_0^1 \int_0^1 \mathcal{C}(u, u^*) d\mathcal{C}(u, u^*),$$

which for the Gumbel distribution evaluates to $\tau = 1 - 1/\rho$.

¹³Recalibrating all parameters as we vary $\tau(\rho)$ produces nearly identical results.

¹⁴As in [Collard-Wexler, Asker and De Loecker \(2011\)](#) and other studies of productivity dispersion, in our theoretical model we abstract from differences in capital and labor intensities, α , across sectors. Since markups affect the labor and capital wedges identically, and since α only affects the relative weight on the two wedges, allowing for heterogeneity in α does not change the model's implications for TFP and the aggregate level of markups in (16) and (17) above.

F_d and F_f , and the number of technologies within a sector, N , to match key concentration statistics in the Taiwanese data. Panel A of [Table 1](#) reports the moments and the counterparts for our benchmark model. Panel B reports the parameter values that achieve this fit.

Our model successfully reproduces the amount of concentration in the data. The largest 7-digit producer accounts for an average 49% of that sector's domestic sales (45% in the data). The model also reproduces well the heavy concentration in the tails of the distribution of sectoral shares, with the 95th (99th) percentile share being equal to about 14% (46%) in both the data and the model. Finally, as in the data, the model produces a very fat-tailed size distribution of establishments: the top 1% and 5% of all producers in the data account for almost one-third and two-thirds of the total value added and wage bill, numbers close to those in Taiwanese manufacturing.

In the data, 25% of producers export. To match this fact, the model requires an export fixed cost F_f equal to 4.5% of steady-state labor. The fixed cost to operate domestically, F_d , is equal to 2.2% of steady-state labor. This level of the fixed cost is required for the model to reproduce the distribution of sectoral shares at the lower end of the spectrum. Absent this fixed cost, the model would predict a much smaller average sectoral share, since many very small producers would operate.

Finally, the distribution of productivity is highly fat-tailed. Although most producers draw from a Pareto with relatively thin tails, $\mu_L = 3.83$, a few producers, $p_H = 0.35\%$, draw from a very fat-tailed Pareto with $\mu_H = 1.5$. Our Appendix shows that the model's ability to fit the concentration in the data worsens significantly for greater values of μ_H .

Estimating θ . In the presence of fixed labor costs of production, the relationship between labor shares and sectoral shares predicted by the model, equation (13), generalizes to:

$$\frac{wl_i}{p_i y_i} = (1 - \alpha) \left(1 - \frac{1}{\gamma}\right) - (1 - \alpha) \left(\frac{1}{\theta} - \frac{1}{\gamma}\right) \omega_i + \frac{wF_d}{p_i y_i}, \quad (25)$$

where wl_i is the wage bill for producer i , $p_i y_i$ is its value added,¹⁵ ω_i is that producer's share in its own sector, and wF_d is the fixed cost, assumed common to all producers. Now consider a regression of labor shares $wl_i/p_i y_i$ on sectoral shares, ω_i , and inverse value added, $1/p_i y_i$ as in (25). For a given value of the within-sector elasticity γ , the *ratio* of the slope coefficient to the intercept uniquely determines θ .

We choose the elasticity of substitution within a sector, $\gamma = 8.45$, to ensure that the model reproduces an Armington elasticity of $\sigma = 8$, a typical number used in trade studies.¹⁶

¹⁵Since we abstract from intermediate inputs in the model, we use data on value added (revenue net of intermediate inputs) as a proxy for sales. We calculate sectoral shares, ω_i , using revenue data, however.

¹⁶See, for example, [Anderson and van Wincoop \(2004\)](#), [Broda and Weinstein \(2006\)](#), or [Feenstra, Obstfeld and Russ \(2010\)](#).

We choose the size of the iceberg trade cost $\tau = 0.21$ so that the model reproduces the Taiwanese manufacturing import share of 26%.

Panel A of [Table 2](#) reports the implied estimates of θ (given $\gamma = 8.45$) from equation (25). We find an OLS estimate of $\theta = 1.20$ when using all observations, including exporters.¹⁷ To check the robustness of these results to outliers, we estimate θ by median regression and find $\theta = 1.18$. Given the large number of observations in our sample, these estimates are very precisely estimated.

One concern about using data on labor shares is that such data cannot isolate the role of markups from that of differences in capital intensities or other forms of misspecification of the production function. To check this, we first use the sum of the labor and capital shares as a dependent variable in equation (25). We find that our estimates of θ increase somewhat, to 1.34 (or 1.65 in the median regression), but the basic picture of a low elasticity of substitution between sectors remains. Second, we allow the underlying technology to be a general *translog* production function rather than Cobb-Douglas. We estimate the translog production function, controlling for endogeneity by using a fixed effects regression in one case and by using the control function methods advocated by [De Loecker and Warzynski \(2012\)](#) in another, and then use the estimated markups in (25).¹⁸ Remarkably, this indirect procedure, which makes none of our strong functional form assumptions about the relationship between markups and cost shares, yields very similar estimates of θ , on the order of 1.2 or 1.3.

Overall, we find that a robust estimate of θ is a number close to 1.25, a number we choose for our baseline quantitative analysis. We note that our choice of θ is slightly higher than that used by [Devereux and Lee \(2001\)](#) and [Atkeson and Burstein \(2008\)](#), both of which set $\theta = 1$. Our robustness section below studies how our welfare results change for alternative values of θ .

Markup distribution. [Table 3](#) reports moments of the distribution of markups and labor shares in our model. We also compare these moments to those in an economy that is identical to our benchmark except that we shut down all international trade.

The benchmark model implies a mean producer markup of 1.17, a median markup of 1.14 and a rather small (0.11) standard deviation of markups across producers. But as equation (17) makes clear, what really matters for the model’s aggregate implications are the *revenue-weighted* markups and markup dispersion. The large producers in the model do have very high markups: the 95th percentile markup is 1.28, whereas the 99th percentile

¹⁷To make full use of our data, we also generalize (25) to cover (i) multi-product establishments, (ii) to include exporters who have potentially different sectoral shares at home and abroad, and (iii) to allow capital intensities to vary across producers. The Appendix discusses these specifications in further detail.

¹⁸We discuss these estimates in detail in the Appendix.

is 1.76. Consequently, the *aggregate* markup is large, 1.48. Because the largest producers charge high markups, the model does a very good job at matching the difference between the average labor share (0.62 in the model and 0.61 in the data) and the aggregate labor share (0.45 in the model and 0.43 in the data).

Consider next what happens if we shut down international trade. Under autarky, more firms operate. As [Table 3](#) shows, there are on average 34 producers in each sector under autarky, as opposed to 26 in the benchmark model. The model thus features a standard *selection effect* — opening to trade forces the smallest, least productive firms to exit.

Interestingly, shutting down trade does not change much the average markup in this economy: the mean markup only increases to 1.19 from 1.17, while the median markup is unchanged. Again, however, the welfare gains are determined by the aggregate markup, not the average. The aggregate markup increases considerably, from 1.48 to 1.75, reflecting an increase in the sales share of high markup producers. Moreover, the economy experiences a sharp increase in misallocation, as measured by the dispersion in markups across producers: the standard deviation of markups triples from 0.11 to 0.33. As we illustrate below, welfare significantly worsens in the autarkic economy, mostly due to the increase in distortions associated with markups, despite the fact that individual moments of the markup distribution change little. As in [Arkolakis, Costinot, Donaldson and Rodríguez-Clare \(2012b\)](#), what matters for welfare is the *joint distribution* of markups and output, which does change substantially as trade is shut down.

