Productivity Spreads, Market Power Spreads and Trade

Ralf Martin*  
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Abstract

Much of recent Trade theory focuses on heterogeneity of firms and the differential impact trade policy might have on firms with different levels of productivity for example. A common problem is that most firm level dataset do not contain information on output prices of firms which makes it difficult to distinguish between productivity differences and differences in market power between firms. This paper develops a new econometric framework that allows estimating both firm specific productivity and market power in a semi-parametric way based on a control function approach. The framework is applied to Chilean firm level data from the early 1980, shortly after the country underwent wide ranging trade reforms. The finding is that in all sectors of the economy market power declined and productivity increased. In sectors with higher import penetration productivity particularly at the bottom end of the distribution increased faster. At the same time market power declined particularly so at the top end of the market power distribution. We also show, that ignoring the effect on market power leads to an underestimation of the positive effects of increased import penetration on productivity.

JEL classification: C81, D24, L11, L25

Keywords: Trade Policy, Productivity Measurement, Imperfect Competition, Productivity Dispersion, Productivity Spread

1 Introduction

Much of recent Trade theory focuses on heterogeneity of firms and the implication this has for trade policy (Melitz and Ottaviano 2008, Melitz 2003) Increasingly such models stress not only interactions between trade policy and the distribution of firm level productivity but also with the distribution of market power across firms. This poses a challenge for measurement when using firm level production datasets. Common methods to analyse firm level productivity require assuming perfectly competitive market structures. Almost all of the limited number of studies that go beyond that (Klette and Griliches 1996, Melitz 2003, Martin 2008, Dobbelaeere and Mairesse 2008, Loecker and Warzynski 2009) rely on a Dixit Stiglitz market structure which implicitly assumes that all firms in an industry have the same degree of market power. This is measured by the degree of markup they can charge over their marginal costs. ¹ This is clearly

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¹Centre for Economic Performance, London School of Economics; r.martin@lse.ac.uk. Thanks to Christos Genakos, Steve Redding and John van Reenen for discussions and James Tybout for making the data available.

¹One exception is Klette (1999) who proposes a Random Coefficients Specification. A random effect specification would not allow to separately identify both: firm specific market power and productivity shocks. Another exception is Katayama et al. (2003). Their framework requires however that all firms face constant marginal costs, thus ruling out increasing returns to scale or adjustment costs which make some factors fixed in the short run.
restrictive as it would not allow that for example a trade reform reduces the market power of some firms whereas it increases that of others. The contribution of this paper is to introduce a new framework for productivity estimation that allows recovering an index of the distribution of markups across firms in addition to productivity estimates. We achieve this by expanding on the control function approach originally introduced by Olley and Pakes (1996) to deal with factor endogeneity in production function regressions. The control function approach exploits assumptions about firm behaviour to recover a control function for un-observed heterogeneity that potentially biases production function estimates. The standard control function approach is only concerned with one type of heterogeneity: a single index capturing Hicks neutral shifts in technical efficiency between firms. We allow in addition that market power as measured by markups can vary arbitrarily between firms. To control for that we introduce a second control index based on mild structural assumptions about firm behaviour. Importantly, this requires no further assumptions about the distribution of the parameters in the population and can therefore be used to compute the complete distribution of market power for all firms at all points in time.

The basic idea is most easily grasped in a simple Cobb-Douglas setting with a log-linear demand function; i.e. output quantity $Q_i$ is

$$Q_i = A_i K_i^{γ−α_L−α_M} L_i^{α_L} M_i^{α_M}$$

where $γ$ measures the returns to scale and demand is

$$Q_i = P_i^{−η_i}$$

although it can easily be extended to a very general class of production functions and demand functions. Consider a production factor that is perfectly flexible in the short run such as materials, $M_i$ where $i$ indexes a firm. In the perfect competition case ($η_i = ∞$) it is a familiar results that short run profit maximisation implies

$$α_M = \frac{W_i M_i}{Q_i} = s_i^M$$

i.e. the production function parameter is equal to materials share in output. With imperfect competition this equation becomes

$$\frac{α_M}{μ_i} = \frac{W_i M_i}{R_i} = s_i^M$$

where $μ_i = \frac{1}{1−η_i}$ captures the (potentially) firm specific markup parameter and output quantity $Q_i$ is replaced by revenue $R_i$, which is all that we can observe in this case at the firm level. Note that the left hand side becomes smaller compared to the perfect competition case (recall that $μ_i > 1$). Intuitively this is because it measures the marginal benefit of increasing usage of materials. With imperfect competition this is smaller ceteris paribus as now an increase in materials not only increases output but also lowers the price that can be charged for this output.

