The relationship between a country’s degree of openness and its economic well-being has been examined extensively both theoretically and empirically. Numerous empirical studies using different openness measures have found a positive effect of openness on growth. However, the validity of such measures have come into question due to data issues. This paper uses a two stage method to analyze the relationship between productive efficiency and trade openness in seventeen Latin American and 24 OECD countries over 25 years. In the first stage, the “output-oriented Malmquist index”, developed by Fare, Grosskopf, and Roos (1998) is calculated through Data Envelopment Analysis (DEA). Through use of bootstrapping techniques I find that 86% of the calculated Malmquist indices are statistically significant. In the second stage, these indices are regressed on a vector of country characteristics, including changes in trade openness. Somewhat surprisingly, I find a negative correlation between
changes in openness and changes in productivity for both Latin American and OECD countries.
Trade Openness and Productivity in Latin American Countries: A DEA Analysis

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Jeffrey P. McCarty, Author
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1 Introduction

The relationship between a country’s degree of openness and its economic well-being has been examined extensively on both theoretically and empirically. Empirical studies using a wide range of openness indicators have generally found a positive relationship between openness and growth. This paper uses a two-stage method to analyze the relationship between productive efficiency and trade openness in seventeen Latin American and 24 OECD countries. In the first stage, the “output-oriented Malmquist index”, developed by Fare, Grosskopf, and Roos (1998) is calculated through Data Envelopment Analysis (DEA). Through use of bootstrapping techniques I find that 86% of the calculated Malmquist indices are statistically significant. In the second stage, these indices are regressed on a vector of country characteristics, including changes in trade openness. Somewhat surprisingly, I find a negative correlation between changes in openness and changes in productivity for both Latin American and OECD countries.

The rest of the paper proceeds as follows: in the remainder of Section 1, I explore previous theoretical and empirical studies. The second section develops the model used in this paper. The third section presents the empirical results of both the first and second stages. The fourth and final section gives a brief summary and conclusions.
1.1 Background

1.1.1 Motivation

There have been many studies examining the relationship between trade openness and productive efficiency on a macro-level. Most have used some variation of Total Factor Productivity (TFP) growth as a measure of productive efficiency (see, for example, Edwards, 1998). One of the main limitations of TFP is that it assumes countries efficiently use their inputs. Thus, changes in TFP presume to capture only shifts in technology. The advantage of the Malmquist index computed through DEA is its ability to be broken down into two components: a technical change that captures “innovation” or shifts in technology, as well as an efficiency change that captures the “catching up effect”, or how efficiently countries are using their inputs (Fare et al., 1994). In addition, TFP requires a specific production function, typically a Cobb-Douglas function. The DEA method assumes an underlying production process, but does not necessitate the use of a production function.

Latin American countries provide an interesting and relevant group of subjects to study. As of 2008, there were 22 Free Trade Agreements (FTAs), either bilateral or multilateral, between countries in the Americas. In addition, there are many other FTAs between Latin American countries and other countries throughout the world. Baier et al. (2007) have argued that the effects of FTAs in the Americas are larger than anticipated. While many studies have examined the gains from an increase in trade in Latin American countries, as far as I can tell, none have done so using DEA.
1.1.2 Literature Review

The relationship between a country’s degree of openness and its economic well-being has been examined extensively both theoretically and empirically. In spite of this, the results are inconclusive. Some of the earlier trade models, such as the Heckscher-Ohlin-Samuelson (HOS) model, have been developed under the assumption that technological frontiers (or production possibility frontiers) do not vary across countries. This assumption is not necessarily motivated from the belief that technologies truly are the same across countries. Rather, the assumption allows us to see precisely how differences in resource endowments affect trade patterns. An important result that comes out of the HOS model is the Stolper-Samuelson theorem. It states that a rise in the relative price of a good will lead to a rise in the real return to the factor used intensively in the production of that good, and, conversely, reduce the real return to the other factor. For example, unskilled workers producing traded goods in a developed country will be worse off as international trade increases, because, relative to the world market in the good they produce, an unskilled worker is a less abundant factor of production than capital. Thus, the Stolper-Samuelson theorem suggests there will be winners and losers from trade.

Other early models, such as the Ricardian model, are motivated entirely by the assumption that technologies differ across countries. This assumption leads to a world in which trade patterns are determined by comparative advantage. Thus, productivity differences motivate trade patterns in the model. However, in contrast to the HOS model with multiple factors of production, the Ricardian model assumes there is only a single input.
By the 1980’s these earlier models had given way to other models of trade, some of which operate under the assumption of imperfect competition, such as "'new trade theory'". Krugman (1979) develops a monopolistically competitive model in which firms experience economies of scale. In his model, he shows that international trade causes firms to experience increased competition and increased demand from abroad. As a result, any firm that produces in autarky and in free trade will increase output, thus exploiting economies of scale. Because of this, however, some firms that produced in autarky must exit the market to make room for the expanding firms. However, the Krugman model makes the assumption that all firms are of the same size and efficiency. Thus, industry efficiency gains from the opening of borders can come from two different effects: the scale effect, in which firms increase output thereby enjoying greater economies of scale and indicating greater efficiency; and the selection effect, in which the least productive firms exit the market thereby increasing average market productivity (Feenstra, 2004). The latter effect is not present in Krugman’s model, as he makes the assumption that all firms are symmetric. The selection effect comes from a model which incorporates heterogeneous firms, such as the one developed by Melitz (2003).

Around the same time, endogenous growth theory was being developed. Previous growth models, such as the Solow model (1956), assumed technological progress was exogenous. Endogenous growth models, such as the model developed by Grossman and Helpman (1992), show that gains from trade can be made by expanding technological frontiers, improving allocative efficiencies, and increasing the rate of technology diffusion or what are referred to as
spillover effects. However, Grossman and Helpman (1992) have also argued that the effect of trade depends on its comparative advantage with respect to the rest of the world. They suggest “intervention in trade could raise long-run growth if protection encourages investment in research-intensive sectors for countries with an international advantage in these kinds of goods” (Harrison, 1996).

Coe et al. (1997) describe how trade affects growth through spillover effects. Trade makes new products available that embody new, foreign knowledge and by making available otherwise costly information. As the authors note, “Both are particularly important for less developed countries that lag far behind the technology frontier.” Thus, less developed countries stand to gain more by trading with developed countries who have higher levels of knowledge than by trading with other less developed countries. They find evidence that research and development spillovers from industrial countries to less developed countries are significant.