[Figure 1](#) illustrates, showing how the distribution of sectoral shares changes as we move away from autarky. The figure shows the share of output accounted for by firms with sectoral shares between 0 and 0.1, 0.1 and 0.2, etc, as well as the optimal markup charged by firms with different sectoral shares. Under autarky, the distribution of sales is much more concentrated. Slightly more than 5% of all revenue is accounted for by producers that have a sectoral share greater than 50% and hence charge very high markups. Reducing tariffs or trade costs exposes these firms to more competition and lowers their sectoral shares, forcing them to reduce markups.

5 Gains from trade

Approach. We now calculate the welfare gains from trade in our model. As we explain at length below, the size of the welfare gains depend crucially on the pattern of comparative advantage, which is determined by the cross-country pattern of correlation in productivity draws. Since there is surely considerable variation across countries in the pattern of comparative advantage, we do not, in this section, take a stand on a particular amount of correlation.

Instead, we provide results for the two extreme cases: (i) *identical* Home and Foreign productivity draws, $\tau(\rho) = 1$, and (ii) *independent* Home and Foreign productivity draws, $\tau(\rho) = 0$. These two cases allow us to show, in the sharpest possible manner, how the mechanisms underlying the gains from trade vary with the pattern of correlation. The first case provides an upper bound on the importance of pro-competitive effects while the second case essentially corresponds to the workhorse BEJK model of variable markups. In [Section 6](#) below, we then consider results for intermediate levels of $\tau(\rho)$ and explain how data on intra-industry trade can be used to identify empirically reasonable values for $\tau(\rho)$.

5.1 Efficiency losses due to misallocation

To begin the analysis, we establish the potential gains from trade by calculating the efficiency losses due to misallocation in an economy closed to international trade. We start with the economy with identical productivity draws, for which $\tau(\rho) = 1$.

5.1.1 Economy with Taiwan’s import share

We conduct the following policy experiment. We choose producer-specific subsidies or taxes to induce each producer to charge the same markup, $\bar{m}$. We assume that such subsidies are financed via lump-sum taxes levied on consumers and hence can fully restore efficiency. We consider two experiments that are reported in [Table 4](#). In the first, labeled first-best, we set $\bar{m} = 1$ and so eliminate both the dispersion and the level of markups. In the second experiment, we set $\bar{m}$ equal to the aggregate markup in the original economy, thus eliminating all the markup dispersion but keeping the aggregate markup unchanged. In all experiments, we compute welfare gains including the *transition path* from the initial steady state; these are slightly smaller than would be obtained from a static comparison across steady states.

Losses relative to first-best. Panel A of [Table 4](#) shows that the efficiency losses due to markups are large. Taking the benchmark economy to the first-best by eliminating markups altogether leads to large increases in output and consumption and welfare gains equivalent to a permanent 16.7% increase in consumption. This increase in welfare is due to a 4.6% increase in TFP and the reduction in the aggregate markup.

Losses from markup dispersion. The last column of Panel A of [Table 4](#) shows that eliminating markup dispersion alone would generate significant welfare gains, equivalent to a 5.9% permanent increase in consumption, due to the 4.6% increase in TFP. Because of our assumption of log utility, with its offsetting income and substitution effects, the increase in TFP here leads to no change in employment.

5.1.2 Economy under autarky

How does international trade affect the efficiency losses from markups and misallocation? To see this, consider the autarky version of the model. As shown in Panel B of Table 4, the aggregate markup would increase from 1.48 to 1.75 in the absence of trade. Moreover, as shown above, the dispersion in markups would greatly increase as well. Starting from autarky, eliminating markups altogether would thus lead to much larger welfare gains of about 53%. Eliminating markup dispersion alone would generate significant welfare gains (34%) due to the 25% increase in TFP that results from reallocating factors of production.

Trade in this model is thus a powerful mechanism that reduces the extent of misallocation of factors of production and distortions to investment and employment decisions.

5.2 Welfare gains. Identical Home and Foreign productivity

We now calculate the welfare gains from trade for the case of *identical* Home and Foreign productivity draws, $\tau(\rho) = 1$. We follow Arkolakis, Costinot and Rodríguez-Clare (2012a, ACR hereafter) and study the welfare gains due to reductions in *trade costs*.¹⁹ The Appendix shows that all our findings are robust if we reduce tariffs rather than trade costs.

Table 5 reports the effect on welfare and the aggregate level of markups and TFP of symmetric trade cost reductions that increase the import share in both countries from 0 to 10%, 10 to 20%, and 20 to 30%. The model predicts large gains from moving from autarky to a 10% import share: the welfare gains are equivalent to a 26.1% permanent increase in consumption. These gains are driven by a nearly 15% drop in markups, as well as by a nearly 13% increase in TFP. Interestingly, markups do not decline uniformly here. While markups in the domestic market decline (the revenue-weighted average markup declines by 13.9%), the markups in the export market increases considerably (the revenue-weighted average markup increases by more than 20%). Intuitively, the reduction in trade costs raises the exporters' sectoral shares, allowing them to raise markups.

The model also predicts a nonlinear relationship between openness and welfare (or TFP). Near autarky, the marginal gains from trade are very high. Even a small increase in the amount of competition faced by domestic producers is enough to reduce their markups significantly. At higher import shares, similar increases in openness lead to smaller welfare gains. As Table 5 shows, moving from an import share of about 10% to 20% increases welfare by 7.6% and TFP by 4.7%. Similarly, moving from an import share of 20% to 30% delivers even smaller gains — welfare increases by 5.8% and TFP increases by 3.9%.

Observe that the welfare gains do *not* arise due to the endogenously variable Armington

¹⁹Here we set the level of tariffs, ξ , equal to zero, as ACR do.

trade elasticity. Although the Armington elasticity does change in response to changes in tariffs, [Table 5](#) shows that these changes are not very large (from 8.45 in autarky to 7.4 in the economy with a 10% import share).

Ricardian gains. We next isolate the welfare gains arising due to pro-competitive effects from those due to standard Ricardian effects (pure comparative advantage and love-of-variety). To do so, recall that allocations in our model are solely a function of the aggregate level of markups and TFP. In our model welfare increases via three channels: (i) the aggregate markup declines, (ii) markups become less dispersed, reducing misallocation and thus bridging the gap between the actual and the first-best level of TFP, and (iii) the first-best level of TFP increases. Since channels (i) and (ii) are only operative in a model with variable markups, while channel (iii) is also present in models with constant markups, we refer to the latter as *Ricardian TFP gains*.

Formally, we decompose the change in TFP in our model into two terms

$$\Delta \ln A_t = \Delta(\ln A_t - \ln A_t^{FB}) + \Delta \ln A_t^{FB},$$

where A_t^{FB} is the first-best level of TFP from (18)-(19). The first term on the right hand side of this expression captures the extent to which opening up to trade reduces the TFP losses due to misallocation — the gap between the actual and first-best level of TFP. The second term is simply the change in the first-best level of TFP. Hence, by comparing the actual TFP changes in our model to those under the first-best, we can gauge the extent to which the increase in TFP is due to a reduction in misallocation, as opposed to Ricardian forces.

The row labeled *Ricardian TFP gains* in [Table 5](#) shows that the increases in the first-best level of TFP are small here, on the order of 1 to 2%, and hence much smaller than the overall TFP gains. We thus conclude that pro-competitive effects account for the bulk of the welfare gains from trade in this version of the model.

5.3 Welfare gains. Independent Home and Foreign productivity

We next calculate the gains from trade for the polar opposite case of *independent* Home and Foreign productivity draws, $\tau(\rho) = 0$. [Table 6](#) shows that the gains from trade are again very large, even for countries that are already open to trade. For example, a reduction in trade costs that raises the import share from autarky to 10% leads to an increase in welfare of 8.9%, while an increase in the import share from 10% to 20% leads to a much larger increase in welfare of 28.8%.

