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**Volatilidad del Crecimiento del PIB en Países Latinoamericanos: Importa la
Apertura y la Diversificación Geográfica?**

**GDP Growth Volatility in Latin American Countries: Do Openness and
Geographic Diversification Matter?**

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Contents

1	Introduction	1
2	Sources of Aggregate Fluctuations: A Review of Literature	3
2.1	Closed Economy	3
2.2	Open Economy	5
3	Data and Stylized Facts	6
3.1	Data	6
3.2	Stylized Facts	8
4	Empirical Model and Results	12
5	Robustness Checks and Extensions	16
5.1	Does the volatility measure present an ARCH process?	16
5.2	What if we measure volatility in another way?	17
5.3	Does entry and exit matter?	19
6	Conclusion	19
7	Appendix	26



List of Tables

Table 1. List of Latin American Countries	28
Table 2. Baseline Results	29
Table 3. Estimated Results with More than One Shock at a Time	30
Table 4. Testing for ARCH(1) Effects	31
Table 5. Estimated Results correcting for ARCH Effects	32
Table 6. Estimated Results with HP Volatility	33

List of Figures

Figure 1. Volatility and GDP Per Capita	34
Figure 2. Volatility and Openness in Latin American Countries	35
Figure 3. Volatility and Openness in Latin American Countries without TTO	36
Figure 4. Trade Openness in Latin American Countries 1970-2009	37
Figure 5. Evolution of Trade between Latin American Countries	38
Figure 6. Fundamental Volatility and Volatility	39
Figure 7. Fundamental Export Volatility Decomposition	40
Figure 8. Fundamental Import Volatility Decomposition	41
Figure 9. Economic Complexity Index and Relative Rank	42
Figure 10. Export Partners and Composition	43
Figure 11. Import Partners and Composition	44
Figure 12. Share of Export Composition Effect by Entrant and Exiters	45
Figure 13. Share of Import Composition Effect by Entrant and Exiters	46

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Abstract

We study whether GDP growth volatility in Latin American countries can be explained by their trade openness and complexity. Using annual data from 1970 to 2009, we analyze the impact of trade openness by constructing a measure of fundamental volatility similar to the one introduced by [Carvalho & Gabaix \(2013\)](#). In an international sense, this represents the volatility that would arise in an economy only due to the presence of trade partners. We divide it into an openness effect (how important are exports/imports relative to a country's GDP), and a composition effect (how important are trade partners inside the export/import basket), our measure of geographical diversification. The results suggest that the responses of GDP growth volatility to the openness effect are asymmetric. While export openness has contributed to increase GDP growth volatility, the converse is true for import openness. Moreover, we find no evidence of an important geographical diversification effect over GDP volatility. Additionally, our results indicate that the complexity of an economy has not played a major role in the observed GDP growth volatility of Latin American countries.

Resumen

Estudiamos si la volatilidad del crecimiento del PIB en países latinoamericanos puede ser explicada por su apertura y complejidad. Usando datos anuales desde 1970 hasta 2009, analizamos el impacto de la apertura comercial construyendo una medida de volatilidad fundamental similar a la implementada por [Carvalho & Gabaix \(2013\)](#). En un contexto internacional, esta representa la volatilidad que se observaría en la economía debido solamente a la presencia de socios comerciales. Dividimos ésta medida en un efecto apertura (que tan importantes son las exportaciones/importaciones relativo al PIB de un país) y un efecto composición (que tan importante son los socios comerciales dentro de la canasta de exportaciones/importaciones), nuestra medida de diversificación geográfica. Los resultados sugieren que la respuesta de la volatilidad del crecimiento del PIB es asimétrica con respecto al efecto apertura. Mientras el efecto apertura de las exportaciones ha contribuido a incrementar la volatilidad, lo contrario es cierto para el efecto apertura de las importaciones. Adicionalmente, no encontramos evidencia de un rol importante de la diversificación geográfica sobre la volatilidad del crecimiento del PIB. Finalmente, nuestros resultados sugieren que la complejidad de una economía no ha jugado un rol importante en la volatilidad observada del crecimiento del PIB en países latinoamericanos.

1 Introduction

A central question in economics is whether it is possible for countries to achieve sustained economic growth. For this task, two basic ingredients are needed: a Gross Domestic Product (GDP) growth rate that is both *positive* and *stable*. However, as we have seen recently in the 2008 Sub-Prime crisis, the economy is permanently exposed to shocks. These shocks alter the “normal” behaviour of GDP, hence GDP growth rate, generating what is known as aggregate fluctuations: deviations of GDP from its trend or normal trajectory¹. Therefore, understanding what is behind these aggregate fluctuations could help countries to stabilize their economic growth rate and be a step closer to achieving sustained economic growth.

This point is particularly important in less developed and developing countries because they have shown a higher GDP volatility than their developed counterpart (Koren & Tenreyro, 2007; Lucas, 1988) and also because this lack of stability may result in lower economic growth (Ramey & Ramey, 1995). While some authors argue that these GDP volatility differences stem primarily from internal causes such as weak political and economic institutions (Acemoglu et al., 2003; Raddatz, 2007), others give importance to external causes such as real trade openness (di Giovanni & Levchenko, 2009), terms of trade shocks (Malik & Temple, 2009) and financial openness (Calderón & Schmidt-Hebbel, 2008).

Nonetheless, until today, less is known about whether whom they trade with matters for countries’ aggregate volatility. From the Markowitz-Tobin portfolio risk view, we know that we can reduce risks in our portfolio – and hence its volatility – in at least two ways. First, we can take positions in a large range of assets. Second, we can invest in less risky ones. In the same way, we can think of countries’ partners as assets in a portfolio. If we allow for this possibility, then countries can benefit from international trade by trading with more partners or less volatile ones. This portfolio view of international trade is often called *geographical diversification*. To our knowledge, only the works of Bacchetta et al. (2007), Farshbaf (2012), Jansen et al. (2015) and Caselli et al. (2015) has explored the link between geographical diversification and aggregate volatility. These works argue that geographical diversification could help countries to alleviate the presence of aggregate volatility. However, Bacchetta et al. (2007) only pay attention to the possibility of imported demand shocks via export’s geographical diversification, while giving no role to the geographical diversification of imports, Farshbaf (2012) and Jansen et al. (2015) group the data in a priori years span thus losing capability to explain variations within countries. Moreover, Caselli et al. (2015) argue that when country-wide shock are large, openness to international trade can help countries to alleviate their GDP volatility by reducing their exposure to their own risks. This is true, as long as the countries with which a country is trading with are not equally volatile or do not present high levels of correlation between their business cycles. However, most of these works implicitly assume that openness to trade via

¹We will use the words aggregate fluctuations, aggregate volatility and business cycles volatility interchangeably throughout the paper.

imports and exports symmetrically impacts GDP volatility.

This research contributions are three-fold. First, we test whether GDP volatility in Latin American countries can be explained by international trade. We do this computing a version of the “*Fundamental Volatility*” measure introduced by [Carvalho & Gabaix \(2013\)](#) for a panel of 19 Latin American countries from 1970 to 2009. In an international sense, this represents the volatility that would arise in an economy only due to the presence of trade partners. As countries can be thought of as sectors and the share that they represent in exports/imports can be thought of as the share that sectors represent in an economy, this construction seems straightforward. We show that this effect can be decomposed into two effects: (i) an *openness effect* which is independent of partners volatility and thus it account for the increasing importance of overall international trade in LA countries; and (ii) a *composition effect* – which does depend in partners volatility – that allows us to investigate how the composition of the import/export basket, or the so called geographical diversification argument, has contributed to GDP volatility in LA countries.

Second, we construct this measure for both imports and exports separately. We do this because most of the literature has focused primarily on the overall impact of trade openness over GDP volatility, while it may be the case that exports and imports does not generate a symmetric impact on GDP volatility. In particular, while openness via exports represents an exposure to international fluctuations via a demand channel, openness via imports represents an exposure to international business cycles via a supply channel. Therefore, by constructing these measures separately, we are departing from the common practice that implicitly treats both of these effects as symmetric.

Third, we control for a measure of the “economic productive structure” not previously used in the literature, namely, the Economic Complexity Index (ECI) constructed by [Hausmann et al. \(2011\)](#). With this, we seek to use a variable that captures the development of the economy other than their GDP per capita, as is commonly used. By its definition, this index captures two important features of an economy. First, it considers how many products it produces, which is a simple measure of diversification. Second, given a product, it takes into account how many countries do produce it, which we will refer to as a product’s ubiquity. We can then go a step further and adjust the measure of diversification, by the ubiquity of its products. We can do the same process from the perspective of a product and adjust its ubiquity by how many products are produced in the countries that produce this particular product. We can then use this adjusted measure of ubiquity to adjust our adjusted measure of diversification and so on. What [Hausmann et al. \(2011\)](#) show is that this process can be solved iteratively and it converges on the index employed here. Note that by construction the ECI provides more information about the productive structure of an economy than common measures of product diversification such as the Herfindahl product index or Theil index.

For this purpose, the structure of this research is as follows. Section 2, discusses the possible sources of aggregate fluctuations in both a closed and in an open economy. Section 3 shows the

data and some stylized facts that arises from it. Section 4 presents the empirical approach and its results. Section 5 shows some robustness checks. Finally, Section 6 concludes.

2 Sources of Aggregate Fluctuations: A Review of Literature

2.1 Closed Economy

Almost forty years ago, Lucas (1977) pointed out the impossibility of observing large aggregate fluctuations coming from independent idiosyncratic shocks due to a sort of cancellation effect. In formal terms, suppose that there is a closed economy environment with N units. These units can represent anything, for example, agents, sectors, countries, firms and so on. For simplicity, take a unit to mean a sector. Suppose that each one of these sectors is affected by an independent idiosyncratic shock, that is, a shock that affects the sector only. Under this particular setting Lucas' argument implies that, as we increase N , each one of these idiosyncratic shocks would be negligible compared to the aggregate by the law of large numbers. This law states that as N goes toward infinity, meaning the number of sectors in the economy becomes sufficiently large, the impact of these shocks in the aggregate fluctuation of the economy should vanish at a rate of $1/\sqrt{N}$. Therefore, why should we be worried about idiosyncratic microeconomic shocks if they tend to *average-out* in the aggregate?

This diversification argument led subsequent works in macroeconomic modelling to assume the existence of a representative firm whose only source of variation is an aggregate technology shock: given that independent idiosyncratic shocks do not matter in the aggregate, the only possibility of observe large aggregate fluctuations should come from a shock affecting the economy as a whole. These models are commonly known today as Real Business Cycles models (RBC).²

Since then, RBC models has dominated the macroeconomic scene. With the few exceptions of the pioneering works of Jovanovic (1987) and Bak et al. (1993); and the economic debate between Horvath (1998, 2000) and Dupor (1999) in the late 90s, the idea of observing aggregate fluctuations coming from independently idiosyncratic shocks to economic units – what we will refer to as the microshock idea – has not received much attention in the economic literature.³ However, this lack of attention has recently changed. This comes from two different, although related, reasons.