Empirical studies measuring the relationship between openness and levels of income have produced mixed results. Dar and Amirkhalkhali (2003) separate OECD countries into three groups based on their level of openness. They find that the relative importance of openness on growth varies greatly across countries. Both Harrison (1996) and Edwards (1998) use a wide range of openness indicators to find a positive, albeit weak, association between openness and growth. However, there have been many skeptics of such studies. Rodriguez and Rodrik (2000) have argued that the methods used in previous studies have serious pitfalls. They argue that many of the openness indicators used are poor
measures of trade policy and are often highly correlated with other factors that affect economic performance.

Many studies have used nonparametric analysis to measure a group of countries’ changes in efficiency and/or productivity. Trefler (1995) computes what can essentially be seen as an input based distance function to measure productivity differences across countries relative to the United States. Trefler finds that most countries are less technologically advanced than the United States and that there is strong correlation between these differences and per capita GDP differences. Fare et al. (1994) use the Malmquist index analyze productivity growth in OECD countries.

There have been some studies which have used DEA to measure a country’s productivity and compare this measure to openness. Mathur (2005) use this approach to measure technical efficiency in EU and southeast Asian countries, while Chortareas, et al. (2003) do the same for OECD countries and find a positive relationship between openness and technical efficiency. Milner and Weyman-Jones (2003) use openness as a proxy for the quality of national policies and institutions and also find a positive relationship between the two.
2 Methodology

This paper implements a two-stage model using panel data on 17 Latin American and 24 OECD countries from 1980 to 2003. In the first stage, I estimate each country’s gains in productivity between years. In the second, I regress these productivity measures on a number of national characteristics, including changes in openness.

2.1 Measuring Productivity

The process described in this section closely follows Fare and Grosskopf (2003) and Fare, Grosskopf and Roos (1998).

2.1.1 Output Distance Functions

The output-oriented Malmquist index is comprised of output distance functions on a technology (set) developed by Shephard (1970). The technology is defined as follows: Let $x$ and $y$ be input and output vectors respectively, where $x \in \mathbb{R}^+_N$ and $y \in \mathbb{R}^+_M$. A production technology $T$ is defined as:

$$T = \{(x, y) : x \text{ can produce } y\}. \quad (1)$$

Three major assumptions are imposed which will aid in the creation of this technology from the data.

- **Constant Returns to Scale (CRS)**
  $$\lambda T = T, \ \lambda > 0.$$
• **Strong Disposability of Inputs**

\[(x^0, y) \in T, \text{ and } x \geq x^0 \Rightarrow (x, y) \in T.\]

• **Strong Disposability of Outputs**

\[(x, y^0) \in T, \text{ and } y \leq y^0 \Rightarrow (x, y) \in T.\]

The Shephard output distance function is defined as:

\[D_o(x, y) = \inf \{\theta : (x, \frac{y}{\theta}) \in T\}.\]  \hspace{1cm} (2)

Figure 1: An illustration of Shephard’s output distance function

In other words, \(D_o(x, y)\) is the smallest \(\theta\) such that \((x, \frac{y}{\theta})\) is still feasible. Figure 1 illustrates this concept in the single-input single-output case.
It will be useful later to denote the efficient level of output corresponding to the input level $x$ as $Y(y|x) = \frac{y}{D_o(x,y)}$. The distance function satisfies the following useful properties:

1. **Representation** (Under Strong Disposability)
   $$D_o(x, y) \leq 1 \Leftrightarrow (x, y) \in T \text{ and } D_o(x, y) = 1 \Leftrightarrow (x, y) \text{ lies on the boundary of } T.$$

2. **Homogeneity in outputs**
   $$D_o(x, \lambda y) = \lambda D_o(x, y), \ \lambda > 0$$

3. **Homogeneous of degree -1 in inputs** (Under CRS)
   $$D_o(\alpha x, y) = \alpha^{-1} D_o(x, y), \ \alpha > 0.$$

### 2.1.2 The output-oriented Malmquist index

It is now possible to define the Malmquist productivity index. Consider two time periods, $t$ and $t+1$. Let $D_o^t(x^t, y^t)$ be the value of the output distance function for time $t$ observation $(x^t, y^t)$ and technology $T^t$, and let $D_o^{t+1}(x^{t+1}, y^{t+1})$ be the value of the output distance function for time $t+1$ observation $(x^{t+1}, y^{t+1})$ and technology $T^t$. (Note: $(x^{t+1}, y^{t+1})$ need not be in the set $T^t$, and thus, it is possible for $D_o^t(x^{t+1}, y^{t+1}) > 1$.) Then, the output-oriented Malmquist index developed by Fare, et al. is defined as:

$$M_o(x^t, y^t, x^{t+1}, y^{t+1}) = \left( \frac{D_o^t(x^{t+1}, y^{t+1})}{D_o^t(x^t, y^t)} \frac{D_o^{t+1}(x^{t+1}, y^{t+1})}{D_o^{t+1}(x^t, y^t)} \right)^{\frac{1}{2}}. \quad (3)$$
This index is a modification of the Malmquist index developed by Caves, Christensen, and Diewert (1982) which is defined as:

\[ M^t_o = \frac{D^t_o(x^{t+1}, y^{t+1})}{D^t_o(x^t, y^t)}. \]  

(4)

This index depends on the technology from only period \( t \). \( M_o(x^t, y^t, x^{t+1}, y^{t+1}) \) builds on this by taking the geometric mean of this index from periods \( t \) and \( t+1 \), and thus, takes into account both relevant technologies. \( M_o(x^t, y^t, x^{t+1}, y^{t+1}) \) can be broken down into two components, namely the Efficiency Change (EC) and Technical Change (TC) components. Consider Figure 2, again a single input, single output example.

The productivity change is computed as follows:

\[ M_o(x^t, y^t, x^{t+1}, y^{t+1}) = (0_a0_y+10_d0_y^t)(0_d0_c0_a)^{1/2}. \]  

(5)

where \((0_y^{t+1}0_a0_d0_y^t)\) is the EC component and \((0_d0_c0_a)^{1/2}\) is the TC component. Then the EC is “catching up effect” and the TC is the “frontier effect” from year to year (Mahadevan, 2004). Notice the TC component gives little information about the specific observation other than to describe the change in the technology at a particular input value. Thus, TC will be of little interest when specific countries are looked at later in the paper.

Sometimes it is useful to consider the cumulative productivity changes over a number of years. This allows us to see the productivity change over multiple
time periods. Cumulative productivity change, $M_{t,T}^c$ is calculated as follows:

$$M_{t,T}^c = \prod_{j=t}^{T} M_o(x^j, y^j, x^{j+1}, y^{j+1})$$  \hspace{1cm} (6)$$

where $j = t$ is the first time period considered, and $j = T$ is the last.