Note that 3 suggests a simple way to control for unobserved variation in $μ_i$. Simply use the inverse revenue share as a proxy:

$$μ_i = \psi(s_i^M) = \frac{α_M}{s_i^M}$$
How can this be used in a regression setting? Using production and demand function in equations 1 and 2 we can write (log) revenue as

$$\ln R_i = \frac{1}{\mu_i} (\alpha_M \ln M_i + \alpha_L \ln L_i + (\gamma - \alpha_L - \alpha_M) \ln K_i + a_i)$$

which we can re-write as

$$\frac{\ln R_i - s_i^M (\ln M_i - \ln K_i) - s_i^L (\ln L_i - \ln K_i)}{s_i^M} = \frac{\gamma}{\alpha_M} k_i + a_i$$

Note that the LHS of equation can be computed directly from standard firm level productivity data. To conduct a regression we need to take into account endogeneity from the TFP shock $a_i$ affecting $k_i$. This can be done by one of the standard control function approaches. With an estimate of $\frac{\gamma}{\alpha_M}$ we can derive a TFP estimate as $LHS_i - \frac{\gamma}{\alpha_M}$ and use $\frac{\gamma}{\alpha_M} s_i^{-1}$ as an index for $\mu_i$.

The following section will show how this can be generalised to a general production and demand function where $\alpha_M$ is not necessarily constant. The two key assumptions required are that the demand curve is downward sloping and that the production function is homothetic. A downward sloping demand curve is a natural assumption implied by a variety of settings. Large parts of the literature equally assume homothetic production functions even though it is potentially a very restrictive assumption. In the current context, for example, it would rule out that some firms adjust to trade liberalisation by outsourcing part of their production thereby becoming more intermediate intensive. However, in appendix B we develop a way of assessing if such concerns are important for a dataset at hand.

Another way of looking at the idea proposed in this paper is as follows: a common approach to measure market power is to look at price margins. With constant unit costs, price costs margins are proportional to factor shares in revenue; i.e. we can measure market power trough factor shares. What we show in the following is then how to use price cost margins as a control even if unit costs are not constant because the production technology is not constant returns or because not all factors are fully flexible.

We apply this new framework to Chilean data. This is of interest for two reasons. Firstly, Chile was subject to fundamental trade reforms in the 1970s and therefore has attracted interest in the Trade Literature before (Pavcnik 2002). Secondly, because firm level micro data for Chile has been relatively freely available previous studies on firm level productivity measurement have used the country as a test case (Levinsohn and Petrin 2003).

Using the new method proposed in this paper we compute firm specific (Total Factor) Productivity and market power for Chilean manufacturing firms. We find that across manufacturing, productivity (TFP) increased and market power declined over the sample period which is from 1979 to 1986. Comparing sectors with high import penetration to those with lower import penetration we find that, productivity increased whereas market power declined by more than in sectors with low import penetration. The productivity effect appears stronger at the bottom of the productivity distribution whereas the increase in market power is more pronounced at the top of the market power distribution. Ignoring the market power effect thus leads to an under-estimation of the productivity effects of higher import penetration.

The remainder of this paper is organised as follows: Section 2 introduces the new framework for firm level market power and productivity estimation. Section 3 contains a basic description of the dataset used, Section 4 reports results, Section 5 concludes.