The first reason is related to the “*network structure*” of the economy. From the graph theory point of view, an economy can be thought of as an intricately related network, where some sectors (nodes) produce inputs for other sectors, that use these inputs to produce goods (outputs) which are finally sold in the markets. Starting at least from the work of Carvalho (2008), this

²See Kydland & Prescott (1982), Long & Plosser (1983), McCallum (1988) and King & Rebelo (1999) for a detailed account of RBC models.

³We are not the first one to define this concept by that phrase. To our knowledge the “microshock idea” was firstly stated by Jovanovic (1987).

perspective has been applied to a macroeconomic setting. He shows, using a class of multisector general equilibrium model, that if we have idiosyncratic microeconomic shocks hitting sectors in the economy, Lucas’ argument only holds for very particular network structures. Namely, he refers to a network without input-output linkages, known as an empty network, or a complete network, where every node is connected to each other. These ideas were expanded by [Acemoglu et al. \(2012\)](#) who argued that Lucas’ argument holds only for symmetric network structures⁴. That is, when the degree variation of sectors is low, aggregate volatility will tend to decay at the rate $1/\sqrt{N}$. So, even if we observe networks with the same average degree, their aggregate volatility will be strongly correlated with their degree variation: thus, economies with higher degree variation will exhibit slower aggregate volatility decay rates. The applications of this perspective range to a large extent of economic phenomena such as financial contagions ([Elliott et al., 2014](#)), natural disasters ([Carvalho et al., 2015](#)), the propagation of sectoral and regional shocks ([Acemoglu et al., 2015](#); [Caliendo et al., 2014](#)) and sectoral comovement ([Carvalho, 2014](#)), among others.⁵

The second reason stem from what is called the “*Granular hypothesis*”. It states that sectors which are “too big” can be behind observed aggregate fluctuations. In particular, [Gabaix \(2011\)](#) shows that if the sectors’ or firms’ sales follow a power law distribution, idiosyncratic shocks play a significant role in aggregate fluctuations. The argument follows from the fact that, given the power law distribution for firms’ sales, the mathematics of the typical central-limit theorem do not apply and aggregate fluctuations will not decline at a rate of $1/\sqrt{N}$, but at a rate $1/\ln(N)$. This hypothesis has been applied, for example, to the study of the banking system ([Blank et al., 2009](#)) and predominantly to analyze the contribution of sectoral or aggregate shocks to aggregate fluctuations ([Foerster et al., 2011](#); [Atalay, 2014](#); [Stella, 2015](#)). Along this line, a particularly study that is relevant to ours, is [Carvalho & Gabaix \(2013\)](#). They propose a measure called “*Fundamental Volatility*”: It is volatility that would arise in an economy made entirely of idiosyncratic shocks to sectors in the economy. They show that this fundamental volatility fairly reproduces the behaviour of aggregate volatility for a number of developed countries despite its simplicity. Additionally, they find that most of the recent increases in the US aggregate volatility stem from the growth of the financial sector.

We pause here, to note that the arguments are quite different. Based on the “Granular hypothesis”, the decay rate of aggregate fluctuations would be much slower than $1/\sqrt{N}$ not because of units that act as a supplier to a large fraction of other sectors through input-output linkages – network perspective argument – but because of the presence of units which represent

⁴A symmetric network structure refers to a case where nodes have the same degree i.e. they have the same number of connections. For directed graphs, however, we have to distinguish between two kinds of degrees. Applied to an input-output structure, the unweighted out-degree refers to how many sectors a given sector supplies to. Conversely, the unweighted in-degree is related to how many sectors a given sector supplies from. As pointed out by [Carvalho \(2008\)](#) and [Acemoglu et al. \(2012\)](#) most of sectors heterogeneity comes from the out-degree distribution and not from the in-degree one.

⁵This is in line with the growing amount of research using the network perspective in microeconomics. For great surveys on these works, see [Jackson \(2008, 2014\)](#) and [Goyal \(2012\)](#).

a large fraction of total sales or output. Thus, idiosyncratic shocks to large sectors are similar to the “aggregate technology shock” in the RBC models but the essence of aggregate fluctuations is different. While aggregate shocks produce volatility due that they affect the economy as a whole, the granular view produces aggregate fluctuations via idiosyncratic shocks affecting the largest sectors in the economy, even if the remaining sectors have not experienced any kind of shock.

2.2 Open Economy

The previous section showed that aggregate fluctuations may be the result of many independent idiosyncratic microeconomic shocks. However, it has offered no possible explanation to why some countries, such as less developed ones, are more volatile than developed ones.

Explanations for the variations in aggregate fluctuations’ seen across countries have focused on the two main factors⁶. The first factor refers to the importance of internal causes that out-weigh the impacts of possible external causes (Raddatz, 2007). In this view, the observed aggregate fluctuations could stem, for example, from poor institutional arrangements (Acemoglu et al., 2003), inflation targeting policies (Cecchetti & Ehrmann, 2002) and the depth of the financial system (Easterly et al., 2001).

The second factor argues that aggregate fluctuations are primarily driven by external causes. For instance, it is argued that real trade openness could have an impact on aggregate fluctuations. While di Giovanni & Levchenko (2009) and Abubaker (2015) find that real trade openness contributes to increase aggregate fluctuations, others find the opposite effect (Calderón & Schmidt-Hebbel, 2008; Haddad et al., 2013). Some arguments behind these inconclusive results are that real trade openness: (i) makes economies more diversified and thus, by a financial portfolio kind of reasoning, reduce aggregate fluctuations (Jansen et al., 2015); (ii) increases sector specialization which, from a granular type of argument, contributes to an increase in aggregate fluctuations (di Giovanni & Levchenko, 2012; di Giovanni et al., 2014); and (iii) effects on aggregate fluctuations are conditional on the level of development of countries, pointing out a possible non-linear relationship between the variables (Koren & Tenreyro, 2007). Other possible explanations refer to terms of trade volatility and geography (Malik & Temple, 2009), financial openness and liberalization (Buch et al., 2005; Bekaert et al., 2006); financial frictions and foreign interest rate shocks (Chang & Fernández, 2013).

Nevertheless, the literature has been relatively silent on whether it matters for countries’ aggregate fluctuations whom they trade with. Borrowing from the finance literature, specifically from the Markowitz-Tobin portfolio risk, we know that we can reduce risks in our portfolio – and hence its volatility – by taking positions in a large range of assets and investing in less risky

⁶We abstract here to discuss explanations using International Real Business Cycles models (IRBC) since our main task is to understand what is behind aggregate volatility, not trying to match the theory to the data. However, see Chang & Fernández (2013) for a clean overview of IRBC models that study aggregate fluctuations in emerging economies.

ones. In the same manner, thinking of a countries' partners as assets in a portfolio, countries can benefit from international trade by trading with more partners or trading with less volatile ones. This portfolio view of international trade is often called *geographical diversification*. To the best of our knowledge, only the works of [Bacchetta et al. \(2007\)](#), [Farshbaf \(2012\)](#), [Jansen et al. \(2015\)](#) and, although not directly, [Caselli et al. \(2015\)](#) have studied this relationship. For instance, [Bacchetta et al. \(2007\)](#) introduce a measure called "*imported demand shocks*" which is a weighted average of export partners volatility. They find that this measure positively affects positively aggregate volatility. Said another way, trade with more partners and less volatile ones help countries to smooth out their aggregate fluctuations. [Farshbaf \(2012\)](#) introduces four measures of geographical diversification. Specifically, he introduces measures that account for (i) the size of trade partners (ii) the level of development of those partners (iii) the partners volatility and (iv) the degree of correlation among business cycles between the origin country and their partners. His findings suggest that countries which trade with countries which are larger, more developed and/or less volatile tend to exhibit lower aggregate fluctuations. Furthermore, once an external shock is accounted for, a country with a business cycle less synchronized with its respective trade partners show lower aggregate fluctuations. Moreover, [Jansen et al. \(2015\)](#) extend the impact of the imported demand shocks variable defined by [Bacchetta et al. \(2007\)](#) by also including the possibility of correlation of business cycles among trade partners. Their finding suggest that correlations between trade partners business cycles plays a more important role in countries' aggregate volatility than partners' aggregate volatility per se. In a related avenue, [Caselli et al. \(2015\)](#) argue that, when country-wide shocks are large, such as when shocks affect all sectors at once, openness to international trade can help countries to reduce GDP volatility by allowing them to diversify their sources of supply and demand across countries. Thus countries that exhibit high GDP volatility levels can benefit from international trade by reducing their exposure to their own risks. Moreover, they find that, in general, this effect tends to out-weight the increase in GDP volatility derived from the specialization mechanism discussed, for example, by [di Giovanni & Levchenko \(2009\)](#).

3 Data and Stylized Facts

3.1 Data

For bilateral trade, we use yearly data compiled by [Barbieri & Keshk \(2012\)](#) in the Correlates of War Project (COW). This data is in current US\$ dollars. Although, the database' period coverage is from 1870 to 2009, we choose the period 1970-2009. The reason is because we do not have enough national accounts of data from Latin American countries until 1970. From this database, we use a sample of 19 Latin American countries which are shown in Table 1.

The Economic Complexity Index (ECI) is obtained from the Observatory of Economic Complexity (OEC). Since we are interested in the effect that this variable can have over GDP volatility, it is worth pausing here to explain its construction. This index captures two important

features of an economy. First, it considers how many products it produces. Second, given a product, it takes into account how many countries produce it. A simple way to think about this index is to consider an undirected and unweighted bipartite graph, where countries are connected to each other only by the products that they produce. This can be represented as a matrix where rows correspond to countries and columns to products. Then, we can place 1's whenever a country produces a product or 0's when it does not produce it⁷. At this point, it is easy to see that the row sum of this matrix corresponds to a diversification measure: it is a simple count of how many goods a country produces. By the same token, the column sum corresponds to how many countries produce a particular product, which can be defined as a product's ubiquity. We can go a step further and adjust countries' diversification by their respective products' ubiquity and vice versa. In doing so, looking at the country's side, we are adjusting the diversification measure by how ubiquitous the products that a given country produces are. Looking at the product's side, we are adjusting the product's ubiquity by how diversified the countries are that produce a given product. As shown by Hausmann et al. (2011), we can do this process recursively, by which we converge on a solution given by the eigenvector of the second largest eigenvalue of this system. This eigenvector (standardized) corresponds to the index used here.

With this index, we seek to use a variable that captures the development of the economy other than its GDP per capita, as is commonly used in the literature. Note that by definition, this index is more informative than common measures of diversification such as the Herfindahl product index, because it does not only rely on how many products a given country produces but it also takes into account how ubiquitous its products are. A drawback, however, is that in its construction it only considers (i) traded products and (ii) manufactured products. Aside from this, Hausmann et al. (2011) show that this index represents a rather good measure of economic structure and also show that it is a good predictor of those country's future development.