It can also be informative to look at the aggregated productivity of a group
of countries. This is done by computing the geometric mean of the productivity changes using share of total GDP as the weights. For example, if one was to look at all Latin American countries, the aggregated productivity for period $t$, $M_{Latin}^t$, would be expressed as follows:

$$M_{Latin}^t = \prod_{k=1}^{K} \left[ M_{o,k}(x_k^t, y_k^t, x_{k}^{t+1}, y_{k}^{t+1}) \right]^{\alpha_k},$$

$$\alpha_k = \frac{GDP_k}{\sum_{k=1}^{K} GDP_k}$$

(7)

where $k = 1, \ldots, K$ denote the Latin American countries.

### 2.1.3 Estimating Distance Functions and the Malmquist Index

Because the true technologies are unknown, the true distance functions and Malmquist indices are also unknown. Thus, given $k = 1, \ldots, K$ input and output observations for each time period $t$, we must estimate a reference technology, $\hat{T}^t$, as well as output distance functions $\hat{D}_o^t$ in order to obtain estimates, $\hat{M}_o(x_k^t, y_k^t, x_{k}^{t+1}, y_{k}^{t+1})$, of the true Malmquist indices. To do this, a linear programming problem must be solved, also known as DEA. The first step is to construct a reference technology, $\hat{T}$, from the observations, as follows:

$$\hat{T} = \{(x, y) : \sum_{k=1}^{K} z_k y_{km} \geq y_m, \ m = 1, \ldots, M$$

$$\sum_{k=1}^{K} z_k x_{kn} \leq x_n, \ n = 1, \ldots, N$$

$$z_k \geq 0, \ k = 1, \ldots, K \}$$

(8)
where $z_k$ is the “intensity variable” for each observation. Note the final inequality which characterizes the CRS assumption.

Then, the output distance function for an observation, $k'$, can be found by solving the following linear programming problem:

\[
(\hat{D}_o(x_{k'}, y_{k'}))^{-1} = \max \theta \\
\text{s.t.} \sum_{k=1}^{K} z_k y_{km} \geq \theta y_{k'm}, \ m = 1, \ldots, M \\
\sum_{k=1}^{K} z_k x_{kn} \leq x_{k'n}, \ n = 1, \ldots, N \\
z_k \geq 0, \ k = 1, \ldots, K. \tag{9}
\]

### 2.2 Bootstrapping Malmquist Indices

Although DEA is a nonparametric based approach to measuring efficiency, as Simar and Wilson (1999) note, it is not deterministic. To see this, notice that the reference technologies we have constructed are estimates of true technologies conditional on the given data set. More specifically, in the case of a single output, an estimated technology is a “lower bound” of the true technology in the sense that adding new observations can only expand the boundary of the technology. Thus, as with any observed data, uncertainty due to sampling variation and measurement errors are present, and calculated Malmquist indices are only estimates of the true indices. Because of this, it is necessary to test hypotheses regarding the true parameter value. Simar and Wilson first (1998) propose a bootstrap approach for estimating both bias and confidence intervals of DEA efficiency scores, and later (1999) expand this approach to Malmquist
indices. The following discussion closely follows the latter approach.

The intention of any bootstrap approach is to estimate the distribution of the parameters of interest. Bootstrapping is a way of using collected data to simulate what the results might be if the data were collected over and over when little or nothing is known about the underlying sampling distribution. The general premise of bootstrapping is to replicate the original case study $L$ times, each time recomputing the parameters of interest. Then, using these $L$ estimates, one can construct an empirical distribution from which inferences can be made about the estimated parameters. The replication is based on an estimated bootstrap Data Generating Process (DGP) of the true DGP creating the observed sample. Thus, a reasonable estimator of the DGP is needed. In the case of nonparametric frontier estimation, the common bootstrap procedure of drawing with replacement from the original set of observations yields inconsistent bootstrap estimation and should not be used. This paper follows the approach proposed by Simar and Wilson (1999).

Suppose that the true, unknown DGP, $P$ generates a random sample $\Gamma = (x^t_i, y^t_i), i = 1, ..., n, t = 1, ..., T$. From this sample, $T^t$ and $M_{o_i}(x^t_i, y^t_i, x^{t+1}_i, y^{t+1}_i)$ can be estimated for each year and observation. Note the sampling properties of these estimates depend on the unknown $P$. The DGP can be described as follows: a given data point $(x^t_i, y^t_i)$ may either be on the technology frontier or on some fixed ray away from $Y^t_{i}$ where $Y^t_{i}$. Thus, the observation may be assumed to be generated conditionally on $x^t_i$ by the random variable $\theta^t_i \in (0, 1]$ (or the output distance function) such that $(x^t_i, y^t_i) = (x^t_i, Y^t_{i}(y^t_i | x^t_i)\theta^t_i)$. Now
suppose that the process generating inefficiencies, $\theta_i^t$, is the following:

$$(\theta_1^t, ..., \theta_n^t) \ i.i.d. \ F$$

(10)

where $F$ is a density function on $(0, 1]$. Because the density $F$ is unknown, it must be estimated from the sample of distance functions estimated with DEA. A straightforward estimate of $F$ is the empirical density function suggested by Efron and Tibshirani (1993):

$$\hat{F}(t) = \begin{cases} 
1/n; & x = \theta_j^t, j = 1, ..., n \\
0; & x \neq \theta_j^t, j = 1, ..., n
\end{cases}$$

(11)

However, this is an inconsistent estimate of the true density function, $F$, which is, by definition, continuous on $(0, 1]$. Simar and Wilson (1998,1999) suggest a smoothed version of the empirical density function. To complicate matters further, because Malmquist indices cover two time periods, there may be temporal correlation between estimated output distance functions $D_o(x_i^t, y_i^t)$ and $D_o(x_{i+1}^t, y_{i+1}^t)$. As an example, consider a relatively efficient firm in period 1. That firm may be more likely to be relatively efficient in period 2 than another firm that is relatively less efficient in period 1. Thus, a bivariate smoothing procedure must be used, providing a consistent estimate of the density function, the details of which can be found in Simar and Wilson (1999). From this estimated density function, $\{(\theta_i^t, \theta_i^{t+1}), i = 1, ..., n\}, t = 1, ..., T$ are
drawn \( L \) times, and pseudosamples (or bootstrap samples)

\[
\{(x^{t_1}_i, y^{t_1}_i), (x^{t+1}_i, y^{t+1}_i), i = 1, ..., n\}
\]

are constructed. From these psuedosamples, reference technologies are constructed. Finally, the original observations are measured against these technologies constructed by the bootstrap samples, yielding \( L \) Malmquist bootstrap estimates.