Crucially, however, the gains from trade here are *not* driven by declines in markups. In fact, the pro-competitive gains from trade are now negative. To see this, note that in

this version of the model the aggregate markup *increases* as the economy moves away from autarky, by 3.9% and 9.6% respectively, as the economy experiences a 0-10% and 10-20% change in the import share. Similarly, as shown in the row labeled *Ricardian TFP gains*, the first-best level of TFP increases by more than the actual level of TFP (8.8% vs. 8.2% for a 0-10% change in the import share and 26.3% vs. 25.4% for a 10-20% change in the import share). Hence, the degree of misallocation also increases as the economy opens to trade. Intuitively, relatively productive exporters face little competition abroad when trade barriers are reduced and thus find it optimal to increase their markups. This effect, unlike in the economy with identical draws, is no longer offset by the declines in markups of domestic producers. The market share of domestic producers is either wiped out by foreign competition if the foreign producer in that industry happens to be the more productive one, or is not affected by foreign competition if the domestic producer happens to be more productive.

Trade does not lead to pro-competitive gains here for the simple reason that trade does not increase the amount of competition faced by highly productive domestic producers. Since productivity draws are independent across countries and drawn from a very fat-tailed distribution, it is rarely the case that a highly productive domestic producer also faces a highly productive foreign counterpart. Countries thus specialize in producing goods in individual sectors and there is little intra-industry trade even when economies are open. The overall gains are nevertheless high due to Ricardian effects. Since different industries are imperfectly substitutable, and since countries differ substantially in how productive producers in different industries are, opening to trade leads to large gains due to comparative advantage.

Finally, note from [Table 6](#) that the Armington elasticity is much lower here in economies that are open to trade. This is because, with a weak pattern of comparative advantage, there is considerable dispersion in sectoral import shares. If import shares are highly dispersed, then, as equation (20) shows, the Armington elasticity is much closer to θ than to γ . We return to this point when discussing the evidence for the amount of cross-country correlation in productivity below.

6 General model

So far we have studied the welfare gains from trade in two extreme parameterizations of the degree of cross-country correlation in productivity $\tau(\rho)$ and hence two extreme patterns of comparative advantage. We now illustrate how this degree of correlation influences the size and composition of the gains from trade more generally. We then provide some evidence on the pattern of comparative advantage for Taiwan and the United States.

6.1 An increase in the import share from 0 to 10%

Figure 2 shows how the welfare and TFP gains due to an increase in the import share from 0 to 10% depend on $\tau(\rho)$.²⁰ Notice that the gains from trade are always large, in excess of 10%. The *composition* of these gains is, however, greatly influenced by $\tau(\rho)$. The gains from trade are entirely Ricardian for values of $\tau(\rho)$ below 0.4, and are mostly due to pro-competitive effects when the degree of dependence between the two countries' productivity is high. In stark contrast to standard trade models, *weakening the pattern of comparative advantage* (raising the cross-country correlation in productivity) actually *increases* the gains from trade in the model with variable markups.

6.2 An increase in the import share from 10 to 20%

Figure 3 shows how the gains from trade vary with $\tau(\rho)$ for economies that are relatively more open and that are contemplating a change in the import share from 10 to 20%. The pattern that emerges is fairly similar to the earlier one: the gains from trade are always large, though the relative importance of pro-competitive effects increase as countries become less specialized. Notice that now an increase in the degree of dependence lowers the welfare gains from trade in the model with variable markups. This result is driven by the fact that pro-competitive effects are much weaker for countries that already open; even a small amount of trade and competition is enough to offset most of the losses due to markups.

6.3 Evidence on the amount of dependence

Given that the composition of the gains from trade is strongly influenced by the degree of correlation $\tau(\rho)$, we next attempt to gauge the extent of this correlation in the data.

Index of import share dispersion. The level of $\tau(\rho)$ directly affects the amount of dispersion in a country's sectoral import shares and therefore directly influences the economy's Armington elasticity. To see this, recall formula (20) for the Armington elasticity in our model. The weight on the within-sector elasticity γ is given by:

$$\int_0^1 s_j \frac{\lambda_j}{\lambda} \frac{1 - \lambda_j}{1 - \lambda} dj = 1 - \frac{\text{Var}[\lambda_j]}{\lambda(1 - \lambda)}, \quad (26)$$

and is negatively related to the dispersion of sectoral import shares. We thus refer to this object as the *index of import share dispersion*. Clearly, this index is *increasing* in the amount of cross-country correlation. For $\tau(\rho) = 0$, productivity draws are independent and, because

²⁰In all these experiments we use our benchmark parameter values as shown in Table 1.

the draws are from a very fat-tailed marginal distribution, most sectors have domestic spending shares that are either close to $\lambda_j = 0$ or $\lambda_j = 1$. Hence there is considerable import share dispersion and the index value is close to zero. As $\tau(\rho)$ rises, there is less dispersion in import shares and the weight on γ increases.

The lower-right panels of [Figure 2](#) and [Figure 3](#) show how the index of import share dispersion varies with the degree of correlation in productivity. Note that these calculations use the post-liberalization import shares to calculate the measure of dispersion, i.e., import shares of 10% and 20% respectively.

Pinning down $\tau(\rho)$. We now use data on sectoral import shares for the US and Taiwan manufacturing sectors to gauge what values of $\tau(\rho)$ best characterize these economies.²¹ The index of import share dispersion ranges from about 0.7 to 0.8 for the US and Taiwan. Since the import share for Taiwan is about 22%, we can get a rough feel for the required $\tau(\rho)$ by consulting the lower-right panel in [Figure 3](#) where the import share is 20%. Here we see that a value of $\tau(\rho)$ in excess of 0.7 is necessary to account for the intra-industry trade data.²²

Observe also that a high value of $\tau(\rho)$ is necessary for our model to produce a realistically high Armington elasticity. By contrast, if there is much less dependence, then the weight on γ is low and the model will in turn produce an Armington elasticity that is too low relative to standard estimates in the empirical trade literature.

To conclude, data on the sectoral dispersion in import shares for the US and Taiwan suggest an important role for intra-industry trade and are consistent with values of $\tau(\rho)$ in excess of 0.7. As [Figure 3](#) shows, this amount of correlation implies large pro-competitive gains.

7 Comparison with standard trade models

We now compare our model's predictions about the gains from trade with those of the standard model with no markups. We do this in two ways. First, we use data on the change in import shares from *our model with variable markups* to calculate the TFP gains such changes would imply in the *standard model*. This calculation is inspired by the work of ACR who show that in standard trade models changes in import shares alone are sufficient to determine

²¹We use [Peter Schott's NAICS-level data](#) for the United States, an update of [Schott \(2008\)](#).

²²An alternative approach would be to measure the amount of intra-industry trade using the [Grubel and Lloyd \(1971\)](#) index. Our model matches empirical Grubel-Lloyd index values when $\tau(\rho)$ is in the neighborhood of 0.5, slightly smaller values than those implied by our index of import share dispersion (26). This degree of dependence still implies sizable pro-competitive gains, however. We focus on the index of import share dispersion because it immediately maps into our model's Armington elasticity and is thus directly interpretable in terms of our underlying theory.

the gains from trade. We find that, even for versions of our model in which Ricardian effects dominate, changes in trade volume are *not sufficient* for determining the gains from trade in our model with variable markups. Second, we calibrate a standard constant markups model and compare its gains from trade to those from our variable markups model.