2Using $s_i^M$ as additional state variable in the proxy function, that is.
2  An augmented control function approach

Suppose there is a representative consumer deriving utility from $m$ differentiated products

$$U = U (\tilde{Q}, Y)$$

(5)

where $\tilde{Q}$ is a $m \times 1$ vector of effective units of the goods consumed, $Y$ is income and $U (\cdot, Y)$ is a differentiable, non convex function.

$$\tilde{Q}_i = \Lambda_i Q_i$$

i.e. $\Lambda_i$ is a specific utility shock derived from consumption of good $i$.

Further suppose that each of the $m$ products is produced by a single producer. Caplin and Nalebuff (1991) derive conditions under which this leads to downward sloping demand curves for a specific producer $i$ conditional on the actions of the other producers. They show that this is the case under a wide variety of market structures.

$$Q_i = D_i (P_i, \Lambda_i)$$

(6)

For a production factor $X$ that can be adjusted instantly in response to demand or supply shocks, short run profit maximisation implies

$$\frac{\partial \ln F_i}{\partial \ln X_i} \mu_i = s_{xi}$$

(7)

where $F_i$ is a homogeneous of degree $\gamma$ production function,

$$F_i = A_i \left[ f (X_i) \right]^\gamma$$

$s_x$ is the revenue share of expenditure on factor $X$ and $\mu_i = \frac{1}{1 - \eta_i}$ with $\eta_i = -\frac{\partial \ln D(P_i)}{\partial \ln P_i}$ measuring elasticity of demand for producer $i$ with. Producers revenue can be written as a function of inputs demand and supply shocks (as well as non firm specific variables which we suppress)

$$R_i = P_i (Q_i(X_i, A_i), \Lambda_i) Q_i$$

Letting $x_i$ the log deviation of a variable $X_i$ from a reference firm $M$ - i.e. $x_i = \ln X_i - \ln X_M$ - we can invoke the mean value theorem (Baily et al. 1992, Klette 1996, Martin 2008)

$$r_i = \sum_X \tilde{\rho}_i^X x_i + \tilde{\rho}_i^A \lambda + \tilde{\rho}_i^A a_i + \eta_i$$

(8)

where $\tilde{\rho}_i^X = \frac{\partial \ln R_i}{\partial \ln X_i}$ and $\tilde{\rho}_i^X \approx \frac{\partial X_i}{\partial X_i} \frac{\partial P_i}{\partial X_i}$; i.e. the mean value theorem suggest that $8\tilde{\rho}_i^X \in [\rho_i^X, \rho_{M}^X]$. We follow common practice by approximating this by averaging across the derivative at firms

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3i.e. max$_{X \neq K} \left\{ Q_i P_i - \sum_{X \neq K} X_i W_i X \right\}$ implies the following first order condition $\frac{\partial Q_i}{\partial X_i} P_i + \frac{\partial P_i}{\partial M_i} Q_i = W_i X$. Because 6 is downward sloping and therefore invertible we get $\frac{\partial P_i}{\partial Q_i} Q_i = -\frac{1}{\eta_i}$ with $\eta_i = -\frac{\partial \ln D(P_i)}{\partial \ln P_i}$ the price elasticity of demand. Multiplying the first order conditions by $X_i$ we then get $\frac{\partial Q_i}{\partial X_i} Q_i \left( 1 - \frac{1}{\eta_i} \right) = W_i X_i Q_i$, which is the condition in equation 7.

4e.g. the median firm in terms of some variable.
\( \eta_i \) and M. We introduce an iid shock \( \eta_i \) allowing for the fact that the mean value theorem and our way of approximating might only hold approximately.

Note that
\[
\frac{\partial \ln R_i}{\partial \ln X_i} = \frac{\partial \ln F_i}{\partial \ln X_i} \frac{1}{\mu_i} = s_{Xi}
\]

for flexible factors. Similarly
\[
\frac{\partial \ln R_i}{\partial \ln A_i} = \frac{1}{\mu_i}
\]

Assume there is one fixed factor \( K \). Then
\[
\frac{\partial \ln R_i}{\partial \ln K_i} = \gamma \frac{1}{\mu_i} - \sum_{x \neq K} s_{Xi}
\]