With respect to GDP, population, real exchange rate and national accounts data (e.g., Government Spending and Investment), we use the Penn World Table database v7.1 provided by the Center for International Comparisons.

We also use a financial openness index constructed by Chinn & Ito (2008), to account for the possible impact of financial openness over GDP volatility, as discussed in Section 2.2.

To account for political factors, we use a political quality index, constructed by the Center for Systemic Peace. This index ranges from -10 (strongly autocratic), where no democracy is present, to 10 (strongly democratic) where full democracy is in place.

The appendix provides a detailed account of what specific series we use from the database and also presents how we constructed certain variables, that were not readily available such as government spending, real exchange rate and investment.

⁷An important point here is that a country gets a 1 in this matrix only if it is a significant exporter of a product. A significant exporter is considered whenever it has a revealed comparative advantage on it. For a detailed account of this, see Hausmann et al. (2011)

3.2 Stylized Facts

To motivate the research question, Figure 1 plots the GDP per capita observed in 1970 against the standard deviation of GDP per capita growth rate over the period 1970-2009. Figure 1 confirms, although weakly, a regularity that has been observed in several studies: there seems to be a negative relationship between volatility and development, as measured by the real GDP per capita of a country.⁸ Moreover, Latin American (henceforth, LA) countries, depicted by a triangle, tend to be located at the centre of the figure and show, on average, a higher volatility than developed countries.

Figure 2 shows the relationship between trade openness, measure as the ratio of the sum of exports and imports over GDP, and volatility among LA countries. This relationship is positive in this particular sub-sample. That is, on average, trade openness in LA countries is related with higher volatility. Nonetheless, there is an outlier, namely Trinidad and Tobago (TTO), which drives most of the positive relationship. In fact, if we take out TTO from the sample, the relationship between trade openness and volatility become negative (Figure 3). This suggests that the relationship between trade openness and GDP volatility is not a clear one in this particular case. This is in line with the broad empirical evidence discussed in Section 2.2.

While trade openness has increased over the last 40 years for almost all the LA countries considered⁹, as shown in Figure 4, Figure 5 shows where this openness went. That is, we plotted for every LA country in our sample, the share of total exports and imports accounted for by LA partners. Looking at this figure a clear pattern arise: with a few exceptions, such as Mexico (MEX) or Trinidad and Tobago (TTO), almost all LA country were relying more in their LA partners in 2009 than they were forty years ago.

In sum, we can comprise these three figures in three stylized facts. First, LA countries exhibit, on average, higher volatility than developed ones. Second, openness to trade does not have a clear relationship with volatility. Third, Latin American countries have increased their international trade dependency on LA partners.

Our hypothesis rests on the interaction of these three facts. The increasing dependency of LA partners – which as we have seen are more volatiles than developed countries – of LA countries could have contributed to their observed GDP volatility. We will argue that concentrating exports and imports in more volatiles partners will make countries more volatiles. As we will see in Section 4, the fact that we do not observe a clear relationship between trade openness and volatility in LA countries stem from two effects. One effect is independent of partners' volatility, which we will refer to as *openness effect*, and the other effect does depend on partners volatility and we will call it the *composition effect*.

To test our hypothesis, let us first define the Fundamental Volatility (FV), as introduced

⁸It is worth noting that we can say nothing about causality up to this point. That is, we do not know whether volatility makes countries less developed or if less developed countries are prompt to generate higher volatility levels.

⁹Two special cases are El Salvador (SLV) and Trinidad & Tobago, which show a decrease in their openness.

by [Carvalho & Gabaix \(2013\)](#), and apply to an international context, as follows

$$\sigma_{it}^F(x) = \sqrt{\sum_{j=1}^{J_{it}(x)} \left(\frac{x_{ijt}}{Y_{it}}\right)^2 \sigma_j^2}, \quad \text{with } x_{ijt} = \{Exports_{ijt}, Imports_{ijt}\} \quad (1)$$

where $\sigma_{it}^F(x)$ is the fundamental export (import) volatility of country i at time t . Y_{it} is the GDP of country i at time t . $J_{it}(x)$ is the set of export/import partners of a country i at time t . $x_{ijt} = \{Exports_{ijt}, Imports_{ijt}\}$ represents the exports (imports) of a country i to (from) country j at time t . σ_j^2 is the GDP growth rate variance of country j for the whole period constructed as

$$\sigma_j^2 = Var[\Delta y_{jt}] \quad \text{with } t \in [1970, 1971, \dots, 2009] \quad (2)$$

where $y_{jt} = \log(Y_{jt})$ and, hence, Δy_{jt} is the GDP growth rate.

It is worth pausing here to explain the main intuition for this variable. Since we are taking an *average* deviation over time (σ_j^2) – thus fixing partners’ volatility as a single value –, then this FV captures how important international trade volatility, measured as the volatility of trade partners, has become in LA countries relative to their overall activity (Y_{it}). Intuitively, what this FV does is to consider each trade partner as if they were a sector in the economy and thus the ratio $(x_{ijt}/Y_{it})^2$ represents how important is a given country j for the overall country i economic activity, it is then multiplied by the respective volatility of the trade partner (σ_j) to obtain a weighted measure of partners volatility.

We will argue that a geographically concentrated country, a country with bigger $(x_{ijt}/Y_{it})^2$ ratios, should experience higher aggregate fluctuations because it relies on a few key trade partners. This effect may come from two sources: (i) a foreign demand shock which should be amplified/weakened via the export ratio and (ii) a foreign supply shock whose effect should be amplified/weakened by the import ratio. While the former channel has been studied elsewhere (see, e.g., [Bacchetta et al., 2007](#); [Jansen et al., 2015](#)), the latter has been less so. We can think of at least two reasons of why the latter effect could contribute to increase GDP volatility.

The first reason is best illustrated by an example. To simplify the exposition, take the case of Chile. While this country is a significant exporter, its exports are principally intermediate inputs such as copper and other commodities. Also, its imports are mainly final goods for durable consumption like cars and laptops. As an extreme case, suppose that one day China, one of Chile’s main commercial partner, stop producing cars. What impact should this *shock* have on the Chilean economy? It would have no effect only if the cost of substitution of cars were low but, even if it is the case, finding the same cars with the same quality and at the same price would prove to be difficult: this sudden stop could have an impact in the Chilean economy. Has Chile experienced any kind of shock via its exports? The answer is a likely no. This example, though extreme and limited, illustrates that international shocks could come in the form of *supply shocks*, not only from *demand shocks*.

The second reason stem from a network perspective kind of reasoning. As intermediate

inputs have become a large fraction of international trade (Johnson, 2014), this has contributed to generating a globalized network of production. Under this setting, there are countries whose main role is to provide the necessary production inputs to others so they can produce complex products. As a result, some hubs may arise. If these countries are particularly large in the total inputs used by some countries, then a shock to them could propagate downstream in the global network to generate aggregate fluctuations in their partners in a similar way that an idiosyncratic shock does in the closed environment that we analyzed in Section 2.1.

To construct the GDP growth volatility series for LA countries, we follow the McConnell & Perez-Quiros (2000) and Carvalho & Gabaix (2013) strategy. That is, we fit for each country the following regression¹⁰

$$\Delta y_t = \delta_0 + \delta_1 \Delta y_{t-1} + \epsilon_{it} \quad (3)$$

As McConnell & Perez-Quiros (2000) point out, if ϵ_t follows a normal distribution, we can construct an unbiased estimator of ϵ_{it} adjusting the sample error ($\hat{\epsilon}_{it}$) by $\sqrt{\frac{\pi}{2}}$. Then, our measure of GDP growth volatility (σ_{it}^R) is given by

$$\sigma_{it}^R = \sqrt{\frac{\pi}{2}} |\hat{\epsilon}_{it}| \quad (4)$$

Unless otherwise noted, we will refer to GDP growth volatility as GDP volatility from now on. Figure 6 shows the FV measure for both exports and imports against the GDP volatility. All variables were standardized to have zero mean and unit standard deviation. A first thing that arises is that both the fundamental export and import volatility seem to track each other rather well. Besides that, there is no clear pattern that can be applied broadly to all countries. For example, there are countries that exhibit a clear positive trend in both series, such as Argentina (ARG), Colombia (COL) and Mexico (MEX), while others like El Salvador (SLV) and Trinidad and Tobago (TTO) have exhibited a clear downward trend after the mid 70's. Additionally, while there are countries in which fundamental volatility and GDP volatility seem to move in the same direction, most notably Venezuela (VEN) and Brazil (BRA), there are others in which no clear relationship is apparent e.g., Costa Rica (CRI) or the Dominican Republic (DOM).

To gain some further insight about what is behind this heterogeneity, note that we can decompose FV as follows

$$\sigma_{it}^F(x) = \sqrt{\sum_{j=1}^{J_{it}(x)} \left(\frac{x_{ijt}}{Y_{it}}\right)^2 \sigma_j^2}$$

¹⁰In order to avoid potential heteroskedasticity and autocorrelation problems, we estimate these regressions using the newey-west standard errors with two lags each.

$$\begin{aligned}
&= \sqrt{\sum_{j=1}^{J_{it}(x)} \left(\frac{x_{ijt} x_{it}}{x_{it} Y_{it}} \right)^2 \sigma_j^2} \\
&= \sqrt{\left(\frac{x_{it}}{Y_{it}} \right)^2 * \sum_{j=1}^{J_{it}(x)} \left(\frac{x_{ijt}}{x_{it}} \right)^2 \sigma_j^2} \\
\sigma_{it}^F(x) &= \underbrace{\frac{x_{it}}{Y_{it}}}_{\text{openness effect}} * \underbrace{\sqrt{\sum_{j=1}^{J_{it}(x)} \left(\frac{x_{ijt}}{x_{it}} \right)^2 \sigma_j^2}}_{\text{composition effect}} \tag{5}
\end{aligned}$$

where $x_{it} = \sum_{j=1}^{J_{it}(x)} x_{ijt}$ represents the total value of country i at time t of the x series which could, as previously stated, stands for exports or imports.

Assume, for a moment that x represents exports. Then the first expression, which we call *openness effect*, shows how important total exports relative to the GDP of a country are, hence it is the common index used to measure trade openness. However, note that we are not imposing that this openness be the sum of exports and imports, it is just export openness. The second expression, that we refer to as a *composition effect*, reflects two things. First, it measures how important a given country j is in the total exports of country i (x_{ijt}/x_{it}). Second, after accounting for the importance of the countries in the export basket, it takes into account their respective volatility (σ_j). This expression is similar to the “imported demand shock” variable defined in [Bacchetta et al. \(2007\)](#), although they only constructed it for exports. Similarly, it is the variance component used by [Jansen et al. \(2015\)](#). They construct this variable for both imports and exports. However, they argue that the import channel does not have an important effect over GDP volatility¹¹. We revisit this result drawing attention to the fact we have not grouped the data in any a priori year span and also because we are focusing on a particular sub-sample, not in the entire sample available.