7.1 Comparison with the ACR approach

Here we follow the approach of ACR and use data on the change in import shares induced by a given change in trade costs to estimate the gains from trade. To do so, we note that *absent markup dispersion*, as in standard trade models, the change in aggregate productivity resulting from changes in trade costs would be equal to

$$\frac{A_t}{A_{t-1}} = \left(\int_0^1 s_{j,t-1} \left(\frac{\Phi_{j,t}}{\Phi_{j,t-1}} \right)^{\frac{\theta-1}{\gamma-1}} \left(\frac{\lambda_{j,t}}{\lambda_{j,t-1}} \right)^{\frac{\theta-1}{1-\gamma}} dj \right)^{\frac{1}{\theta-1}}, \quad (27)$$

where

$$\Phi_{j,t} = \frac{1}{N} \sum_{i=1}^N \phi_{ij,t}^H a_{ij}^{\gamma-1}$$

summarizes the participation decision of domestic producers in sector j . Given that the high productivity producers always sell domestically, regardless of the volume of international trade, equation (27) states that the change in productivity in an economy without markup dispersion is essentially summarized by the change in import shares at the sectoral level.

Expression (27) generalizes the multiple-sector formula for the gains from trade that ACR derive for the Cobb-Douglas ($\theta = 1$) case, namely:

$$\Delta \ln A_t = \frac{1}{1-\gamma} \int_0^1 s_j \Delta \ln \lambda_{j,t} dj. \quad (28)$$

This itself is a generalization of their single-sector ($\theta = \gamma = \sigma$) formula

$$\Delta \ln A_t = \frac{1}{1-\gamma} \Delta \ln \lambda_t,$$

where $\lambda_t = \int_0^1 s_j \lambda_{j,t} dj$ is the aggregate share of spending on domestic goods.

Figure 4 shows the results using data generated by our model for various levels of correlation $\tau(\rho)$. When evaluated through the lens of the ACR formula, the TFP gains are inferred to be much smaller than the true TFP gains, even for versions of the model in which $\tau(\rho)$ is low and the gains from trade are entirely Ricardian. For example, going from a 0 to 10% increase in the import share implies TFP gains in excess of 10%, much greater than the 2-3% gains predicted by the above expressions that only use data on changes in import

shares. Notice also that the TFP calculations based on (27) are very close to those of the multi-sector ACR formula.

The discrepancy between the actual Ricardian gains and the gains predicted by the ACR approach arises because, in our economy with variable markups, trade flows respond less than they would if markups were constant. Since exporters increase markups in response to a reduction in trade costs, they expand their export sales by less than would be optimal under the first-best allocations. Hence, data on the actual responses of imports in the economy with variable markups *understate* the true extent to which welfare could increase had markups been constant — i.e., understate the Ricardian gains from trade.

7.2 Comparison with calibrated standard model

Next, we contrast the predictions of our model with variable markups to those of a standard trade model. To do this, we calibrate a standard trade model — identical in all respects to our model but in which all firms charge a constant markup — to match the same set of moments we target in the model with variable markups. The calibrated parameters and a full set of results are reported in the Appendix.

Figure 4 shows that, for values of $\tau(\rho)$ consistent with the data on import share dispersion, the welfare gains from trade are substantially larger in the model with variable markups than in the standard model.

8 Robustness experiments

We now consider several variations on our model with identical Home and Foreign productivity draws, each designed to examine the sensitivity of our results to parameter choices or other assumptions. All of our parameter choices and a full set of results for these experiments are reported in the Appendix.

Single Pareto distribution. In our benchmark model we use the double Pareto distribution (23) of productivities to simultaneously match the lower and upper tails of the size distribution of producers. Our Appendix illustrates the importance of matching these concentration patterns by showing how our results change if instead we use a single Pareto. It turns out that a single Pareto cannot simultaneously account for all the features of the data reported in Table 1. We thus consider two alternative calibration strategies. First, we study a single Pareto economy that targets all the moments *except* the size distribution of establishments. Second, we study a single Pareto economy that targets *only* the size distribution of establishments.

We find that the welfare gains from trade are smaller in these alternative economies than in our original setup. For example, the welfare gains from a reduction in tariffs that increases the import share from 0 to 10% leads to a 31.6% welfare gain in our benchmark model, and only a 4.1% and 8.2% gain, respectively, in the two single Pareto calibrations we consider. Likewise, the gains from an increase in the import share from 10 to 20% are 6.5% in our benchmark model, and only 3.6% and 5.8% in the single Pareto economies.

The welfare gains in these economies are smaller precisely because of these models' inability to account for the pattern of concentration in the data. The failure to account for the pattern of concentration implies that the distortions arising due to markups are much smaller now and so there is less scope for trade to improve allocations. For example, the level of TFP in the two single Pareto economies is 8.9% and 15.4% away from its first-best level, and 24.6% away from it first-best in our benchmark economy. These results thus reinforce our conclusion that the size of the pro-competitive gains from trade is larger, the larger is the amount of misallocation due markups in the economy.

Elasticities γ and θ . We found that lowering γ to 5.2 (such that the Armington elasticity falls to 5) has little effect on the welfare numbers we report above. If we lower θ to 1, in line with [Atkeson and Burstein \(2008\)](#), then the gains from trade are somewhat larger. If, however, we increase θ to 3, a number larger than any of our estimates in [Table 2](#), then the gains from trade fall sharply (though they remain larger than in a standard model with constant markups). With such a high value of θ the model's implications are, however, grossly at odds with the data.²³ For example, the aggregate labor share in the model increases substantially to 0.50 (0.43 in the data), implying a much smaller aggregate markup. Consistent with our findings above, we find that the extent of misallocation in the economy has an important role in determining the pro-competitive gains from trade.

Bertrand competition. In our benchmark model, we assume that firms engage in Cournot competition. If we assume instead that firms engage in Bertrand competition, then the model changes in only one respect. The demand elasticity facing producer i in sector j is no longer a harmonic weighted average of θ and γ , as in equation (10), but is now an arithmetic weighted average, $\varepsilon_{ij} = \omega_{ij}\theta + (1 - \omega_{ij})\gamma$. We find that the gains from trade in the Bertrand model are almost identical to those with Cournot competition.

²³IO studies typically find elasticities of substitution across sectors that are also close to unity. For example, a large literature has followed the work of [Hausman, Leonard and Zona \(1994\)](#) to estimate multi-stage systems for individual products (peanut butter, cereals, beer, etc). This work typically finds elasticities of substitution of these goods that are in the neighborhood of one.

5-digit sectors. Are our results driven by the focus on 7-digit sectors? To examine this, we study a version of our model that we calibrate to 5-digit data. At this higher level of aggregation there is less concentration in sectoral shares than there is at the 7-digit level. We find that increasing the level of aggregation to 5-digits reduces the gains from trade implied by our model, though they are still large compared to a standard trade model. A tariff reduction that takes the economy from autarky to an import share of 10% produces a gain of 14.4% as opposed to 31.6% in the benchmark model (and still considerably larger than in a standard trade model).

In this experiment we have kept the key across-sector elasticity θ fixed at its benchmark value of 1.25. Thus, these results can also be viewed as a further check on the plausibility of $\theta = 1.25$. While $\theta = 1.25$ may be considered low for 7-digit data, it is perhaps more appealing for 5-digit data.²⁴

Entry and exit. To assess the role of entry and exit, we compute results for a version of our model with $F_d = 0$ and $F_f = 0$ in which all firms operate in both their domestic and foreign markets. This version of the model yields almost identical results to our benchmark model. Shutting down entry and exit makes little difference because the typical entering or exiting firm is small and has negligible impact on aggregate outcomes.