Finally, because \( D(\cdot) \) is monotone in \( P \) and demand shocks are "consumption augmenting" we get that
\[
\frac{\partial \ln R_i}{\partial \ln \lambda_i} = \frac{1}{\mu_i} \tag{9}
\]

Consequently we can write
\[
\tilde{r}_i - \sum_{X \neq K} \tilde{s}_X (x_i - k_i) = \tilde{r}_i = \gamma \frac{T}{\mu_i} k_i + \frac{T}{\mu_i} (\lambda_i + a_i) + \tilde{\eta}_i \tag{10}
\]

Now, from Equation 7 we see that
\[
\frac{1}{\mu_i} = s_{xi} \left( \frac{\partial \ln F_i}{\partial \ln X_i} \right)^{-1} = s_{xi} \Psi(X_i)
\]

i.e. because the productivity shock is Hicks neutral, the (inverse of) firm level markups can be expressed as the product of factor shares and a function of observable factor inputs only. While \( \Psi(\cdot) \) is not known we can specify a general functional form and let it be determined by the data. We can combine this with the usual strategy of a proxy variable for TFP\(^6\) (Olley and Pakes 1996, Levinsohn and Petrin 2003, Bond and Söderbom 2005, Martin 2008). Martin (2008) shows that conditional on markups TFP can be expressed as a function of net revenue and capital. Now, the factor share of a variable factor becomes an additional argument in this function to control for varying degrees of market power between firms. Thus in terms of deviation from a reference firm we can write
\[
\omega_{it} = \phi_\omega(k_{it}, k_M, \ln\Pi_{it}, \ln\Pi_M, s_{xi}, s_xM)
\]

Finally assume that \( \omega \) is driven by a Markov Process\(^7\) so that
\[
\omega_{it} = g(\omega_{it-1}, \omega_{it-1}) + \nu_{it}
\]

where \( g(\cdot) \) is \( E_{i-1}\{\omega_{it}\} \) and \( \omega_{it} = \lambda_{it} + a_{it} \). Further, \( \omega_{it-1} \) is a threshold value that summarises the firm’s rule regarding exiting.

We can now specify a 3 stage regression procedure similar to Olley and Pakes (1996), Levinsohn and Petrin (2003), Bond and Söderbom (2005), Martin (2008). First, to control for exit we conduct a probit regression on a dummy indicating if a firm exits the following period:
\[
P_{it} = \Phi(\ln X_{it-1}, \ln X_{M\text{t}-1}, s_{xti-1}, s_xM_{t-1}, \ln\Pi_{it-1}, \ln\Pi_{M\text{t}-1}, t)
\]

\(^5\)See appendix A for more details.

\(^6\)In the remainder I refer to the sum of technology and demand shock - \( \omega = a + \lambda \) as TFP for simplicity. See Martin (2008) for a depth discussion of this.

\(^7\)This follows the common assumption in the literature but is not a necessary assumption here.
This yields a predicted exit probability \( \hat{P}_{it} \) which we can use in subsequent stages to control for the un-observed exit threshold, \( \omega_{it-1} \). Next to smooth the shock \( \tilde{\eta}_{it} \) in Equation 10 we can run the following regression

\[
\tilde{r}_{it} = \phi_r (\ln X_{it}, \ln X_{Mt}, s_{xit}, s_{xMt}, \ln \Pi_{it}, \ln \Pi_{Mt}) + \tilde{\eta}_{it}
\]

where \( \phi_r (\cdot) \) is an arbitrary function approximated by a polynomial.

Finally, we can devise a number of moment conditions to recover \( \Psi (\cdot) \) and in turn indices of relative productivity and relative markups. For that purpose notice that conditional on trial values for the parameters that define \( \Psi (\cdot) \) we can compute an estimate of \( \omega_{it} \) over \( \gamma \) as

\[
\hat{\omega}_{it} = \frac{\hat{\phi}_{rit}}{g_\mu (\ln X_{it}, \ln X_{M0}, s_{xit}, s_{xM0})} - k_{it}
\]

where \( \hat{\phi}_{rit} \) is an estimate of \( \phi_r (\cdot) \) derived from the second stage in Equation 12 and

\[
g_\mu (\ln X_{it}, \ln X_{M0}, s_{xit}, s_{xM0}) = \frac{\gamma}{2} [s_{xit} \Psi (\ln X_{it}) + s_{xM0} \Psi (\ln X_{M0})]
\]