Figure 7 and 8 shows this decomposition for both series¹². Variables were standardized to have mean zero and unit standard deviation. As we can see, on average, the openness effect accounts for almost all the trend presents in the fundamental volatility series. In fact, the pooled correlation between the fundamental volatility and its openness effect, both for exports and imports, is around 92%. Things are different when we consider the composition effects. While there are countries where the export composition effect follows the export openness effect very closely (e.g., Honduras (HND) and, Colombia (COL)), most of them do not exhibit a clear

¹¹Specifically, in footnote 5 they write: “To control for this channel of diversification, we also constructed an import-weighted measure of total variance of trading partners GDPs and introduce it in our regression as an additional regressor. We find that while our export-weighted total variance of trading partners GDPs remains significant, the import-weighted variance is not. Hence, we omit the import-weighted GDP volatility in what follows.”

¹²Although we do not have all the GDP data for all the countries in the COW database, we account for almost 95% of the transactions over the period, with a minimum of 94%.

pattern.

Looking at the import composition effect, we can see that there are also countries in which this composition effect mimics the fundamental volatility behavior rather well, for example, Argentina (ARG), Jamaica (JAM) and, to a lesser extent, Brazil (BRA). Nonetheless, in contrast to the export composition effect, there exist countries where the import composition effect accounts for significant changes in the fundamental volatility. This is the case of, for example, Uruguay (URU) during the 70's, Chile (CHL) between the 70's and 90's, and Mexico (MEX) during the 2000's.

4 Empirical Model and Results

We saw in the previous section that fundamental volatility showed an increasing trend. We also show that this trend can be divided into two components: an openness component and a composition component. With this in mind, we can ask how much of the GDP volatility can be attributed to each of these effects. Specifically, in this section we seek to answer the following questions: (i) Does trade openness (openness effect) have an impact over LA countries' GDP volatility and if so, (ii) does it matter whether trade openness is via exports or imports?; (iii) What impacts does the composition effect (geographical diversification) have over GDP volatility? and (iv) Is it the same effect whether we look at imports or exports?

To gain some initial insight, we start by fitting the following regression

$$\log(\sigma_{it}^R) = \alpha_i + \zeta_t + \beta_1 \log(\sigma_{it}^F(X)) + \beta_2 \log(\sigma_{it}^F(M)) + \epsilon_{it} \quad (6)$$

where σ_{it}^R is the GDP standard deviation of country i at time t . α_i is a country fixed-effect and ζ_t a time fixed-effect. σ_{it}^F is the fundamental export (X) or import (M) volatility as defined previously. ϵ_{it} is an error term. We applied the logarithm transformation to avoid scale problems¹³.

In what follows, we implement a panel estimation strategy using fixed effects estimators and not random effects. We defend this choice in light of the fact that we have selected a sub sample of the total population of countries and thus using a random effect estimator is inappropriate in this case.

Column (1) in Table 2 shows the results associated with this regression. We find that both measures of fundamental volatility have an impact over the GDP volatility in LA countries. In particular, we find a positive effect of fundamental export volatility and a negative effect for fundamental import volatility. This suggests, although vaguely, that there could be a difference between trade openness via exports or via imports.

In Section 3.2, we argued that most of the trend presents in the fundamental volatility comes

¹³It is easy to note that by applying the logarithm transformation to the FV measure and including it as a regressor in equation 6 we are essentially imposing to our model that the openness effect and the composition effect affect in the same way GDP volatility.

from an openness effect. To see whether these descriptive results have any statistical support, we fit

$$\log(\sigma_{it}^R) = \alpha_i + \zeta_t + \beta\Omega_{it}^F + \epsilon_{it} \quad (7)$$

with

$$\beta = (\beta_1 \quad \beta_2 \quad \beta_3 \quad \beta_4) \quad \Omega_{it}^F = \begin{pmatrix} \log(\sigma_{it}^{OE}(X)) \\ \log(\sigma_{it}^{CE}(X)) \\ \log(\sigma_{it}^{OE}(M)) \\ \log(\sigma_{it}^{CE}(M)) \end{pmatrix}$$

where we separate fundamental volatility into its openness (OE) and composition effect (CE). Therefore, we are not imposing that both effects impact GDP volatility in the same way. Formally, applying log to equation 5, we have

$$\log(\sigma_{it}^F(x)) = \underbrace{\log\left(\frac{x_{it}}{Y_{it}}\right)}_{\text{openness effect}} + \underbrace{\log\left(\sqrt{\sum_{j=1}^{J_{it}(x)} \left(\frac{x_{ijt}}{x_{it}}\right)^2 \sigma_j^2}\right)}_{\text{composition effect}} \quad (8)$$

As is clear from Column (2) in Table 2, the results confirm our descriptive findings. Specifically, when we separate the fundamental volatility, there is no significant composition effect. That is, the relationship between fundamental volatility, both for exports and imports, and GDP volatility comes exclusively from an openness effect. In this case, selling to foreign markets has been associated with an increase in GDP volatility in LA countries, while buying from foreign markets has contributed to a decrease in GDP volatility. Up to this point, it seems that who do you sell (buy) to (from) does not matter for GDP volatility. However, this has to be considered carefully, given that we have not included any other control variables which could, in principle, alter this result.

To check the robustness of these results, we extend equation 7 to allows for specific controls as follows

$$\log(\sigma_{it}^R) = \alpha_i + \zeta_t + \beta\Omega_{it}^F + \Gamma\mathbf{Z}_{it} + \epsilon_{it} \quad (9)$$

which differs with equation 7 in \mathbf{Z} that is a vector of time-variant control variables. In particular

$$\Gamma = (\gamma_1 \quad \gamma_2 \quad \gamma_3 \quad \gamma_4 \quad \gamma_5 \quad \gamma_6 \quad \gamma_7) \quad \mathbf{Z} = \begin{pmatrix} \text{Polity Index} \\ \text{Financial Openness Index} \\ \text{ECI} \\ \log(\text{GDP per capita}) \\ \log(\sigma_G^R) \\ \log(\sigma_{RER}^R) \\ \log(\sigma_I^R) \end{pmatrix}$$

where σ_G^R : Government spending growth volatility, σ_{RER}^R : Real exchange rate growth volatility, σ_I^R : Investment growth volatility. To construct these series, we follow the same procedure used to construct σ_{it}^R . From now on, unless otherwise noted, we will refer to these variables simply as government spending volatility, real exchange rate volatility and investment volatility respectively. Furthermore, we have omitted the sub-index i and t in order to have a compact notation to represent the matrices that contain the control variables.

Columns (3) to (10) in Table 2 show the results after applying these controls. We include one volatility measure at a time to study their impact over GDP volatility separately. Also, we include the Polity Index and the Financial Openness Index in all the controls. Finally, we use the ECI and GDP per capita (in logs) separately to see whether the ECI has any explanatory power over GDP volatility different to the one expected by including the GDP per capita.

We pause here to explain what impacts we expect from including these controls. As is customary in the literature, we expect that countries with higher GDP per capita levels be associated with lower levels of GDP volatility. Additionally, we also expect the Polity index to be negatively correlated with our dependent variable, since more democratic economies tend to be more stable and as a result they should exhibit lower GDP volatility levels. For the financial openness index, we are uncertain about its impact given the discussion in Section 2.2. Turning to the expected effect of the ECI, we argue that a more complex economy, should exhibit lower GDP volatility levels. Our logic is straightforward. As Hausmann et al. (2011) show, the ECI tends to be correlated with the development of an economy (measured as the GDP per capita). Thus, given that more complex economies tend to be the developed ones or vice versa, we expect this positive correlation to be reflected in our results. Therefore, we should observe a negative impact of ECI over GDP volatility.

With regard to the impacts of these control variables, all of them behave as expected except for the ECI. Specifically, we observe a stabilizer effect of the Polity index and GDP per capita, although they are not statistically significant in the specifications where they are included. Also, we find no evidence of a significant effect of financial openness or of the ECI.

Moreover, we find that all the volatility measures contribute to an increase in GDP volatility. We observe that the impact of investment volatility is quite big when it is compared to the others shocks. In fact, it is approximately 2 times bigger than the observed impact of government spending volatility. These are expected results, since investment tends to be the most volatile component of GDP. Additionally, we find that the impact of government spending volatility and real exchange rate volatility are roughly the same order of magnitude.

Looking at our decomposed fundamental volatility measures, we can see that both the export and the import openness effect, when compared to the case without control variables, (i) remain significant throughout all the specifications (ii) do not show any sign reversion and (iii) their estimated coefficients are of the same order of magnitude. The only big change in the estimated coefficients occur when we include investment volatility. For example, we can compare the estimated coefficient for the export openness effect in Column (3) with the one in Column (6).

In such a case, we observe an estimated coefficient of 0.513 in Column (3) and of 0.41 in Column (6), which represent a 20% reduction in the estimated parameter for the export openness effect. Note that this result can be expected since, as we previously discussed, investment tends to be a highly volatile series. Thus, when we include it as an exogenous variable, it can account for some of the effect that we were previously attributing to our openness effects.

What is puzzling are the observed changes in the statistical significance of the export and import composition effect when we include or exclude certain control variables. In particular, we observe several asymmetries when we include shock variables. For instance, if we control for real exchange rate volatility (Column (5) and (9)), there is no significant impact of the import composition effect, which is in line with the observed results in Column (2). Nonetheless, controlling for this variable, we now observe a significant impact of the export composition effect (Column (5)). This latter effect is also true when we control for government spending volatility. We see no statistically significant change in the export composition effect when we include investment volatility as a control. What we observe instead, is that the import composition effect becomes statistically significant (Column (10)), although only weakly (90% of confidence). This result does not hold when we replace the GDP per capita for the ECI.

We explore up to what extent the results – associated to the decomposed fundamental volatility measures and the ECI – change when we include more than one shock at a time in Table 3. Since Table 2 suggests that the results do not change in a significant way when we include either the ECI or the GDP per capita, we opt to include the ECI due to the fact that we are primarily interested in its effect over GDP volatility.

As Table 3 shows, both the export and import openness effect remain significant even after including more than one shock at a time, although their estimated coefficients are lower when compared to the cases where we control for one shock. Note that, as we control for more shocks, the estimated coefficients for both variables are strikingly similar. To bring some numbers onto the table, in Column (4) we see an estimated coefficient of 0.393 for the export openness effect and -0.393 for the import openness effect. This means that if the share of imports and exports over GDP increases by a 1% each, then we should observe a 0.393 percent increase in GDP volatility, due to exports, and a 0.393 percent reduction in GDP volatility driven by imports. The net effect of these increases will be unnoticeable within GDP volatility (0%), although trade openness is increasing.

Additionally, the export composition effect becomes significant only in Column (2) where we control for both government spending volatility and real exchange rate volatility. On the other hand, the import composition effect remains insignificant throughout all the specifications. Note that in all the columns, these effects show a positive impact over GDP volatility. However, we can not reject the null that these effects are statistically different from zero. Moreover, similar to Table 2, the ECI is not significant in all the specifications and shows the same sign as before.