9 Evidence for the pro-competitive mechanism

Versions of our model with strong pro-competitive effects predict that industries that face more import competition should, *ceteris paribus*, be characterized by lower and less dispersed markups and therefore higher and less dispersed labor and capital shares. We next test this prediction of the model using Taiwanese and US manufacturing data.²⁵

9.1 Taiwanese manufacturing

Labor shares and import shares. Panel A of Table 7 reports regressions of sectoral labor shares on sectoral import shares for the Taiwanese manufacturing data. Consistent

²⁴A 5-digit sector in Taiwan best corresponds to a 4-digit sector in the US.

²⁵See also Levinsohn (1993), Harrison (1994), and Krishna and Mitra (1998) for evidence for other countries and episodes of trade liberalizations. Tybout (2003) systematically reviews this literature and concludes that “results for Mexico (1985-90), Colombia (1977-85), Chile (1979-86), and Morocco (1984-89) all reveal the same basic pattern: in *every* country studied, relatively high sector-wide exposure to foreign competition is associated with lower price-cost margins, and the effect is concentrated in *larger* plants.” More recently, Feenstra and Weinstein (2010) estimate a translog demand system for the US and infer large markup reductions from the observed changes in US market shares from 1992–2005. Chen, Imbs and Scott (2009) estimate a version of the Melitz and Ottaviano (2008) model on EU data 1989-1999 and likewise find pro-competitive effects.

with versions of our model in which pro-competitive effects are important, we find that sectors with higher import shares have substantially higher labor shares in value added. The regression coefficient on the sectoral import share ranges from 0.055 (unweighted regression) to 0.13 (weighted regression), with standard errors about 0.01. This effect is economically substantial. For the weighted regression, for example, increasing the import share from zero to 100% leads to a 13 percentage point increase in the labor share (e.g., from 50% to 63%).

Controlling for variation in capital intensities. One concern with these regressions is that labor shares across sectors might be driven by variation in capital intensities rather than variation in markups. In particular, more tradable goods may be more capital intensive. To examine this possibility, we now use the sum of the labor and capital share as the dependent variable in the regression. We once again find, in Panel A of [Table 7](#), that the sum of the labor and capital shares is strongly increasing with a sector’s import penetration.

Dispersion in labor and capital share. Panel B of [Table 7](#) shows that the *dispersion* in labor shares across producers within a sector is negatively related to the sectoral import share. In the model, most of the changes in labor share dispersion induced by changes in trade come from changes in the tails of the distribution: the large producers that have the lowest labor shares are forced to reduce markups and thus increase their labor shares. Given this, in the table we report sector-level dispersion as the logarithm of the ratio of the 50th and 5th percentiles of the distribution of the labor share. This gives elasticities varying from -0.13 (unweighted) to -0.20 (weighted), with standard errors around 0.03. We obtain similar results when controlling for variation in capital intensities.

9.2 US manufacturing

We now consider the relationship between import penetration and labor shares in US 4-digit NAICS data from the NBER’s Productivity Database. We examine the cross-sectional relationship between import shares and labor shares both in levels and in changes over the period 1995–2005.

Cost shares and import shares. Panel A of [Table 8](#) reports regressions of sectoral labor shares on sectoral import shares and a full set of sectoral and time dummies. As with the Taiwanese data, we find that sectors with higher import shares have substantially higher labor shares. The regression coefficient on the sectoral import share ranges from 0.074 (unweighted regression) to 0.055 (weighted regression), with standard errors about 0.01 or 0.02. Again, these effects are large. For the weighted regression, increasing the import share from zero

to 100% leads to a 7.4 percentage point increase in the labor share and a corresponding decrease in markups. We obtain very similar results when controlling for variation in capital intensities by running the regression on the sum of the labor and capital shares.

Changes over time in cost shares and import shares. Since the mid-1990s, the US economy has experienced a large increase in exposure to foreign trade. Our model predicts that sectors that have experienced increases over time in their exposure to foreign competition should also be sectors that have had increasing cost shares (and hence decreasing markups) over the same period. To examine this prediction, Panel B of [Table 8](#) reports regressions of sectoral *changes* in labor shares on sectoral changes in import shares over the period 1995–2005. Consistent with the model’s predictions, sectors that have experienced greater increases in their import shares have also experienced the larger increases in their labor shares. In the unweighted regression the coefficient on changes in import shares is about 0.12, with a standard error of 0.04. In the weighted regression, the coefficient is smaller (0.04) and not significant (standard error 0.05), but we find that if we look at the sub-period 1998–2005, where most of the increase in the US import share occurs, then the coefficient is substantially larger and significant.

By looking at changes over time within a given sector, these regressions control for any time-invariant sector-specific differences in capital intensity or productivity. In this sense, these regressions provide strong evidence that increases in import penetration do indeed have pro-competitive effects.

10 Conclusions

We study the gains from international trade in a quantitative model with endogenously variable markups. We find that the pro-competitive gains from trade can be large, but only if two conditions are satisfied: (i) there must be large inefficiencies associated with markups, and (ii) there must be a weak pattern of comparative advantage in individual sectors. We find strong evidence for both of these ingredients in Taiwanese product-level data. Viewed through our model, this suggests that the pro-competitive gains from trade are significant.

There is, however, surely a great deal of variation in the size of these ingredients across different industries and countries. Our analysis thus helps rationalize the mixed empirical evidence on the size of the pro-competitive gains from trade. Indeed, we have presented versions of our model in which the pro-competitive effects are negative and variable markups reduce the gains from trade. Our conclusion thus is not that the pro-competitive gains from trade are always and everywhere large. Rather, the size of the gains from trade depends a

great deal on the underlying micro-details, in striking contrast to what standard Ricardian models of trade predict.

To keep our paper focused, we have made a number of important simplifying assumptions. For example, we have abstracted entirely from aggregate and sectoral differences in technologies, factor intensities and elasticities, innovation decisions, frictions that restrict capital and labor mobility, non-traded goods, as well as distributional concerns. We consider all of these issues to be important directions for future research.

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Table 1: Parameterization

Panel A: Moments		Panel B: Parameters	
	Data	Model	
<i>Within-sector concentration, domestic producers</i>			
mean inv HH	7.25	5.50	N , number competitors 95
median inv HH	3.95	5.08	μ_L , first Pareto tail 3.83
mean highest share	0.45	0.49	μ_H , second Pareto tail 1.50
median highest share	0.39	0.35	p_H , mass second Pareto 0.0035
<i>Distribution of sectoral shares, including importers</i>			
mean share	0.029	0.028	F_f , fixed cost export, % S.S. labor 4.5
s.d. share	0.087	0.074	
median share	0.0036	0.0045	
mean 75th p.c. share	0.016	0.016	
mean 95th p.c share	0.141	0.143	
mean 99th p.c. share	0.461	0.460	F_d , fixed cost, % S.S. labor 2.2
<i>Size distribution of establishments</i>			
fraction value added by top 1%	0.48	0.40	γ , elasticity within sector 8.45
fraction value added by top 5%	0.67	0.68	τ , iceberg trade cost 0.21
fraction wage bill by top 1%	0.32	0.32	θ , elasticity across sectors 1.25
fraction wage bill by top 5%	0.53	0.62	
<i>Additional statistics</i>			
mean industry import share	0.26	0.26	β , discount factor 0.96
fraction export	0.25	0.25	δ , capital depreciation 0.10
Armington elasticity	8	8	α , capital intensity 0.33
			ξ , tariff rate 0.064

Target moments in the Taiwanese manufacturing data and in our model and the parameter values that achieve this fit. The value $\theta = 1.25$ for the cross-sector elasticity is a robust estimate implied by the cross-sectional relationship between market shares and labor and capital shares, as summarized in [Table 2](#) below. The baseline tariff rate $\xi = 0.064$ is the OECD estimate for Taiwanese manufacturing.