Using the estimates of \( \omega_{it} \) we can recover estimates of the shocks \( \nu_{it} \) using a regression of the following equation:

\[
\hat{\omega}_{it} = \tilde{g} \left( \frac{\hat{\omega}_{it-1}}{\gamma}, \hat{P}_{it} \right) + \nu_{it}
\]

where \( \tilde{g} (\cdot) \) is version of \( g (\cdot) \) accounting for the fact that we re-scaled \( \omega_{it} \) using the constant scale parameter \( \gamma \).

The shock \( \nu_{it} \) are independent of all variables determined before period \( t \). We assume that this includes \( k_{it} \); i.e. capital that is productive in period \( t \) has been determined before \( \nu_{it} \) realises.\(^8\) We can then use the following moment restrictions involving \( \nu_{it} \) to identify all remaining parameters:

\[
E \left\{ \left[ X_{it-1} \times k_{it} \right] \nu_{it} \right\} = 0
\]

i.e. to identify \( \Psi (\cdot) \) we use the zero moment conditions from the interaction of current levels of capital with lagged levels of all production factors. Note that we cannot use conditions on lagged production factor variables without interaction, as these have already been exploited in the regression implied by Equation 15.

Finally, recall that the focus of this estimation framework is to derive firm specific TFP and markup estimates. We get those by evaluating equations 14 and 13 at the parameter values that solve 16.

3 Data

We are using a dataset that been used in a series of papers before (Pavcnik 2002, Levinsohn and Petrin 2003). The reader should refer to those papers for a more in depth description of the dataset. Interest in this data is sparked both because Chile has been subject to fundamental trade reforms in the 1970s\(^9\) and because data from the Chilean Census of Businesses has been

\(^8\)Again this is a common assumption in the literature.

\(^9\)Reforms which have been brought about by a highly repressive and un-democratic regime.
relatively freely available. Clearly, it would be good to compare outcomes from before to those from after these trade reforms were implemented. Unfortunately such data is not available at the micro level. Similar to Pavcnik (2002) we therefore look at trends over the sample period. Table 2 reports descriptive statistics by year. We see that using various measures of size - revenue, employment or capital - the size of the average firm increased over the sample period. Equally, labour productivity - measured as value added per employee increased dramatically.

4 Results for Chile

Figures 1 and 2 shows density estimates of markups and TFP - $\lambda + a$ - relative to the median firm in terms of revenue per employee in 1979.

$$\tilde{\mu} = \ln \mu_{it} - \ln \mu_M$$

(17)

Density estimates are reported separately for sectors with high and low rates of import penetration as well as for the earlier and later years of the sample period. Following Pavcnik (2002) we code a (3 digit) sector with an import penetration of more than 15% as being highly exposed to foreign imports. We can see that for both, sectors with high and low import penetration the density curve shifts to the left in the later period in Figure 1. Contrarily, for TFP in Figure 2 we see that both distributions shift to the right suggesting that TFP increases. To examine if these shifts are significant we run quantile regressions for both variables on a set of dummy variables that distinguish between the various cases reported in Figures 1 and 2. That is we run regressions of the following form:

$$y_{it} = \beta_{s > 83} I\{t > 1983\} + \beta_{High} High_{S(i)} + \epsilon_{it}$$

(18)

where $y_{it} \in \{\tilde{\mu}_{it}, \omega_{it}\}$ and $High_{S(i)} = 1$ if the three digit sector firm $i$ belongs to has an import penetration of 15% or more. The first panel of Table 3 reports results for market power. We see that at various points in the distribution the coefficients of the interaction between the post 83 indicator and the “High” dummy are negative, implying that in sectors with high import penetration the decline in market power is stronger. The difference is larger and statistically more significant at higher points in the distribution. In the second panel of Table 3 we report the same quantile regressions for TFP. Again we find that there is a significant difference between sectors with high and low import penetration in the later years. Firm level productivity in sectors with high import penetration increases significantly more. The effect appears slightly stronger at the bottom of the distribution.