From these results we can conclude three things. First, we find strong evidence supporting the idea that the effect of trade openness over GDP volatility depends heavily on whether this

openness is associated with exports, imports or a mix of both. In particular, we find that the export openness contributes to increase GDP volatility in LA countries, while the import openness shows the opposite effect. Second, we do not find strong evidence that supports the relevance of the composition effects. Although in some specifications we observe some statistically significant impact of the export composition effect, these are not the rule and are almost undistinguishable from zero in most of our tests. Given this, we can not take these exceptions as broadly mean impacts of the export composition effect on GDP volatility. In the case of the import composition effect, our interpretation is straightforward since we do not find any specification in which this effect has any important role in explaining GDP volatility. Third, we do not find significant evidence in favour of an important impact of the ECI on GDP volatility. This suggest that, at least for the Latin American countries considered in this research, complexity – as measured by the ECI – plays no role in explaining the observed GDP volatility.

5 Robustness Checks and Extensions

In this section we explore whether our results are robust to different settings. In particular, we investigate what happen to them if we control for the presence of an ARCH process in our primary GDP volatility measure. We also analyze how these results change when we use another GDP volatility measure. Finally, we provide some descriptive evidence that the composition effects are mainly driven by compositional changes at the intensive margin and not by entrants and exiters (extensive margin).

5.1 Does the volatility measure present an ARCH process?

A common concern in the time series literature, is the possible presence of autocorrelation in the error term estimated after a regression. In our case, it is sufficient to test if our volatility measure shows any sign of autocorrelation.

As Table 4 suggests, only 3 of the 19 LA countries considered show important signs of autocorrelation. These are Honduras (HND), Paraguay (PRY) and El Salvador (SLV). Given that this autocorrelation could introduce some bias in our results extracted from Table 3, we tackle this in two ways. First, we estimate the same specifications presented in Table 3 without considering the countries that present signs of autocorrelation. Second, we include as an exogenous variable, the lagged value of our volatility measure.

The results are reported in Table 5. We observe that the export and import openness effect exhibit the same behavior, as the one presented in Table 3. What differs are the size of the estimated coefficients. This is the case whichever control we use, be it remove the countries that present an ARCH structure or include a lagged dependent variable.

The export composition effect is not significant in any specification. This suggests that, after controlling for the possibility of ARCH structure, this effect has a negligible or even null

impact over GDP volatility. This behavior stem in sharp contrast with the one observed for the import composition effect. In particular, we can extract two regularities for it. First, it is not significant when we exclude the countries that exhibit an ARCH process in its residual. Second, it is significant when we include the lagged dependent variable, except for the case where we control for the government spending and real exchange rate volatility (Column(6)). Nevertheless, they are significant at a 90%, which we interpret as an indicative result but not a very robust one.

5.2 What if we measure volatility in another way?

In Section 3.2 we constructed the GDP volatility series after fitting an AR(1) process to the GDP growth series and used it as our measure of GDP volatility. We now ask whether our results are driven by this particular choice. To answer this question we construct another measure of volatility. Specifically, we applied the Hodrick-Prescott (HP) filter to the GDP series (in logs). Given that we are working with annual data, we use a penalty parameter $\lambda = 100$ as is customary in the literature. We also estimate the results using a parameter $\lambda = 6.25$ as Ravn & Uhlig (2002) suggest for annual data. After computing the trend, we then construct the GDP volatility series taking the absolute value of the observed deviation from the trend. More formally,

$$\sigma_{it}^{HP} = |y_{it} - \bar{y}_t| \quad (10)$$

where, as before, y_{it} is the log of GDP and \bar{y}_t represents the estimated trend using the HP filter. To create the shock variables, we follow the same procedure and estimate them using $\lambda = 100$ or $\lambda = 6.25$.

It is worth pausing here to explain why these different penalty parameters could alter our measure of volatility and, by this channel, our results. As pointed out by Mohr (2005), the choice of a *correct* penalty parameter is crucial. This makes the difference between having a cycle with too much trend on it or having a trend with too much cycle on it. As he argues, many economists tend to choose higher penalty parameters in order to avoid excessively volatile trend growth rates i.e. trends that exhibit huge changes so often. This is the reason why $\lambda = 100$ as become the standard value for annual data. Given this trade-off between the ideal cycle and the ideal trend when choosing the penalty parameter, we expect that the GDP volatility measure which uses a penalty parameter $\lambda = 100$ be a more volatile measure than the one constructed using $\lambda = 6.25$.

Table 6 shows the results using these measures of volatility. Due that we are primarily interested in study how our estimated results for the decomposed fundamental volatility variables and ECI change when we construct volatility in another way, we will restrict our analysis to these variables.

From Column (1) to (4) we can infer that if we use $\lambda = 100$ as a penalty parameter, we observe a major significant change when compared to the results found in Section 4. Namely, the import openness effect become insignificant in all the specifications. Although, we can not

statistically distinguish them from zero, note that the estimated parameters for the import openness effect are now pretty small. Note, also, that the estimated parameters for the export composition effect are smaller than the ones found in Table 3. We interpret this as a result stemming from the fact that we are using a $\lambda = 100$, which makes the dependent variable more volatile when compared to the one that we constructed in Section 3.2.

To see whether this is the case, Column (5) to (8) show the results estimated using a penalty parameter $\lambda = 6.25$. A first result that arises is from the size of the estimated coefficients. In particular, we observe that they are approximately in line with our observed results in Table 3. Besides that, we can see two main differences with Table 3. First, as was the case for Column (1) to (4), we do not observe a significant import openness effect. Second, we now observe that the import composition effect and the ECI are significant throughout Column (5) to (8). With respect to the former effect, we observe that it has the expected sign but it is mostly significant at a 90% level, except in Column (7) where it is significant at a 95%. The latter effect, however, does not have the expected sign and its significance is particularly high, given that we can not reject the null that this effect is equal to zero even at a 99% level. This result poses a challenge, which stems from the fact that it is counterintuitive. It is telling us that a LA country which has shown higher complexity levels – measure as the ECI – has also exhibited a higher GDP volatility. We can think of two reasons of why we observe this result. First, if the penalty parameter chosen is the ideal, we can understand this result by observing that most LA countries have not been very complex: they have never exceeded the top 15% of the ECI ranking¹⁴. We construct a relative ranking by taking the ratio of the absolute ranking position that a country has given its ECI over the number of countries from which the ECI can be computed. Therefore, higher values in this relative ranking correspond to low absolute ranking positions and vice versa. As is clear from Figure 9, there exist only 3 out of 19 LA countries which were at a clearly better position in the ranking in 2009 than in 1970: Brazil (BRA), Colombia (COL) and Mexico (MEX). All the others were worse, in terms of their complexity, in 2009 than in 1970.

Second, as the above discussion suggests, given the penalty parameter chosen, it could be the case that we are placing in the cycle some portion of the series that does belong to the trend. In such a case, the positive estimated parameter that we find for the ECI may arise from this portion misleadingly attributed to the cycle component. If this is true, then the observed positive relationship between the ECI and GDP volatility that we find in Column (5) to (8) is just a reflection of the positive relationship between the ECI and GDP per capita found by Hausmann et al. (2011).

¹⁴The ECI ranking is also constructed by the Observatory of Economic Complexity. In fact, at every year, it is computed by ordering the ECI values from the higher to the lower one. Then, it assigns a 1 to a country with the higher ECI value, 2 to the following higher ECI value and so on.

5.3 Does entry and exit matter?

In [Carvalho & Gabaix \(2013\)](#) they construct the fundamental volatility considering a closed economy where sectors are constant over time. As a result, all the observed changes in their fundamental volatility comes exclusively from changes at the intensive margin. In our case, however, this is not plausible. As shown in [Figure 10](#) and [11](#), the number of export and import partners has increased over time in all the LA countries considered. Moreover, it suggests that there is a lot of action occurring at the extensive margin, specifically in the case of imports. With this in hand, we can ask: how much of the observed composition effect, for both exports and imports, comes from entrants and exiters?

[Figure 12](#) and [13](#) show the answer for this. As we can see, albeit there is an increase in the number of partners over time, the composition effect fraction accounted for entrants and exiters is negligible for most countries, except for particular episodes. For instance, in [Figure 12](#), the export composition effect accounted by entrants present big peaks in the cases of Panama (PAN) and Jamaica (JAM) in the middle 70's; Bolivia (BOL) at the end of the 90's; Peru (PER) during the middle 80's; and Ecuador (ECU) at the beginning of the 70's. Nevertheless, note that these shares never exceed the 50%. In fact, the only huge entry is observed in the case of Panama (around 50%), while all the others examples are well below the 20%.

Beside these peaks, in general, what this figure is telling us is that most of the export composition effect come from countries that previously were importing from LA countries. That is, the bulk of the export composition effect comes from stayers.

When we look at [Figure 13](#), the general results are similar. Indeed, as was the case in [Figure 12](#), Panama shows the biggest import composition effect accounted by entrants. This was approximately 60% around the end of the 90's. Also, most of the share of composition effect by entrants in this case does not exceed the 20%. Nonetheless, unlike the previous figure, the import composition effect tend to exhibit a few cases where the exiters represent a significant fraction of the composition effect. In particular, we observe that Uruguay (URY), Trinidad and Tobago (TTO), Chile (CHL) and Panama (PAN) exhibited big peaks in this measure. However, these are not rule and we think on them as exceptions in a more general framework. What we infer from this figure, is that again most of the action in our import composition effect variable comes from countries that were previously trading with LA countries and not by entrants and exiters.

6 Conclusion

We have analyzed what impact international trade has had on GDP volatility in LA countries over the past forty years. We did so by constructing measures of fundamental import and export volatility: the fraction of volatility that will arise in an economy due to trade partners volatility. Interestingly, this measure can be divided into an *openness effect* which is independent of partners volatility and a *composition effect* which does depend on partners volatility. We

have also analyzed whether the economic structure of an economy – as measured by the ECI – plays any role in explaining the observed GDP volatility in LA countries.

Our findings provide three main results. First, the fact that we have observed different results on the impacts of trade openness over GDP volatility in the literature could be explained by two effects working in different directions. In particular, we find that openness to trade via exports has contributed to an increase in GDP volatility in LA countries, while the converse is true for openness to trade via imports. We provide estimates that these effects are roughly of the same order of magnitude but with different signs. As a result, whether trade openness contributes to GDP volatility will depend on the specific channel by which a LA country is opening to trade, in other words, through exports or imports. Second, we find no strong statistical evidence supporting the idea that geographical diversification has an impact on GDP volatility in LA countries. Aside from the fact that we find some evidence that the composition effects may be positive in some cases, most of our estimated results suggest that these effects are not statistically distinguishable from zero. We also provide some descriptive evidence that allows us to confirm that this result is not due to major changes at the extensive margin but to changes at the intensive margin. In other words, we find that our composition effects are driven by countries which were previously trading with the domestic country (intensive margin) and not by entrants and exiters (extensive margin). Third, we find no evidence suggesting that the level of complexity of an LA country has contributed in any way to GDP volatility in these countries. Although in a robustness check, we find some evidence that this relationship is positive, we interpret this as a result due to the way in how we measure volatility in that particular robustness check and not as a broadly general result.