Table 2: Estimates of θ

	OLS	Median Regression	# Obs
exclude exporters	1.23 (0.039)	1.20 (0.046)	58895
include exporters	1.20 (0.036)	1.18 (0.039)	64677
labor and capital shares	1.34 (0.610)	1.65 (0.051)	55273
<i>Translog production function</i>			
fixed effects	1.17 (0.032)	1.13 (0.035)	55271
De Loecker/Warzynski	1.29 (0.049)	1.19 (0.053)	55248

Estimates of the across-sector elasticity θ from the cross-sectional relationship (25) between sectoral shares and labor and capital shares. The first row runs the regression of labor shares on market shares excluding exporters, the second allows for exporters, using the generalization of (25) discussed in the Appendix, while the third row runs the regression of labor + capital shares on market shares. To compute the capital shares, we assume a user cost of capital of 15%. The correlation between the labor and the (labor + capital) share in the data is 0.84. We then consider estimates of θ from the markups implied by a translog production function estimated using fixed effects regression or using the ‘control function’ methods advocated by De Loecker and Warzynski (2012). For all regressions we drop a small number of outliers with individual shares > 0.9 . See the Appendix for more details. Standard errors in parentheses.

Table 3: Markup Distribution With and Without Trade

	Data	Model	
		<i>Taiwan</i>	<i>Autarky</i>
Panel A: <i>Markup distribution</i>			
aggregate markup		1.48	1.75
mean markup		1.17	1.19
s.d. markup		0.11	0.33
median markup		1.14	1.14
75th p.c. markup		1.15	1.15
95th p.c. markup		1.28	1.27
99th p.c. markup		1.76	1.65
Panel B: <i>Labor share and other statistics</i>			
s.d. labor product	0.68	0.10	0.16
mean labor share	0.61	0.62	0.62
median labor share	0.65	0.62	0.62
aggregate labor share	0.43	0.45	0.38
mean number producers	26	26	34
median number producers	11	29	39

Additional implications for markups and labor shares. The Taiwan column shows the results for the benchmark model which reproduces Taiwan's average import share of 26% (using the parameters listed in [Table 1](#) above). The Autarky column shows the results from the model with exactly the same parameters except that the tariff rate is raised to $\xi = 1$ to shut down all trade.

Table 4: Losses Due to Markups

	First-Best	No Markup Dispersion
Panel A: <i>Economy with Taiwan's import share</i>		
markup	1	1.48
$\Delta \ln \text{TFP}, \%$	4.6	4.6
$\Delta \ln Y, \%$	57.4	6.0
$\Delta \ln C, \%$	48.1	6.0
$\Delta \ln L, \%$	31.1	0
welfare gains, %	16.7	5.9
Panel B: <i>Economy in autarky</i>		
markup	1	1.75
$\Delta \ln \text{TFP}, \%$	24.6	24.6
$\Delta \ln Y, \%$	107.4	37.0
$\Delta \ln C, \%$	95.0	37.0
$\Delta \ln L, \%$	42.6	0
welfare gains, %	53.0	33.9

To calculate the losses due to markups, we consider two counterfactual economies. In one, we choose producer-specific subsidies or taxes such that all producers set a markup of 1 (the *first-best*). In the other, we choose subsidies or taxes such that all producers set a markup equal to the aggregate markup in the benchmark economy (*no markup dispersion*). In both cases the subsidies/taxes are financed with a lump-sum tax on the representative consumer. Panel A shows the results for the benchmark economy with an average import share of 26%. Panel B shows the same exercise but for an economy that starts in autarky. The welfare gains are measured as consumption-equivalent variations including the transition path. All the results in this table use the model with identical Home and Foreign productivity, $\tau(\rho) = 1$.

Table 5: Gains from Trade. Identical Home and Foreign Productivity, $\tau(\rho) = 1$

Δ import share	0% to 10%	10% to 20%	20% to 30%
welfare gains, %	26.1	7.6	5.8
markup change, %	-14.5	-2.7	-1.2
TFP gains, %	13.4	4.7	3.9
Ricardian TFP gains, %	0.1	0.8	1.7
Armington elasticity (post)	7.4	7.8	8.2

Gains from trade due to changes in iceberg trade costs that change the average import share in the model with identical productivity draws, $\tau(\rho) = 1$. Welfare gains measured in consumption equivalents including transition. The row labeled *Ricardian TFP gains* uses the first-best level of TFP defined in (18)-(19). All other calculations use our benchmark parameters except that, to make our results comparable to Arkolakis, Costinot and Rodríguez-Clare (2012a), for this exercise we set the tariff rate $\xi = 0$.

Table 6: Gains from Trade. Uncorrelated Home and Foreign Productivity, $\tau(\rho) = 0$

Δ import share	0% to 10%	10% to 20%	20% to 30%
welfare gains, %	8.9	28.8	35.3
markup change, %	3.9	9.6	2.3
TFP gains, %	8.2	25.4	26.6
Ricardian TFP gains, %	8.8	26.3	27.1
Armington elasticity (post)	4.1	2.2	3.2

Gains from trade due to changes in iceberg trade costs that change the average import share in the model with independent productivity draws, $\tau(\rho) = 0$. Welfare gains measured in consumption equivalents including transition. The row labeled *Ricardian TFP gains* uses the first-best level of TFP defined in (18)-(19). All other calculations use our benchmark parameters except that, to make our results comparable to Arkolakis, Costinot and Rodríguez-Clare (2012a), for this exercise we set the tariff rate $\xi = 0$.

Table 7: Trade and Markups in Taiwanese Manufacturing

	Unweighted	Weighted
Panel A: <i>Sectoral labor and capital shares vs. import share</i>		
labor share	0.055 (0.010)	0.131 (0.012)
(labor + capital) share	0.064 (0.024)	0.226 (0.028)
Panel B: <i>Sectoral dispersion in labor and capital shares vs. import share</i>		
labor share	-0.130 (0.032)	-0.198 (0.036)
(labor + capital) share	-0.127 (0.029)	-0.285 (0.040)

Evidence of pro-competitive effects from Taiwanese manufacturing data. Panel A shows regressions of sectoral labor shares (or labor + capital shares) on sectoral import shares. Standard errors in parentheses. Panel B shows regressions of sectoral *dispersion* in labor and capital shares on sectoral import shares with dispersion measured as the log of the 50th minus the log of the 5th percentiles of the distribution. See the main text for further discussion.

Table 8: Trade and Markups in US Manufacturing

	Unweighted	Weighted
Panel A: <i>Sectoral labor and capital shares vs. import share</i>		
labor share	0.074 (0.007)	0.055 (0.018)
(labor + capital) share	0.096 (0.009)	0.094 (0.020)
Panel B: <i>Change in labor and capital shares vs. change in import share, 1995–2005</i>		
labor share	0.121 (0.036)	0.039 (0.048)
(labor + capital) share	0.336 (0.068)	0.168 (0.119)

Evidence of pro-competitive effects from 4-digit US manufacturing data. Panel A shows regressions of sectoral labor shares (or labor + capital shares) on sectoral import shares and a full set of time and sector dummies. Standard errors in parentheses. Panel B shows regressions of the sectoral *change* over time in labor and capital shares on sectoral changes in import shares, 1995–2005. See the main text for further discussion.