### 2.3 Estimating Confidence Intervals

The bootstrap interval percentile method is used to created confidence intervals for the Malmquist indices and proceeds as follows. First, the bootstrap procedure outlined in the previous section is performed yielding bootstrap Malmquist estimates

\[
\hat{M}^*_{o}(x^t_k, y^t_k, x^{t+1}_k, y^{t+1}_k).
\]  

(12)

Then, bias-corrected estimates and confidence intervals of the Malmquist indices can be computed in the following manner: define the bootstrap bias estimate of the original estimate of the Malmquist index as

\[
\text{bias} \left( \hat{M}^t_{o}(x^t_k, y^t_k, x^{t+1}_k, y^{t+1}_k) \right) = L^{-1} \sum_{l=1}^{L} \hat{M}^*_{o}(x^t_k, y^t_k, x^{t+1}_k, y^{t+1}_k) - \hat{M}^t_{o}(x^t_k, y^t_k, x^{t+1}_k, y^{t+1}_k)
\]

(13)
Then, the bias-corrected bootstrap estimate may be computed as

\[
\hat{M}_o^t(x^t_k, y^t_k, x^{t+1}_k, y^{t+1}_k) = M_o^t(x^t_k, y^t_k, x^{t+1}_k, y^{t+1}_k) - bias \left( \hat{M}_o^t(x^t_k, y^t_k, x^{t+1}_k, y^{t+1}_k) \right)
\]

\[
= 2 \hat{M}_o^t(x^t_k, y^t_k, x^{t+1}_k, y^{t+1}_k) - L^{-1} \sum_{l=1}^{L} \hat{M}_o^*(x^t_k, y^t_k, x^{t+1}_k, y^{t+1}_k)_l \tag{14}
\]

However, as Simar and Wilson (1999) show, the bias corrected estimator will have a much higher variance than the original Malmquist estimator and should only be used if the mean-square error of the bias corrected estimator is less than that of the original estimator. Specifically, \( \hat{M}_o^t(x^t_k, y^t_k, x^{t+1}_k, y^{t+1}_k) \) has an estimated mean-square error of \( 4s_{si}^2 \) and \( \hat{M}_o^*(x^t_k, y^t_k, x^{t+1}_k, y^{t+1}_k) \) has an estimated mean-square error of \( s_{si}^2 + \left( bias \left( \hat{M}_o^*(x^t_k, y^t_k, x^{t+1}_k, y^{t+1}_k) \right) \right)^2 \) where \( s_{si}^2 \) is the variance of the bootstrap values. Simar and Wilson (1999) show the mean-square estimator of the bias corrected estimator will be less than the mean-square error of the original estimator when

\[
s_{si}^2 < \frac{1}{3} \left( bias \left( \hat{M}_o^*(x^t_k, y^t_k, x^{t+1}_k, y^{t+1}_k) \right) \right)^2, \tag{15}
\]

The confidence intervals are constructed by the percentile method developed by Efron. The assumption for construction of the confidence intervals is that the unknown distribution of \( \hat{M}_o^*(x^t_k, y^t_k, x^{t+1}_k, y^{t+1}_k) - M_o^t(x^t_k, y^t_k, x^{t+1}_k, y^{t+1}_k) \) can be estimated from the distribution of \( \hat{M}_o^*(x^t_k, y^t_k, x^{t+1}_k, y^{t+1}_k) - \hat{M}_o^t(x^t_k, y^t_k, x^{t+1}_k, y^{t+1}_k) \).
That is, the values $a_\alpha$ and $b_\alpha$ such that

$$
Pr \left( a_\alpha \leq \hat{M}_o^t(x_k, y_k, x_{k+1}^t, y_{k+1}^t) - \hat{M}_o^t(x_k, y_k, x_{k+1}^t, y_{k+1}^t) \leq b_\alpha \right) = 1 - \alpha \quad (16)
$$

can be estimated by $a^*_\alpha$ and $b^*_\alpha$ such that

$$
Pr \left( a^*_\alpha \leq \hat{M}_o^t(x_k, y_k, x_{k+1}^t, y_{k+1}^t) - \hat{M}_o^t(x_k, y_k, x_{k+1}^t, y_{k+1}^t) \leq b^*_\alpha \right) = 1 - \alpha. \quad (17)
$$

(17) is said to be true with high probability in the sense that as $L \to \infty$ the probability that (17) is true approaches 1.

The percentile method used to find $a^*_\alpha$ and $b^*_\alpha$ involves sorting

$$
\hat{M}_o^t(x_k, y_k, x_{k+1}^t, y_{k+1}^t)_l - \hat{M}_o^t(x_k, y_k, x_{k+1}^t, y_{k+1}^t), \ l = 1, ..., L
$$

from least to greatest, removing $(\frac{\alpha}{2} \times 100)$ percent from either end of the sorted array and setting $a^*_\alpha$ and $b^*_\alpha$ equal to the resulting endpoints of the array. The resulting confidence intervals can be used for inference in that if the interval does not include 1, the Malmquist index is said to be statistically different from unity. That is, if an entire confidence interval is less (greater) than 1, it can be said with $(1 - \alpha) \times 100$ percent certainty that the observation experienced a(n) decrease (increase) in productivity.

### 2.4 Productivity vs. Openness

One of the first measures of productivity was Gerard Debreu’s “Coefficient of Resource Utilization” (1951). Debreu hypothesized three sources of inefficiency
(p. 275):

(1) the underemployment of physical resources, (2) the technical inefficiency of production units, and (3) the inefficiency of economic organization (due, for example, to monopolies or a system of indirect taxes or tariffs).

Clearly, a relatively closed economy falls under the third source. As Debreu notes (p.286), “This kind of loss is the most subtle (in fact, perhaps hardly conceivable to the layman) and therefore the one for which a numerical evaluation is most necessary.”

I hypothesize that gains in productivity from increased trade come through two channels:

(Positive) Technical Change: This is the “frontier effect” or change through innovation. Increased openness may intensify competition causing domestic firms to innovate new technologies to compete with new foreign firms in the market. However, the contrary argument may be plausible as well. Some, such as Grossman and Helpman (1992), have suggested that, by lowering expected profits, increased competition could discourage innovation.

(Positive) Efficiency Change: This is the “catching up effect”. This measure would capture a diffusion of technology from foreign to domestic firms. It would also capture countries specialize in more efficient sectors in which they have a comparative advantage.
Using the overall Malmquist index and EC as measures of efficiency, the following regression model will be estimated:

\[ \theta = (X)\beta + \epsilon \]

where

\( \theta \) is the measure of efficiency being considered and \( X \) is a vector of national characteristics, including some measure of trade policy.