We can think of some policy implications that arise from our findings. First, given that openness to trade via exports has been associated to with an increase in GDP volatility for the LA countries considered, this suggests the existence of a trade-off faced by pro-exports policies. On the one hand, exports can be beneficial for growth. On the other hand, this could makes the economy less stable. Thus policy makers have to be aware of this when thinking about supporting, for example, policies that encourage entry to export markets. Second, given that an increase in the import openness of a country has been related to a decrease in GDP volatility, it suggests that policy makers should look at this channel as a possible way to escape from internal volatility. This result is in line with the findings of [Caselli et al. \(2015\)](#). Third, we find that geographical diversification, measured as our composition effects, plays no role in explaining GDP volatility. It is worth pointing out that this is not to be confused with whether geographical diversification is important for economic growth. Instead, what the results tell us is that, if GDP stability is a relevant issue for policy makers, then geographical diversification does not impose, at least for the LA countries, a constraint to achieving this goal, since it does not matter for GDP volatility who you are trading with.

To sum up, our main results indicates that GDP volatility in LA countries has been mainly affected by the increasing trade openness observed over the last forty years and not by geo-

graphical diversification.



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7 Appendix

Data description

Bilateral trade data: For bilateral trade data we used the data compiled by Barbieri & Keshk (2012) in the Correlates of War Project (COW) v3.0. It is in current US\$ dollars. This data can be downloaded in the following link: <http://www.correlatesofwar.org/data-sets/bilateral-trade>

Economic Complexity Index (ECI): We obtain data about the complexity of an economy from the Observatory of Economic Complexity (OEC). We use the ECI of a country not of a product. This data can be downloaded in the following link: <http://atlas.media.mit.edu/en/rankings/country/>. Note that, by downloading this database, we also have the information about the position in the world ranking of our analyzed countries used to construct Figure 9.

GDP: The GDP series correspond to the *tcgdp* series defined in the Penn World Database v7.1. This data is in current million of international dollars, it is adjusted by PPP, and according to our bilateral trade data it is not deflated.

GDP per capita: This corresponds to the *cgdp* series of the PWT v7.1.

Population: For population we used the *pop* series defined in the PWT v7.1. This data is in millions of people.

Real Exchange rate: To construct the real exchange rate series we take data on nominal exchange rate and purchasing power parity (PPP) from the PWT v7.1. These correspond to the *xrat* and *ppp* series, respectively. We then compute the Real exchange rate as the ratio of the nominal exchange rate over the PPP.

Consumption: For the construction of the consumption series we take data on GDP per capita, Population and the consumption share of GDP per capita. We then construct the consumption (C) series as $C = (cgdp * pop * cc) / 100000$. Where *cgdp* corresponds to the GDP per capita series, *pop* to population and *cc* gives the consumption share of GDP per capita. All these variables were extracted from the PWT v7.1.

Government Spending: In a similar way as we did for the consumption series, we construct the government spending one only changing the government share of GDP per capita. We then construct the government spending variable in a straightforward manner as $G = (cgdp * pop * cg) / 100000$. The government spending share of GDP per capita corresponds to the *cg* series in the PWT v7.1.

Investment: As before, we now change the share for the relevant one, in this case for the investment share of GDP per capita. This corresponds to the *ci* variable defined in the PWT

v7.1. Then the investment (I) series are $I = (cgdp * pop * ci)/100000$.

The PWT v7.1 database can be downloaded here: <http://www.rug.nl/research/ggdc/data/pwt/pwt-7.1>

Polity Index: We used data compiled by the Center for Systemic Peace. Specifically, we use the *polity2* index presented in the database of the Polity IV project. This data can be downloaded here: <http://www.systemicpeace.org/inscrdata.html>

Financial Openness Index: The financial openness index is constructed by Chinn & Ito (2008). We use the variable called *kaopen* to assess the financial openness of an economy. This data can be downloaded from here: http://web.pdx.edu/~ito/Chinn-Ito_website.htm



TABLE 1. List of Latin American Countries

List of Latin American Countries		
Argentina (ARG)	Bolivia (BOL)	Brazil (BRA)
Chile (CHL)	Colombia (COL)	Costa Rica (CRI)
Dominican Republic (DOM)	Ecuador (ECU)	Guatemala (GTM)
Honduras (HND)	Jamaica (JAM)	Mexico (MEX)
Panama (PAN)	Peru (PER)	Paraguay (PRY)
El Salvador (SLV)	Trinidad & Tobago (TTO)	Uruguay (URY)
Venezuela (VEN)		



TABLE 2. Baseline Results

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Log(Fundamental Export Volatility)	0.396*** (0.092)									
Log(Fundamental Import Volatility)	-0.228* (0.130)									
Log(Export Composition Effect)		0.254 (0.204)	0.340* (0.180)	0.371* (0.193)	0.332* (0.184)	0.285 (0.172)	0.332* (0.188)	0.370* (0.202)	0.321 (0.194)	0.266 (0.177)
Log(Import Composition Effect)		0.316 (0.186)	0.294 (0.208)	0.302 (0.205)	0.304 (0.215)	0.309 (0.189)	0.289 (0.200)	0.291 (0.198)	0.299 (0.206)	0.323* (0.184)
Log(Export Openness Effect)		0.512*** (0.116)	0.513*** (0.120)	0.502*** (0.123)	0.500*** (0.122)	0.410*** (0.116)	0.531*** (0.113)	0.521*** (0.115)	0.516*** (0.115)	0.416*** (0.110)
Log(Import Openness Effect)		-0.477** (0.177)	-0.490** (0.181)	-0.477** (0.178)	-0.480** (0.184)	-0.408** (0.170)	-0.466** (0.183)	-0.454** (0.181)	-0.457** (0.185)	-0.389** (0.173)
Polity Index			-0.011 (0.008)	-0.011 (0.008)	-0.009 (0.007)	-0.005 (0.008)	-0.006 (0.009)	-0.006 (0.009)	-0.004 (0.009)	-0.003 (0.009)
Financial Openness Index			0.119 (0.160)	0.149 (0.165)	0.209 (0.176)	0.133 (0.143)	0.132 (0.168)	0.164 (0.173)	0.220 (0.182)	0.141 (0.148)
Economic Complexity Index			0.113 (0.117)	0.117 (0.108)	0.114 (0.114)	0.068 (0.113)				
Log(GDP Per capita)							-0.314 (0.237)	-0.344 (0.226)	-0.289 (0.239)	-0.139 (0.235)
Log(σ_G)				0.089* (0.047)				0.095** (0.045)		
Log(σ_{RER})					0.082* (0.044)				0.081* (0.043)	
Log(σ_I)						0.187*** (0.046)				0.184*** (0.046)
Observations	760	760	757	757	757	757	760	760	760	760
R-squared	0.134	0.142	0.143	0.151	0.151	0.177	0.144	0.154	0.152	0.177
Number of id	19	19	19	19	19	19	19	19	19	19

Note: Robust standard errors in parentheses. All specifications consider time (yearly) and country fixed effects. Time period spans from 1970 to 2009 in all cases. σ_G : Government spending growth volatility, σ_{RER} : Real exchange rate growth volatility, σ_I : Investment growth volatility. *** p<0.01, ** p<0.05, * p<0.1

TABLE 3. Estimated Results with More than One Shock at a Time

Variables	(1)	(2)	(3)	(4)
Log(Export Composition Effect)	0.316 (0.185)	0.361* (0.197)	0.280 (0.175)	0.309 (0.189)
Log(Import Composition Effect)	0.317 (0.188)	0.311 (0.212)	0.317 (0.197)	0.324 (0.195)
Log(Export Openness Effect)	0.400*** (0.117)	0.490*** (0.124)	0.402*** (0.115)	0.393*** (0.116)
Log(Import Openness Effect)	-0.397** (0.168)	-0.469** (0.182)	-0.403** (0.173)	-0.393** (0.171)
Polity Index	-0.006 (0.007)	-0.010 (0.007)	-0.004 (0.007)	-0.005 (0.007)
Financial Openness Index	0.161 (0.148)	0.229 (0.180)	0.206 (0.162)	0.226 (0.166)
Economic Complexity Index	0.072 (0.105)	0.117 (0.106)	0.071 (0.110)	0.074 (0.103)
Log(σ_G)	0.086* (0.047)	0.082* (0.045)		0.080* (0.045)
Log(σ_{RER})		0.075* (0.043)	0.067 (0.046)	0.061 (0.044)
Log(σ_I)	0.185*** (0.046)		0.181*** (0.045)	0.180*** (0.045)
Observations	757	757	757	757
R-squared	0.185	0.158	0.183	0.189
Number of id	19	19	19	19

Note: Robust standard errors in parentheses. All specifications consider time (yearly) and country fixed effects. Time period spans from 1970 to 2009 in all cases. σ_G : Government spending growth volatility, σ_{RER} : Real exchange rate growth volatility, σ_I : Investment growth volatility.

*** p<0.01, ** p<0.05, * p<0.1

TABLE 4. Testing for ARCH(1) Effects

Country	Parameters	
	Constant	Lagged Volatility
Argentina	-2.844*** (0.374)	0.098 (0.102)
Bolivia	-2.947*** (0.670)	0.782 (0.187)
Brazil	-3.295*** (0.560)	0.016 (0.147)
Chile	-3.303*** (0.535)	-0.062 (0.117)
Colombia	-3.896*** (0.688)	-0.003 (0.166)
Costa Rica	-3.399*** (0.583)	0.140 (0.146)
Dominican Republic	-3.448*** (0.660)	-0.020 (0.167)
Ecuador	-2.912*** (0.546)	0.086 (0.150)
Guatemala	-3.599*** (0.615)	0.093 (0.117)
Honduras	-2.679*** (0.509)	0.256** (0.125)
Jamaica	-3.434*** (0.384)	0.094 (0.100)
Mexico	-2.938*** (0.391)	0.112 (0.113)
Panama	-4.105*** (0.484)	-0.116 (0.122)
Peru	-3.156*** (0.580)	0.066 (0.145)
Paraguay	-4.203*** (0.596)	-0.266** (0.131)
El Salvador	-1.847*** (0.423)	0.466*** (0.112)
Trinidad & Tobago	-3.330*** (0.570)	-0.161 (0.139)
Uruguay	-2.924*** (0.323)	0.093 (0.094)
Venezuela	-2.818*** (0.552)	0.029 (0.186)

Note: Robust standard errors in parentheses. All regressions were estimated for the period 1970-2009 using Newey-West standard errors with 2 lags each.