Figure 1: Markups and sectoral shares

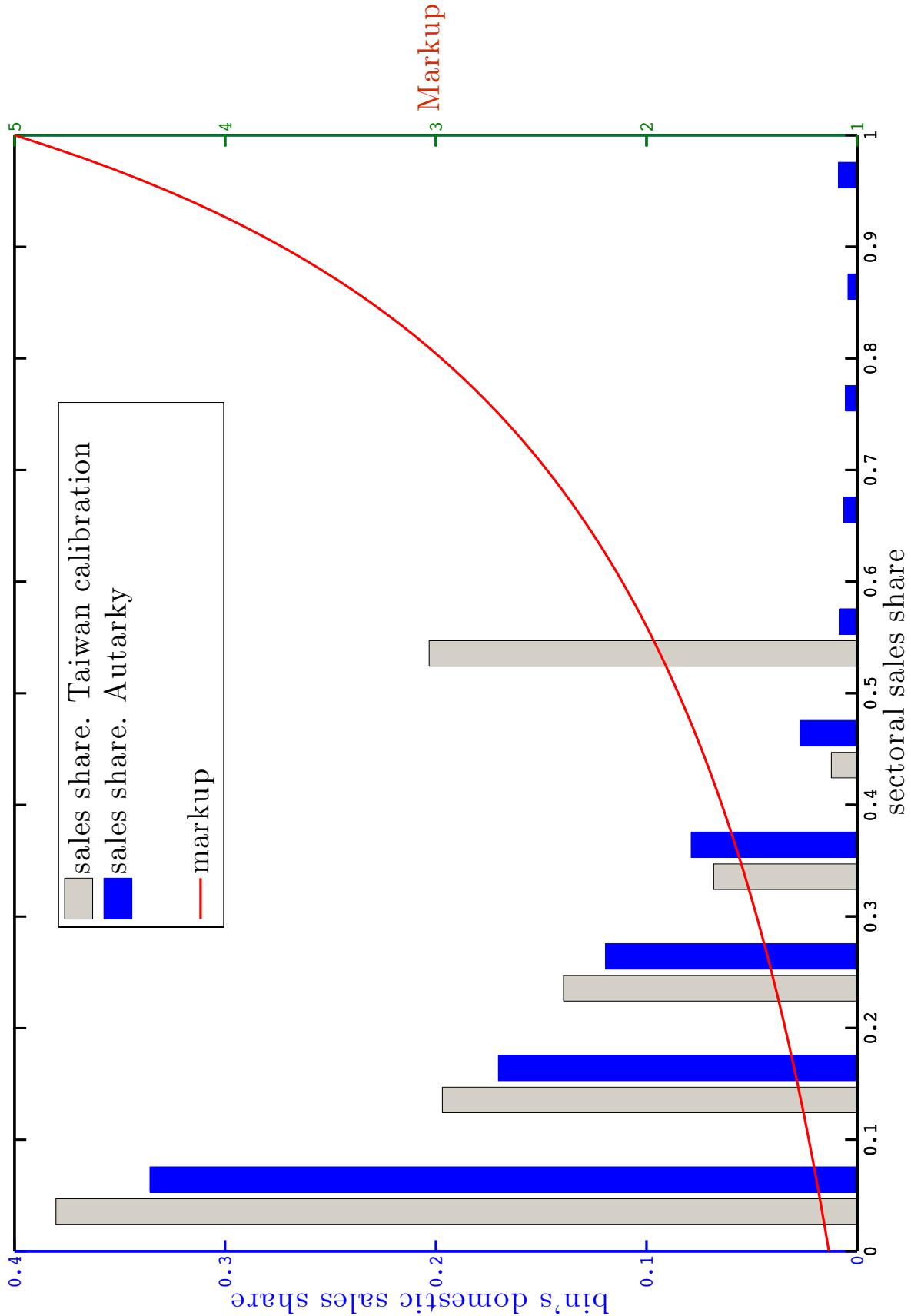


Figure 2: Gains from a 0 to 10% change in import share

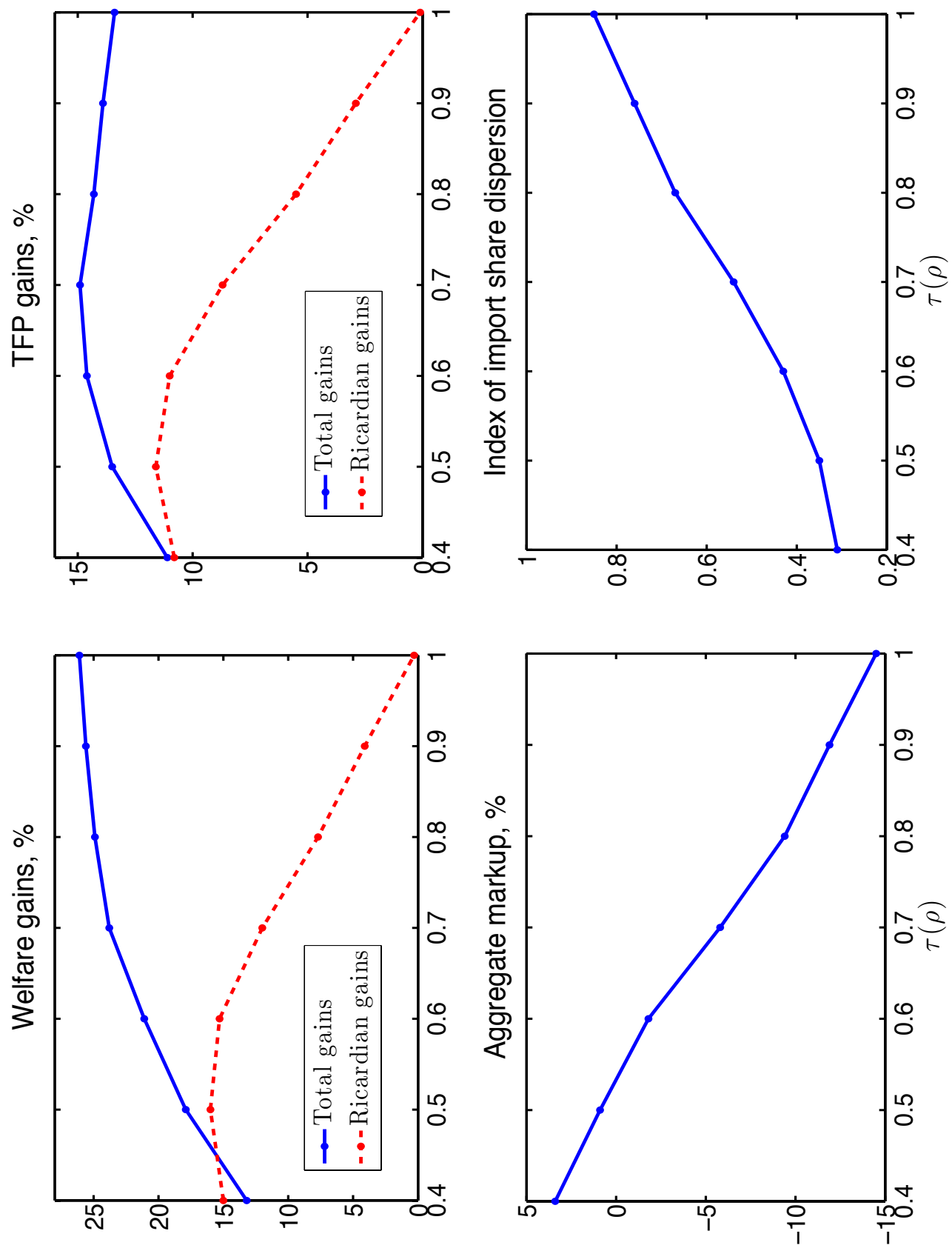


Figure 3: Gains from a 10 to 20% change in import share