### 2.4.1 Accounting for Serial Correlation of Malmquist Indices

In addition to the bias associated with DEA estimates, there is a second, and potentially more serious problem that relates to these estimates. The productivity estimates, and hence, the error terms in the second-stage, are serially correlated. To understand this, consider that changing observations lying on the estimated frontier will in many, if not all, cases change the estimated productivity indices of the other observations. This is clearly a problem when these estimates are used as dependent variables in the second stage of the model. Moreover, the way in which these Malmquist indices are serially correlated is unknown. As a result, the variance associated with the estimator of \( \beta \) is unknown. This variance is denoted as

\[
\Psi = var \left[ \hat{\beta} \right] = (X'X)^{-1}X'\Omega X(X'X)^{-1} = \frac{1}{n}X'X^{-1}\frac{1}{n} \Phi \left( \frac{1}{n}X'X \right)^{-1}
\]

where \( \Phi = n^{-1}X'\Omega X \) is essentially the covariance matrix of \( V_i(\beta) = x_i(y_i - x_i'\beta) \).

Simar and Wilson (2007) propose a bootstrap procedure for the two-stage problem when DEA efficiency estimates such as output distance functions are
used as the dependent variable. However, because the Malmquist index combines multiple DEA estimates, the bootstrap procedure becomes much more complicated. Other studies, such as Balcombe et al. (2008), have suggested a specific form for the covariance matrix with little justification as to why they have chosen such a form. As a result, this paper chooses to use the Newey-West (1987) heteroskedasticity and autocorrelation consistent (HAC) estimator to obtain an estimate, $\hat{Ψ}$, of $Ψ$.

The Newey-West HAC estimator, as the name suggests, provides a consistent estimate of the covariance of the model parameters in the face of autocorrelation and heteroskedasticity of an unknown form. It is defined as

$$\hat{Ψ} = \frac{1}{n} \sum_{i,j=1}^{n} \left(1 - \frac{|i-j|}{p+1}\right) \hat{V}_i \hat{V}_j'$$

where $\hat{V}_i = V_i(\hat{β})$ and $1 - \frac{|i-j|}{p+1}$ is a weight that decreases linearly as $|i-j|$ increases. Newey-West (1994) describe a non-parametric bandwidth procedure for selecting the value of $p$ the details of which are omitted here. This procedure is used in this study.

### 2.4.2 Measuring Openness

Economists have long searched for a reliable way to measure a country’s trade policy. The general goal of these measures is to determine how distorted domestic prices are compared to world prices due trade costs such as tariffs, quotas, and transportation costs. Ideally, then, one would like to be able to quantify differences in domestic and world prices. However, the data necessary to
compute these differences is often difficult to obtain.\textsuperscript{1} As a result, there have been many attempts to create proxies for openness such as trade liberalization indices (Thomas and Nash, 1992) or deviations from predicted trade (Balassa, 1985). The most widely used of these proxies is a measure of trade volume: nominal imports plus exports relative to nominal GDP.

This measure in particular, however, has a weakness. As Alcala and Ciccone (2004) have argued, using nominal GDP may lead to a skewed measure of productivity gains from trade. To see this, consider productivity gains which are greater in tradable (manufacturing) goods than nontradables (services). The authors argue that “...the relatively greater productivity gains in manufacturing lead to a rise in the relative price of services, which may result in a decrease in openness” (p. 614). Alcala and Cicone give a new definition of openness which they call ‘real openness’:

\[ OPEN^i = \frac{EX^i + IM^i}{PPPGDP^i} \]  

where \( OPEN^i \) is real openness of country \( i \), \( EX^i \) is total exports in U.S.\$, \( IM^i \) is total imports in U.S.\$, and \( PPPGDP^i \) is a measure of GDP in purchasing power parity U.S.\$. This is the measure of openness used through the remainder of this study.

\textsuperscript{1}A notable exception is Bernard et al. (2006). In this paper, the authors explicitly compute industry level tariff and transportation costs from U.S. import data to find that industries experience gains in productivity when trade costs fall.
2.4.3 Trade Endogeneity

A major concern of this study is the well documented endogeneity of trade. The problem with measuring how a country’s trade share affects its productivity is that there might be other factors which affect both productivity and trade. Thus, it is not an entirely appropriate way to identify the impact of trade. Moreover, as Barnum and Gleason (2008) note, second-stage estimates could be biased if inputs in the first stage are correlated with inputs in the second stage. For example, Rodrik (1995) finds in the case of South Korea and Taiwan, government intervention in capital markets has helped spur both economic growth demand for imported capital goods since the early 1960’s.

Other studies have attempted using other measures of trade policy as an instrument for trade share, but, as Frankel and Romer (1999) note, the instruments are generally still correlated with other factors that could affect economic well being and trade. That is, countries often embark on multiple policy reforms simultaneously, making it difficult to disentangle the effects of changes in trade policy from other variables. Unfortunately, no suitable instrumental variable exists for the current model. The instrumental variables perhaps most successful at overcoming endogeneity, geographic characteristics, as used by Frankel and Romer (1999), clearly do not vary over time. Thus, they are not appropriate in this panel data setting.

A minor alteration to the model that helps the causality argument is to lag openness by 1 to 3 years. This has other benefits as well. Rodrik (1998) argues that it takes time for the effects of trade to be felt. This lag is used in this study.
2.5 The Empirical Model and Data

In the first stage, a production correspondence is assumed such that the following are taken as the output and inputs (data sources in parentheses):

- **y** Output:
  
  Real GDP in 2000 US$ (Worldbank.org)

- **x<sub>1</sub>** Capital:
  
  Gross Capital Formation in 2000 US$ (Worldbank.org)

- **x<sub>2</sub>** Labor:
  
  Economically Active Population in thousands (Laborsta.org)

- **x<sub>3</sub>** Energy Used:
  
  KG of Oil Equivalent in thousands (Worldbank.org)

\[ M_0(x_t, y_t, x_{t+1}, y_{t+1}) \] is computed for each country and each time period through use of the FEAR package in the statistical software, R.

The specific form of the second stage model is specified as follows:

\[
M_{o,1}(x_t^i, y_t^i, x_{t+1}^i, y_{t+1}^i) = \beta_0 + \beta_1 \Delta Open_{t,t+1}^i + \beta_2 \Delta Health_{t,t+1}^i + \beta_3 \Delta Income_{t,t+1}^i + \beta_4 Size_t^i + \epsilon_t^i. \tag{18}
\]

Changes in independent variables (except for size, which is a share) are used in order to match the fact that the Malmquist index measures changes in productivity. New trade theory suggests an increase in a country’s size will lead to efficiency gains through economies of scale. Milner and Westaway (1994) argue
that, in smaller countries, the quality of institutions is constrained by limits on the size of the public sector. An argument could also be made that size and economic development affects both the diffusion and innovation of technology. Countries with lower income levels might be less capable of diffusing technologies than richer countries. Similarly, improved health levels could lead to better utilization of both physical and human capital, thus increasing productivity.