*** p<0.01, ** p<0.05, * p<0.1

TABLE 5. Estimated Results correcting for ARCH Effects

Variables	Excluding HND, PRY and SLV				Including lagged $\log(\sigma_{it}^R)$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log(Export Composition Effect)	0.280 (0.245)	0.349 (0.270)	0.246 (0.240)	0.277 (0.258)	0.172 (0.171)	0.197 (0.173)	0.125 (0.157)	0.158 (0.167)
Log(Import Composition Effect)	0.376 (0.246)	0.353 (0.270)	0.381 (0.254)	0.386 (0.252)	0.352* (0.199)	0.339 (0.212)	0.354* (0.201)	0.357* (0.203)
Log(Export Openness Effect)	0.384** (0.162)	0.513*** (0.154)	0.393** (0.152)	0.380** (0.159)	0.381*** (0.116)	0.466*** (0.121)	0.379*** (0.113)	0.373*** (0.115)
Log(Import Openness Effect)	-0.488** (0.197)	-0.555** (0.212)	-0.488** (0.208)	-0.473** (0.206)	-0.375** (0.168)	-0.449** (0.181)	-0.379** (0.173)	-0.370** (0.171)
Polity Index	-0.006 (0.008)	-0.012 (0.007)	-0.005 (0.008)	-0.005 (0.008)	-0.006 (0.008)	-0.009 (0.008)	-0.004 (0.008)	-0.005 (0.008)
Financial Openness Index	0.178 (0.169)	0.275 (0.204)	0.244 (0.192)	0.255 (0.192)	0.147 (0.146)	0.219 (0.174)	0.193 (0.158)	0.213 (0.162)
Economic Complexity Index	0.046 (0.133)	0.102 (0.134)	0.045 (0.140)	0.049 (0.133)	0.077 (0.108)	0.120 (0.106)	0.071 (0.112)	0.077 (0.105)
Log(σ_G)	0.070 (0.059)	0.071 (0.059)		0.064 (0.058)	0.086* (0.045)	0.081* (0.044)		0.080* (0.044)
Log(σ_{RER})		0.093** (0.040)	0.075* (0.041)	0.070 (0.041)		0.080* (0.045)	0.073 (0.048)	0.066 (0.047)
Log(σ_I)	0.200*** (0.055)		0.193*** (0.055)	0.191*** (0.055)	0.188*** (0.045)		0.182*** (0.044)	0.182*** (0.044)
Log($\sigma_{i,t-1}^R$)					-0.032 (0.037)	-0.011 (0.037)	-0.026 (0.038)	-0.031 (0.036)
Observations	638	638	638	638	738	738	738	738
R-squared	0.190	0.162	0.191	0.195	0.187	0.160	0.185	0.192
Number of id	16	16	16	16	19	19	19	19

Note: Robust standard errors in parentheses. All specifications consider time (yearly) and country fixed effects. Time period spans from 1970 to 2009 in all cases. σ_G : Government spending growth volatility, σ_{RER} : Real exchange rate growth volatility, σ_I : Investment growth volatility.

*** p<0.01, ** p<0.05, * p<0.1

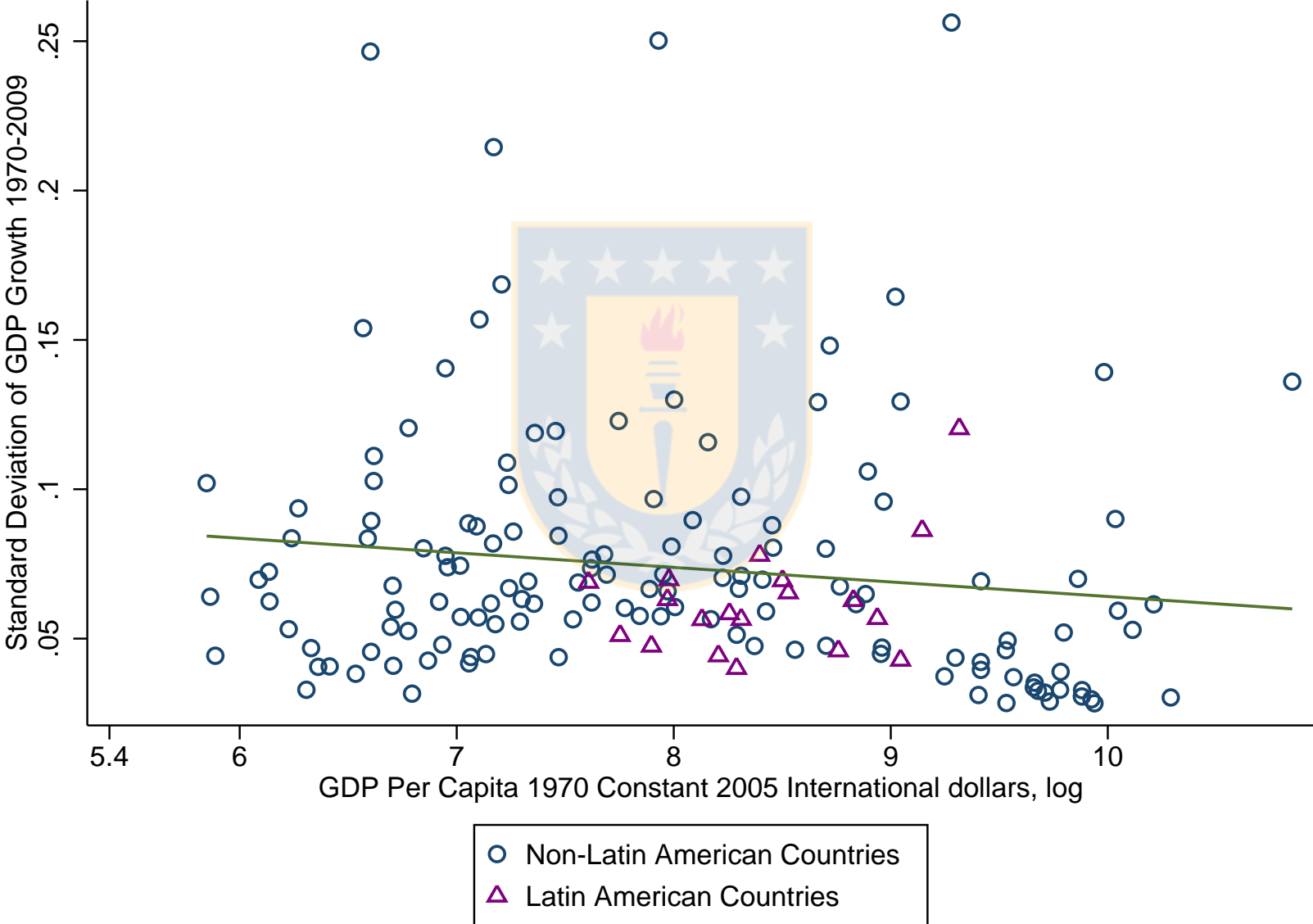
TABLE 6. Estimated Results with HP Volatility

Variables	$\lambda = 100$				$\lambda = 6.25$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log(Export Composition Effect)	0.000 (0.274)	0.057 (0.297)	-0.026 (0.274)	-0.013 (0.271)	0.173 (0.317)	0.184 (0.302)	0.185 (0.318)	0.180 (0.314)
Log(Import Composition Effect)	0.279 (0.226)	0.258 (0.281)	0.298 (0.232)	0.283 (0.225)	0.443* (0.218)	0.415* (0.224)	0.485** (0.220)	0.454* (0.216)
Log(Export Openness Effect)	0.224* (0.113)	0.290** (0.125)	0.248* (0.118)	0.231* (0.113)	0.316* (0.158)	0.382** (0.159)	0.343** (0.158)	0.318* (0.157)
Log(Import Openness Effect)	0.019 (0.159)	-0.029 (0.173)	0.007 (0.160)	0.017 (0.158)	-0.362 (0.248)	-0.418 (0.248)	-0.395 (0.248)	-0.368 (0.244)
Polity Index	-0.020* (0.010)	-0.021 (0.012)	-0.020* (0.010)	-0.020* (0.010)	-0.002 (0.010)	-0.006 (0.010)	-0.000 (0.009)	-0.001 (0.009)
Financial Openness Index	0.138 (0.145)	0.180 (0.179)	0.169 (0.142)	0.162 (0.141)	0.220 (0.156)	0.262 (0.168)	0.270 (0.165)	0.243 (0.162)
Economic Complexity Index	0.115 (0.088)	0.144 (0.095)	0.104 (0.092)	0.109 (0.088)	0.282*** (0.077)	0.323*** (0.075)	0.286*** (0.077)	0.283*** (0.078)
Log(σ_G^{HP100})	0.051 (0.034)	0.041 (0.037)		0.046 (0.036)				
Log(σ_{RER}^{HP100})		0.074* (0.036)	0.053* (0.029)	0.049 (0.030)				
Log(σ_I^{HP100})	0.255*** (0.055)		0.249*** (0.054)	0.250*** (0.055)				
Log($\sigma_G^{HP6.25}$)					0.075** (0.032)	0.078** (0.030)		0.074** (0.033)
Log($\sigma_{RER}^{HP6.25}$)						0.040 (0.045)	0.031 (0.040)	0.028 (0.041)
Log($\sigma_I^{HP6.25}$)					0.187*** (0.047)		0.186*** (0.045)	0.184*** (0.045)
Observations	757	757	757	757	757	757	757	757
R-squared	0.236	0.181	0.237	0.238	0.237	0.203	0.232	0.238
Number of id	19	19	19	19	19	19	19	19

Note: Robust standard errors in parentheses. All specifications consider time (yearly) and country fixed effects. Time period spans from 1970 to 2009 in all cases. σ_G : Government spending growth volatility, σ_{RER} : Real exchange rate growth volatility, σ_I : Investment growth volatility. Superscript $HP100$ and $HP6.25$, indicates the λ parameter chosen to apply the Hodrick-Prescott filter.