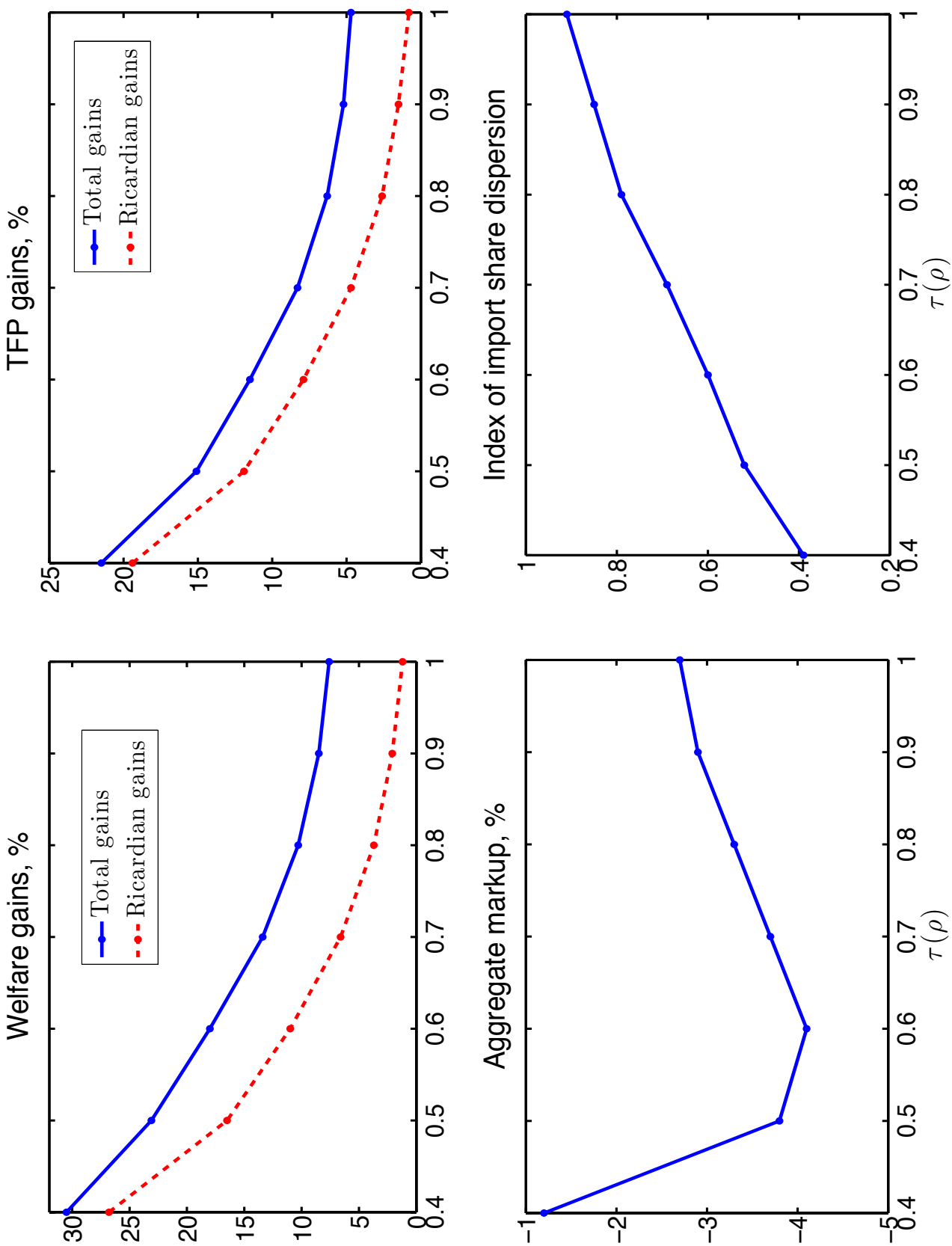


Figure 4: TFP gains, %. Comparison with ACR approach

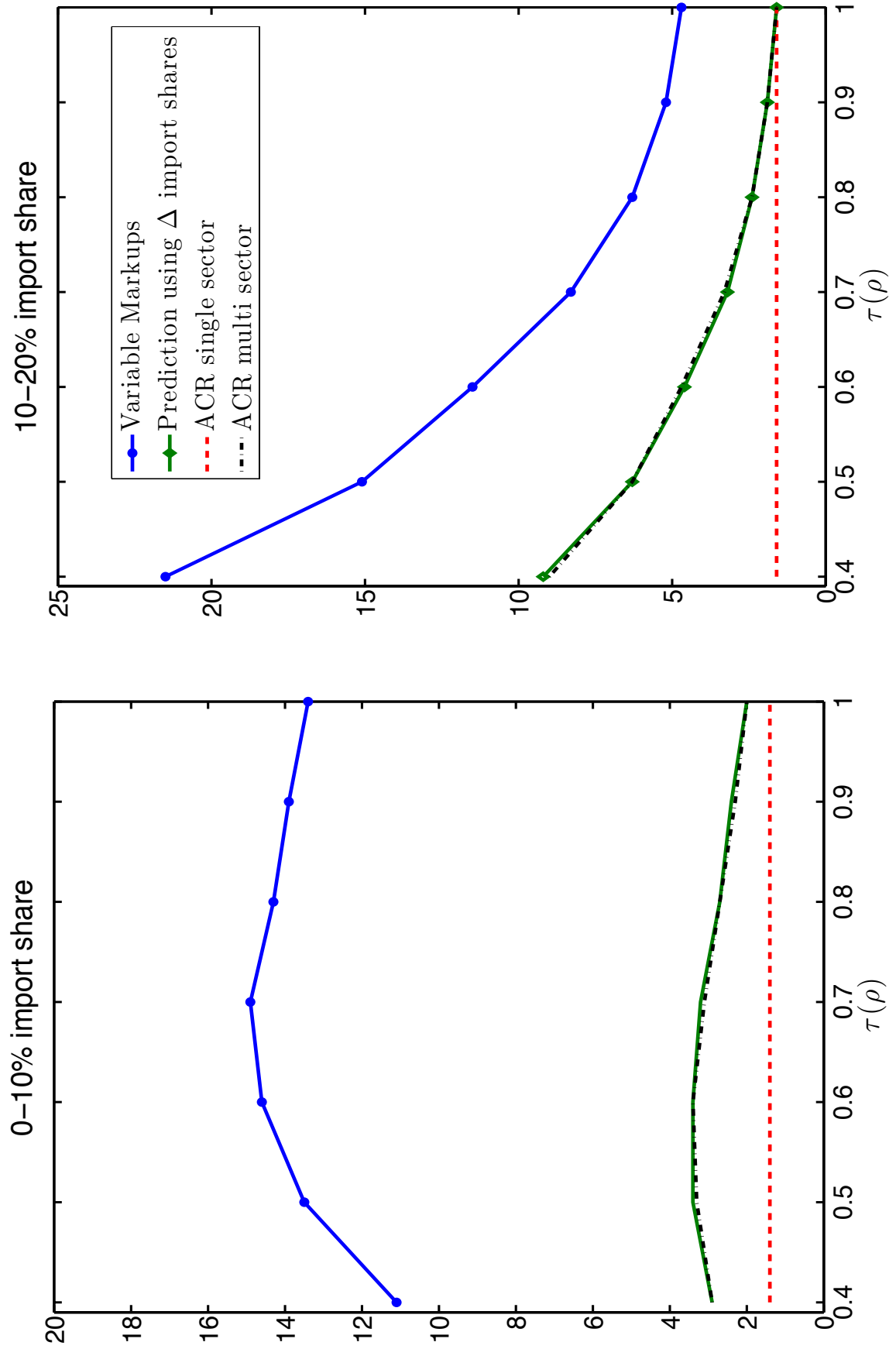


Figure 5: Gains from trade. Comparison with standard model