In summary, the following are used to explain changes in productivity:

- \( \Delta \text{Open}_{i,t+1} \):  
  Change in real openness as defined in the previous section (Worldbank.org)

- \( \Delta \text{Health}_{i,t+1} \):  
  Change in the average life expectancy of country \( i \) in years (Worldbank.org)

- \( \Delta \text{Income}_{i,t+1} \):  
  Change in country \( i \)'s per capita GDP in 2000 US$ in thousands of dollars (Worldbank.org)

- \( \text{Size}_{i+1} \):  
  The relative size of country \( i \) measured in terms of the country’s share of the sample labor force (Laborsta.org)

Other variables measuring the quality of institutions, such as degree of democracy, level of corruption, etc..., might also be included. However, there are skeptics who question the strength of these measures.
The sample refers to the time period 1980 to 2003 and comprises 17 Latin American and 24 OECD countries yielding 943 data points\(^2\). OECD countries are included to help build a more accurate technology (in the sense of creating a technology closer to the “true” technology through the sheer number of countries) as well as to compare poorer Latin American countries to richer and presumably more productive OECD countries. Tables 1 and 2 summarize the properties of the key variables for each stage.

Table 1: Summary Statistics: Calculating Malmquist Indices

<table>
<thead>
<tr>
<th>Variables</th>
<th>Units</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Max</th>
<th>Min</th>
</tr>
</thead>
<tbody>
<tr>
<td>Labor</td>
<td>Thousands</td>
<td>14295.212</td>
<td>24506.723</td>
<td>152284.540</td>
<td>121.363</td>
</tr>
<tr>
<td>Capital</td>
<td>US $</td>
<td>9957549832</td>
<td>22563652060</td>
<td>2.0007E+11</td>
<td>61363717</td>
</tr>
<tr>
<td>Energy</td>
<td>Thousands</td>
<td>3007.679</td>
<td>2252.164</td>
<td>11800</td>
<td>420.268</td>
</tr>
<tr>
<td>Real GDP</td>
<td>US $</td>
<td>5.175E+11</td>
<td>1.317E+12</td>
<td>1.024E+13</td>
<td>4047510458</td>
</tr>
</tbody>
</table>

Table 2: Summary Statistics: Openness vs. Malmquist

<table>
<thead>
<tr>
<th>Variables</th>
<th>Units</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Max</th>
<th>Min</th>
</tr>
</thead>
<tbody>
<tr>
<td>M_0</td>
<td>#</td>
<td>1.0243</td>
<td>0.0768</td>
<td>1.5705</td>
<td>0.6437</td>
</tr>
<tr>
<td>EC</td>
<td>#</td>
<td>1.0017</td>
<td>0.0798</td>
<td>1.5712</td>
<td>0.6593</td>
</tr>
<tr>
<td>Δ Open</td>
<td>#</td>
<td>0.569</td>
<td>5.965</td>
<td>36.561</td>
<td>-33.157</td>
</tr>
<tr>
<td>Δ Health</td>
<td>years</td>
<td>0.260</td>
<td>0.228</td>
<td>1.870</td>
<td>-0.821</td>
</tr>
<tr>
<td>Per Capita</td>
<td>US $</td>
<td>26.513</td>
<td>19.013</td>
<td>71.860</td>
<td>2.750</td>
</tr>
<tr>
<td>Income Size</td>
<td>(Thousands)</td>
<td>0.05343</td>
<td>0.08445</td>
<td>0.47243</td>
<td>0.00041</td>
</tr>
</tbody>
</table>

Figure 3 gives an idea of how openness changed over the time period considered within each country group. As you can see, in 1980 Latin American\(^2\)Latin American countries such as Bolivia, Nicaragua, and most of the island countries were excluded due to lack of available data.
countries were trading considerably less than OECD countries. Both groups as a whole saw increases in real openness. However, Latin American countries saw their real openness almost double so that by 2003, they had caught up to, and even surpassed OECD countries in terms of openness.

Figure 3: Aggregated Real Openness: 1980-2003
3 Results

3.1 Malmquist results

Although the main goal of the paper is to explore the relationship between openness and productivity, the productivity scores are interesting in and of themselves, and as such, I take a moment to examine the Malmquist indices I have estimated.

I begin by considering the statistical significance of the indices. 95% confidence intervals were obtained for each of the 943 observations by the bootstrap procedure outlined previously. An estimated Malmquist index is said to be statistically different from unity (which would indicate no change in productivity) if the confidence interval does not include 1. Estimated Malmquist indices and their confidence intervals are reported in the appendix. Overall, the confidence intervals are quite small with an average size of 0.031. Thus, there are a large number of statistically significant estimates: 816 (86%) Malmquist indices are significant. Of those, 596 are significantly greater than 1.

By calculating the variance of the bootstrap values and the bias of the Malmquist indices from the bootstrap values, I find that (15) holds for only 81 (8.5%) of the observations. Thus, because the bias corrected estimates yield a higher mean-square error than the calculated Malmquist indices in most instances, the calculated Malmquist indices are used in the second stage.

To gauge each country’s overall productivity gains, consider the cumulative productivity of each country, $c, M^{1980,2003}_c$ over the entire time period being considered, 1980-2003 (Table 3). Argentina, El Salvador, Guatemala, Peru,
and Trinidad and Tobago all experienced a decrease in productivity over the entire period ($M_{c}^{1980,2003} < 1$). All other countries experienced productivity gains. South Korea saw the largest gains by far with a cumulative productivity value of 4.582, over one and a half times larger than the next closest country, the United States (2.755).

The United States was the only country with an $EC = 1$ throughout the entire period considered, implying it was technically efficient in all years. Thus, the United States consistently determined the frontier. In later years, Sweden, the United Kingdom, and Uruguay were also technically efficient, while Argentina and Switzerland were technically efficient in the earlier years.

Figure 4 reveals that Latin American countries had lower Malmquist indices on average, as well as a wider range of Malmquist indices. Also notice from this figure that both groups of countries had average Malmquist scores greater than 1.