If market power and thus output prices decline while TFP increases, measuring TFP with revenue based output measures should lead to an underestimate of the TFP increase. We can confirm this by conducting the same analysis as above, yet imposing a constant markup. Table 4 reports the results. We see that at various points in the distribution TFP still increases by more in sectors with high import penetration. However, the effects are much smaller than in Table 3. For example at the median (p50) we find an increase of 11.3 percentage points in Table 3 whereas the same value is 4.3 percentage points in Table 4.

We might also ask if the reduction in market power could have been detected more simply. For that purpose, Figure 3 reports similar density plots as before for the price cost margin estimated as revenue over variable costs. As in Equation 17 we report the log deviation from the the median firm in the base year. As discussed in the introduction, this is an index of firm level market power under the assumption that the production technology is Cobb-Douglas. The density plot makes apparent that rather than a decline in market power - as found in before -
this would suggest that market power increased. An implication of this is, which we can derive from Equation 7, is that the marginal productivity of the variable factors must have declined. Potentially, this could be explained by a reduction in capital stocks.

5 Conclusion

This paper develops a new structural approach to production function estimation that can recover both, estimates of firm specific TFP as well as market power. While structural, the assumptions needed are very mild compared to what is often assumed in the literature. The method is of interest in any situation where firm level productivity is estimated with revenue rather than quantity information which is almost always the case. In this paper we apply it to study the impact of trade reforms in Chile in the 1970s. We find that in sectors with higher import penetration market power decreased and productivity increased. Importantly, the increase in productivity is under-estimated if the market power effects are ignored.

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Recall that the factor share is the inverse of the price cost margin measure used in Figure 3.
A The response of prices to quality shocks

This section works out the response of prices and revenue to quality shocks $\Lambda_i$; i.e. it proves the result stated in equation 9 implying that quality shocks affect revenue in the same way as Hick’s neutral TFP shocks. This allows us to combine TFP and quality shocks and separate them from firms specific demand factors affecting markups.

Suppose consumers maximise a general differentiable utility function subject to budget $M$:

$$\max \left\{ U (\tilde{Q}) - \kappa \left( \sum_i Q_i P_i - M \right) \right\}$$

where $\kappa$ is a Lagrange multiplier and $\tilde{Q}$ is a vector of elements $\Lambda_i Q_i$. The first order conditions of this problem imply

$$\frac{\partial U}{\partial Q_i} \frac{\partial \tilde{Q}_i}{\partial Q_i} = \frac{\partial U}{\partial Q_i} \Lambda_i = \kappa P_i$$

Taking logs implies

$$\ln \frac{\partial U}{\partial Q_i} + \lambda_i = \ln \kappa + \ln P_i$$

(19)

Solving all these conditions will give us demand functions for all products including that of firm $i$. Even if we knew the exact form of $U (\cdot)$ this might be tricky to work out. Notice, however what 19 tells us about the shape of demand function. Differentiating w.r.t to $\ln Q_i$ yields

$$\frac{\partial \ln P_i}{\partial \ln Q_i} = -\frac{1}{\eta_i} = \frac{\partial \ln \frac{\partial U}{\partial \tilde{Q}_i}}{\partial \ln \tilde{Q}_i} \frac{\partial \ln \tilde{Q}_i}{\partial \ln Q_i} = \frac{\partial \ln \frac{\partial U}{\partial \tilde{Q}_i}}{\partial \ln \tilde{Q}_i}$$

Similarly we find that

$$\frac{\partial \ln P_i}{\partial \lambda_i} = \frac{\partial \ln \frac{\partial U}{\partial \tilde{Q}_i}}{\partial \ln \tilde{Q}_i} \frac{\partial \ln \tilde{Q}_i}{\partial \lambda_i} + 1 = \frac{\partial \ln \frac{\partial U}{\partial \tilde{Q}_i}}{\partial \ln \tilde{Q}_i} + 1$$

i.e. the elasticity of prices with respect to output quantity differs from the elasticity of prices w.r.t to the quality shock by one. Moreover, because of the demand function is invertible we get

$$\frac{\partial \ln P_i}{\partial \lambda_i} = 1 - \frac{1}{\eta_i} = \frac{1}{\mu_i}$$