Figure 4: Malmquist Indices by Country Type
Table 3: Cumulative Malmquist Indices

<table>
<thead>
<tr>
<th>Cumulative Malmquist Indices</th>
</tr>
</thead>
<tbody>
<tr>
<td>TrinTob 0.53198</td>
</tr>
<tr>
<td>Peru 0.84783</td>
</tr>
<tr>
<td>Argentina 0.87271</td>
</tr>
<tr>
<td>ElSalv 0.91654</td>
</tr>
<tr>
<td>Guatemala 0.95374</td>
</tr>
<tr>
<td>Panama 1.05882</td>
</tr>
<tr>
<td>Honduras 1.12103</td>
</tr>
<tr>
<td>Venezuela 1.21051</td>
</tr>
<tr>
<td>Ecuador 1.23787</td>
</tr>
<tr>
<td>NZ 1.25689</td>
</tr>
<tr>
<td>Uruguay 1.26686</td>
</tr>
<tr>
<td>DR 1.28708</td>
</tr>
<tr>
<td>Mexico 1.31157</td>
</tr>
<tr>
<td>Greece 1.32530</td>
</tr>
<tr>
<td>Columbia 1.39426</td>
</tr>
<tr>
<td>CR 1.39691</td>
</tr>
<tr>
<td>Paraguay 1.54181</td>
</tr>
<tr>
<td>Iceland 1.57065</td>
</tr>
<tr>
<td>Chile 1.65140</td>
</tr>
<tr>
<td>Canada 1.69397</td>
</tr>
<tr>
<td>Hungary 1.75477</td>
</tr>
</tbody>
</table>

Figure 5 shows the aggregated, cumulative Malmquist indices for both Latin American and OECD countries. It again illustrates that both sets of countries achieved productivity gains, but the gains were larger for OECD countries.

3.2 Second-Stage Results

Following the methodology explained previously, the regression in equation (18) is run to obtain OLS estimates for each $\beta_i$. Standard errors are corrected for autocorrelation and heteroskedasticity using the Newey-West HAC estimator.
described in section 2.4.1. The results are displayed in Table 4.

Table 4: Analysis of Productivity Changes: Full Sample, No Lag

| Estimate | Std. Error | t value | Pr(>|t|) | Signif. |
|----------|------------|---------|----------|---------|
| chopen   | -0.0008162 | 0.0004875 | -1.6739932 | 0.0944638 |
| chhealth | -0.002180  | 0.0118816 | -0.183537  | 0.8544161 |
| chincome | 3.27E-06   | 4.80E-06  | -0.6825847 | 0.4950370 |
| size     | 0.0692632  | 0.0283598 | 2.4422970 | 0.0147770 |

N=943
Signif. codes: ***: 0.001 **:0.01 *:0.05 :.1

Somewhat surprisingly, increases in changes in openness lead to decreases in productivity. The coefficient on changes in openness is just statistically significant at the 10% level. Size is the only other variable that is significant. The sign is as suspected. Relative larger countries experience greater productivity
gains than smaller ones.

However, these results could be misleading for two reasons. First, countries’ productivity levels could be affected by changes in openness differently based on country-specific regressions. Thus, a dummy variable is included for each country to control for country-specific variations for all the regressions that follow. This fixed effects model controls for any continuing differences across countries, “such as initial conditions, higher level of technical know-how, cultural differences, or freer access to knowledge” (Harrison, 1996). Second, the trade share may be endogenous. To obtain a better causal relationship showing how trade affects growth, regressions are run using a lag of zero to three years on openness. The results are displayed in table 5.

<table>
<thead>
<tr>
<th>Table 5: Analysis of Productivity Changes: Full Sample, Fixed Effects</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variable</td>
</tr>
<tr>
<td>--------------------</td>
</tr>
<tr>
<td>chopen</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>chhealth</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>chincome</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>size</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>F-stat</td>
</tr>
<tr>
<td>N</td>
</tr>
</tbody>
</table>

Signif. codes: ***: 0.001 **:0.01 *:0.05 .:0.1
(HAC estimated t-stats in parentheses)

The F-statistic tests the null hypothesis that country fixed effects are not important. This hypothesis is rejected at the 10% in the no lag regression and at the 5% level in the 1 and 2 year lag regressions. Thus, the country-specific
dummy variables are jointly significant, indicating there are differences across countries. Not only are the dummy variables significant, but they change the coefficients of the other independent variables considerably.

In all of the regressions, both changes in income and and, as before, size are significant and positive, as expected. As a country’s income increases more and more quickly, it becomes more and more productive. Specifically, in the first regression, if the rate at which per capita income changes increases by $1,000, the country will experience a 1.09% increase in productivity. Also, relatively larger countries are more productive than relatively smaller countries. If a country’s relative size increases by 1% the country will become 1.36% more productive. This suggests countries experience economies of scale on a national level. Contrasting this with table 4 (no fixed effects), notice that not only does the coefficient on size become more significant, but the magnitude increases dramatically. This could be because the dummy variables control for initial conditions including the initial size of the countries. After initial conditions are controlled for, changes in size have a considerably larger effect on productivity.

After lagging the independent variables in two of the for cases, there is still significant but negative correlation between changes in openness and changes in productivity.\textsuperscript{3} The final regression indicates that if the rate at which real openness is changing increases by 1, the country will experience productivity losses of .9%. While this seems small, if it occurred three years in a row, it would result in productivity losses of 3%. There are some possible explana-

\textsuperscript{3}The regression was also run using the composite trade intensity measure, 
\[
\frac{n(\text{EX}+\text{IM})_i^2}{\text{GDP}_i \sum_{j=1}^{n} (\text{EX}+\text{IM})_j},
\]
developed by Squalli and Wilson (2006) as a measure of openness. In this case, the coefficient on the new proxy was no longer significant. Thus, the results in this paper depend on the measure of openness being used.
tions for this negative correlation. It could be that as countries trade more and more, they specialize in those industries in which they have a comparative advantage. However, some of these industries could be less productive than others. Specifically, it could be Latin American countries specialize in more labor intensive, but less productive industries, while the more developed, OECD countries specialize in more productive, capital intensive industries. To explore this, the data is separated into two groups, Latin American countries and OECD countries, and the same regressions from above are run for each group separately. First, the results from the 17 Latin American countries are displayed in table 6.