B Testing the validity of the homogeneity assumption

As discussed in the main text, homogeneity of the production function is a key assumption of the proposed estimation approach. While this is an explicit or implicit assumption widely made in the literature this does not necessarily mean it is reasonable. An example of why it might
Table 1: R² across 3 digit sectors

<table>
<thead>
<tr>
<th>Sample</th>
<th>mean</th>
<th>min</th>
<th>p5</th>
<th>p10</th>
<th>p20</th>
<th>p40</th>
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<tr>
<td>Across firms</td>
<td>0.90</td>
<td>0.71</td>
<td>0.75</td>
<td>0.78</td>
<td>0.86</td>
<td>0.92</td>
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<tr>
<td>Across Sectors</td>
<td>0.89</td>
<td>0.71</td>
<td>0.75</td>
<td>0.76</td>
<td>0.81</td>
<td>0.88</td>
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</table>

Notes: The table shows statistics of $R^2$ of regressions of equation 20 at each 3 digit sector. The statistics in row 1 are weighted by the number of firms in a sector whereas row 2 reports unweighted statistics across 3 digit sectors.

No hold is the following: suppose that after a change in trade policy some firms respond by outsourcing parts of their production. Therefore, to examine its validity of the homogeneity assumption we propose the following. Above we derived that under homogeneity factor shares of variable factors are equal to a function of observable production factors divided by markups. We can therefore model deviations from this assumption by writing e.g. for materials

$$s_{mi} = \frac{\Psi_m(X_i)}{\mu_i} \Xi_{mi}$$

where $\Xi_{Mi}$ measures firm specific deviations from this assumption. If we have at least one other variable factor - labour say - we can write

$$\ln s_{mi} - \ln s_{li} = \ln \Psi_m(X_i) - \ln \Psi_l(X_i) + \xi_{mi} - \xi_{li}$$

(20)

where $\xi_{Xi} = \ln \Xi_{Xi}$. Hence the log difference in factor share of two variable factors becomes a function of observable variables and any homogeneity destroying shocks. Hence, to examine the validity of the homogeneity assumption we can run regressions of equation 20. If homogeneity is a reasonable assumption, most of the variation in the share difference should be explained by the function of observables. In other words, we can look at the $R^2$ statistic which should be rather high. Table 1 reports statistics of $R^2$ computed for each 3 digit sector after regressing equation 20 with the Chilean data. Row 1 of the table reports statistics weighted with the number of firms in a sector whereas row 2 reports unweighted statistics. We see that no sector has an $R^2$ lower than 71%. The majority of firms in the sample are in a sector with $R^2$ larger than 90%.

### C Tables and Figures

11 Although we should note that this is a necessary although not sufficient condition. Our test would bear no power if $\xi_m$ and $\xi_l$ are perfectly negatively correlated.

12 We used a simple non-linear least squares approach. A more sophisticated approach would consider various assumption about the dynamics and correlation of the $\xi$ shocks with the observed explanatory variables.
Table 2: Descriptive Statistics by year

<table>
<thead>
<tr>
<th>variable</th>
<th>year</th>
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Notes: Stars indicate if the mean for a specific year is significantly different from that for the first year. *,**,***=significant at 10, 5, 1%. 

11
Table 3: Quantile Regressions of Markups and Productivity

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<th>90</th>
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<td>-0.003</td>
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Combined TFP and demand shock (ω)

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Notes: The table reports results from quantile regressions as described in Equation 18.

Table 4: Quantile Regressions of Productivity imposing constant markups

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Notes: The table reports results from quantile regressions as described in Equation 18. The dependant variable is a TFP measure obtained with a control function approach where markups are restricted to be constant.
Figure 1: The distribution of market power
Figure 2: The distribution of Productivity
Figure 3: Revenue over variable costs
References