Table 6: Analysis of Productivity Changes: Latin America, Fixed Effects

<table>
<thead>
<tr>
<th></th>
<th>No Lag</th>
<th>1 Year Lag</th>
<th>2 Year Lag</th>
<th>3 Year Lag</th>
</tr>
</thead>
<tbody>
<tr>
<td>chopen</td>
<td>-0.00079</td>
<td>-0.00192</td>
<td>0.00031</td>
<td>-0.00070</td>
</tr>
<tr>
<td></td>
<td>(-1.256)</td>
<td>(-3.141)**</td>
<td>(0.418)</td>
<td>(-1.177)</td>
</tr>
<tr>
<td>chhealth</td>
<td>-0.03329</td>
<td>-0.03779</td>
<td>-0.02602</td>
<td>-0.03275</td>
</tr>
<tr>
<td></td>
<td>(-0.946)</td>
<td>(-1.003)</td>
<td>(-0.687)</td>
<td>(-0.776)</td>
</tr>
<tr>
<td>chincome</td>
<td>0.03524</td>
<td>0.03296</td>
<td>0.04386</td>
<td>0.05455</td>
</tr>
<tr>
<td></td>
<td>(2.263)*</td>
<td>(2.005)*</td>
<td>(2.434)*</td>
<td>(3.611)**</td>
</tr>
<tr>
<td>size</td>
<td>-3.33054</td>
<td>-2.49166</td>
<td>-1.27119</td>
<td>-4.20006</td>
</tr>
<tr>
<td></td>
<td>(-0.925)</td>
<td>(-0.696)</td>
<td>(-0.291)</td>
<td>(-0.935)</td>
</tr>
<tr>
<td>F-stat</td>
<td>0.464</td>
<td>0.426</td>
<td>0.432</td>
<td>0.498</td>
</tr>
<tr>
<td>N</td>
<td>391</td>
<td>374</td>
<td>357</td>
<td>340</td>
</tr>
</tbody>
</table>

Signif. codes: ***: 0.001 **:0.01 *:0.05 .:0.1  
(HAC estimated t-stats in parentheses)

Now, size no longer has an affect on productivity. However, changes in income are still positive and significant. Notice also, the dummy variables are no longer significant as a group. Even though many Latin American countries have similar cultures, this result is still somewhat surprising, given the other
differences, such as size, between these countries.

Again, the variable of interest, openness, is negatively significant in two of the four regressions. This lends support to the hypothesis outlined above that labor abundant countries will see their productivity fall as they become more and more open. Perhaps, then, OECD countries will be more productive. The results for OECD countries are displayed in table 7.

Table 7: Analysis of Productivity Changes: OECD Countries, Fixed Effects

<table>
<thead>
<tr>
<th></th>
<th>No Lag</th>
<th>1 Year Lag</th>
<th>2 Year Lag</th>
<th>3 Year Lag</th>
</tr>
</thead>
<tbody>
<tr>
<td>chopen</td>
<td>-0.00125</td>
<td>-0.00057</td>
<td>-0.00209</td>
<td>-0.00140</td>
</tr>
<tr>
<td></td>
<td>(-1.954)</td>
<td>(-0.733)</td>
<td>(-2.848)**</td>
<td>(-2.319)*</td>
</tr>
<tr>
<td>chhealth</td>
<td>0.00125</td>
<td>0.00234</td>
<td>0.00311</td>
<td>0.00620</td>
</tr>
<tr>
<td></td>
<td>(0.138)</td>
<td>(0.241)</td>
<td>(0.316)</td>
<td>(0.578)</td>
</tr>
<tr>
<td>chincome</td>
<td>0.00475</td>
<td>0.00712</td>
<td>0.00781</td>
<td>0.00932</td>
</tr>
<tr>
<td></td>
<td>(1.108)</td>
<td>(1.401)</td>
<td>(1.517)</td>
<td>(1.918).</td>
</tr>
<tr>
<td>size</td>
<td>1.70104</td>
<td>2.25279</td>
<td>2.19762</td>
<td>1.97158</td>
</tr>
<tr>
<td></td>
<td>(4.085)***</td>
<td>(5.337)***</td>
<td>(4.361)***</td>
<td>(4.807)***</td>
</tr>
<tr>
<td>F-stat</td>
<td>2.104**</td>
<td>2.576***</td>
<td>2.247***</td>
<td>1.784*</td>
</tr>
<tr>
<td>N</td>
<td>552</td>
<td>528</td>
<td>504</td>
<td>480</td>
</tr>
</tbody>
</table>

Signif. codes: ***: 0.001 **:0.01 *:0.05 .:0.1
(HAC estimated t-stats in parentheses)

Now, changes in income are no longer significant. The fact that income no longer affects productivity is not surprising. All OECD have relatively high levels of income, and any marginal changes will have little affect on overall productivity. Relatively size is, however, significant and still positive. Also, the dummy variables are back to being significant as a group. This is not surprising given that this group of countries comes from all over the world.

Yet again, changes in openness have a negative effect on productivity. This time, the correlation is even larger and stronger than before. This contradicts
the hypothesis that one group of countries experiences productivity gains while another experiences decreases in productivity due to changes in openness. A few explanations for this might be that firms anticipate growth with openness and increase inputs, or, perhaps, openness spurs investment from abroad (FDI) leading to the same result. It also could be that, as Grossman and Helpman suggested (1992), the governments in these countries created trade barriers which promoted investment in more productive industries.

The regressions were also run using EC as the dependent variable. However, none of the dependent variables, including openness and the group of country-specific dummy variables, were significant at any level. Finally, the regressions were run using TC as the dependent variable. In this case, the coefficients on changes in openness were negative and significant. This could indicate that increases in openness discourage innovation because of increased competition.
4 Conclusions

Perhaps the most fundamental question in international trade is how a country’s trade policies affects economic growth. In spite of this, both theoretical and empirical evidence give mixed results. Theoretically, the results of the model depend greatly on the underlying assumptions. Likewise, empirical models can give vastly different results depending on, for instance, how a country’s trade policies are measured.

In this paper, I attempted to determine the relationship between a country’s degree of openness and its productivity through a two stage process. First, the output-oriented Malmquist index was calculated as a measure of productivity changes for 17 Latin American and 24 OECD countries over 24 years. I found that on average, OECD countries experienced larger productivity gains than Latin American countries. Then a proxy for trade policies, “real openness”, was regressed against the Malmquist indices. I found that changes in openness had a negative effect on productivity changes in the case of both Latin American and OECD countries. This goes against what most previous studies have found. There are some theoretical explanations for why this might be true, however none are entirely convincing.

Unfortunately, this study comes with multiple caveats. First and foremost, as has been discussed, the measure used as a proxy for trade policies in this paper, real openness, may not accurately reflect how much domestic prices are distorted from international prices due to trade costs. Further, even after lagging real openness, this trade share may still be endogenous. There may also be other, better explanatory variables of productivity that could be used
in the second stage. Finally, it may be that the HAC estimation used did not adequately handle the serial correlation of the Malmquist indices, leaving all second stage results irrelevant.

All of these areas are ways in which this study could be expanded and improved upon. In addition, the Malmquist index can be broken down multiple ways, some of which include the assumption of variable returns to scale, allowing one to distinguish between short run and long run efficiency or technical changes.
References