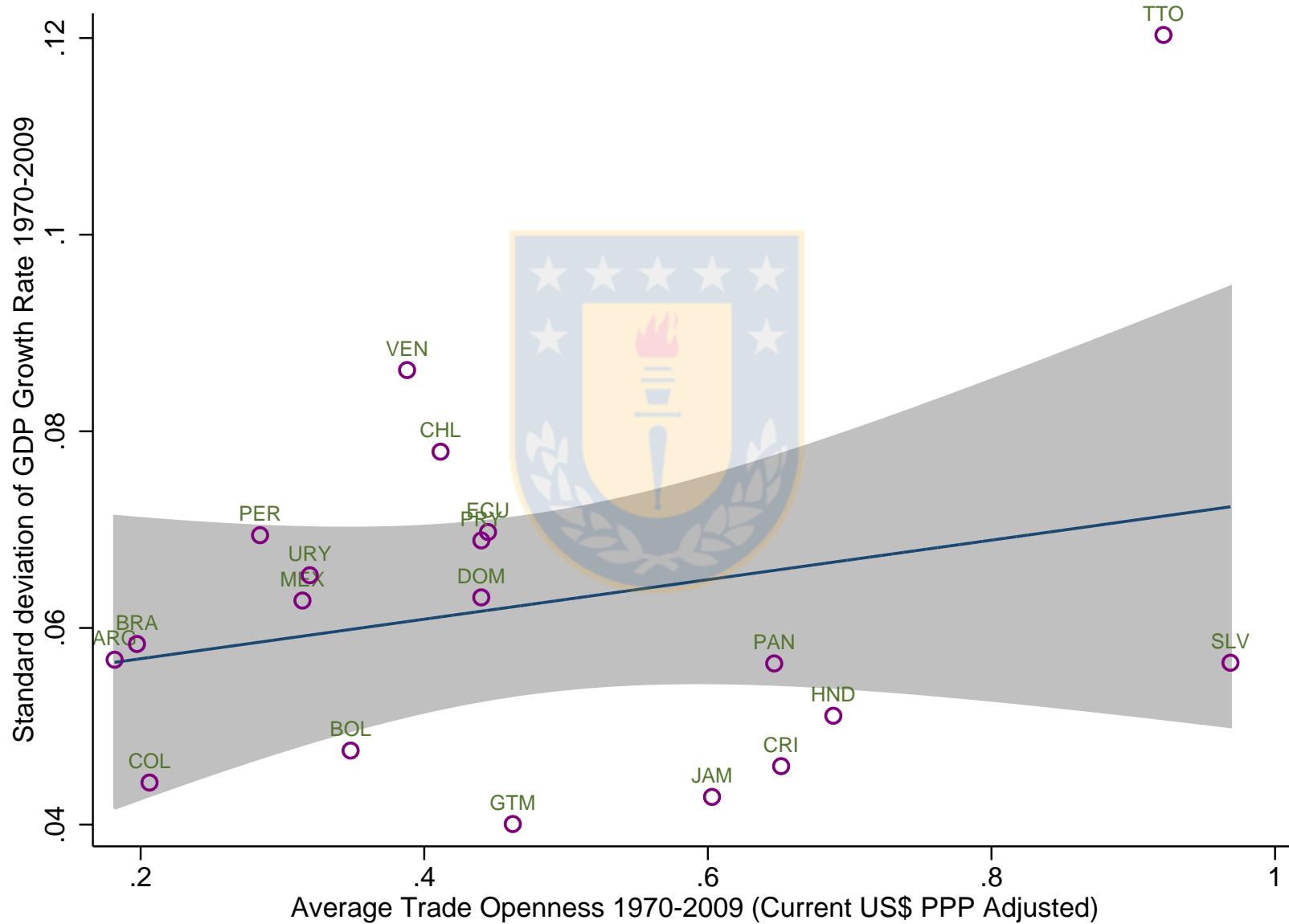
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

FIGURE 1. Volatility and GDP Per Capita



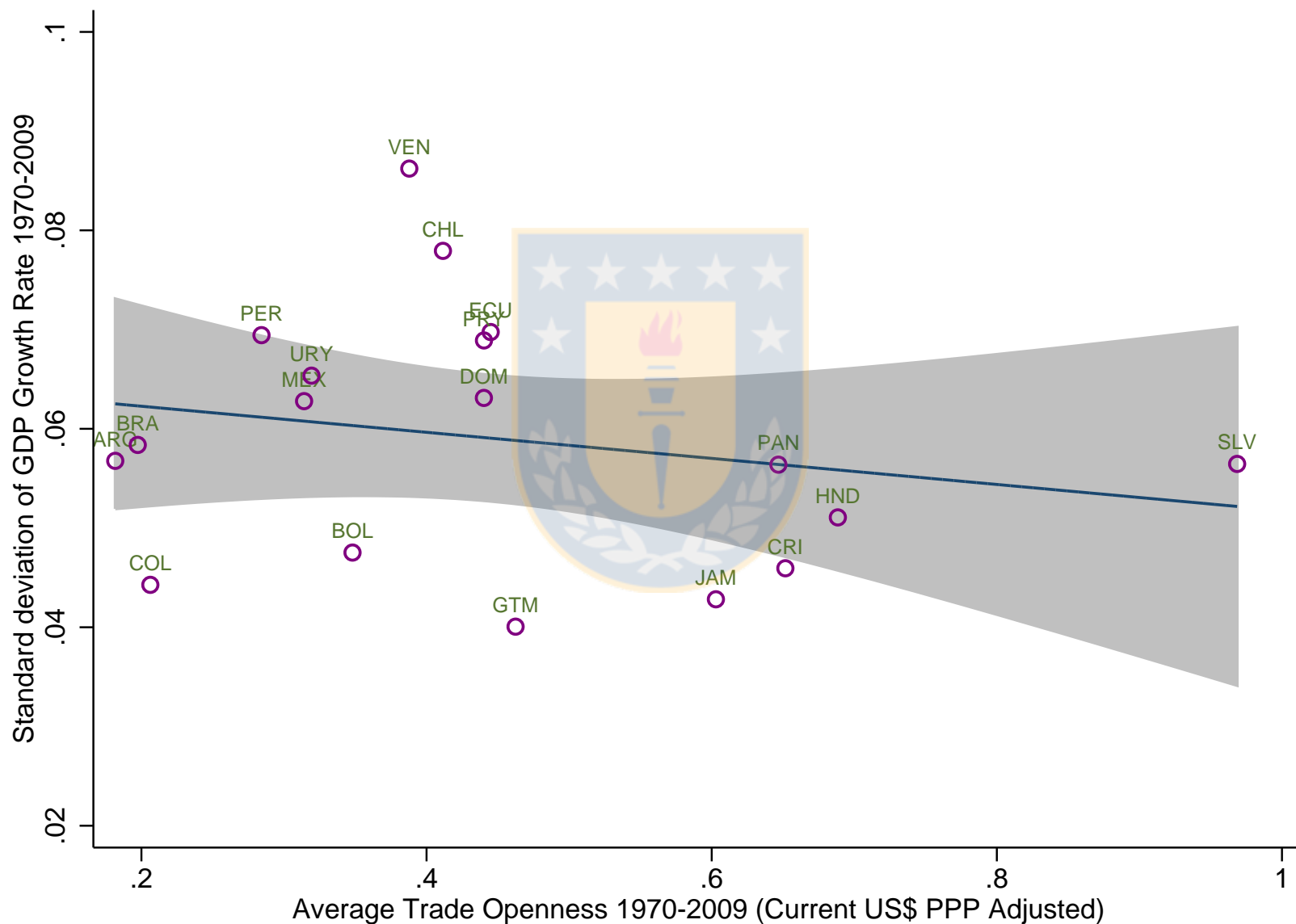
Note: GDP per capita is presented in a log scale. Data was extracted from the Penn World Table (PWT) database v7.1. GDP and GDP per capita series correspond to the tcgdp and cgdg series respectively, defined in the PWT.

FIGURE 2. Volatility and Openness in Latin American Countries



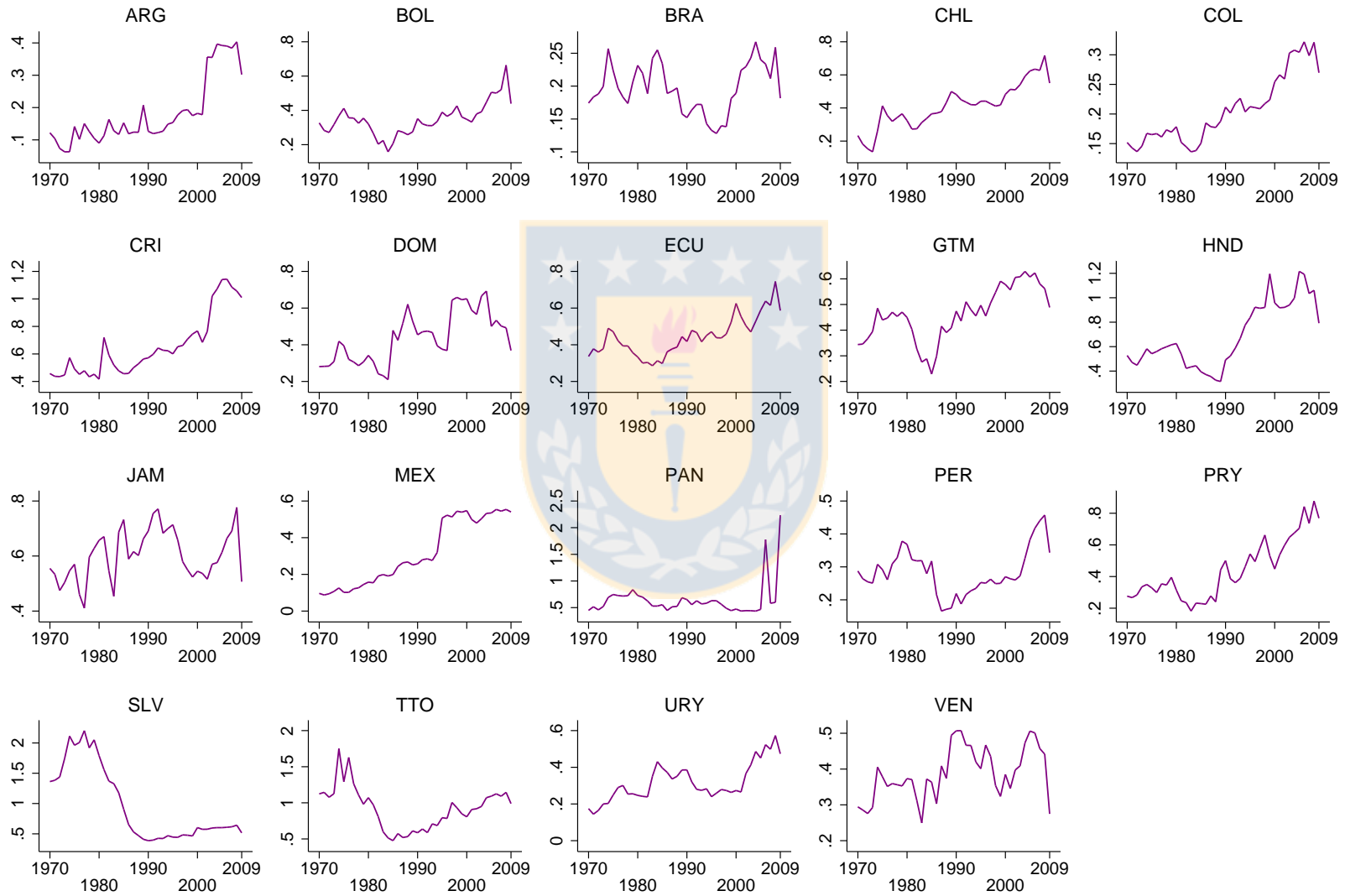
Note: GDP series correspond to the *tcgdp* series defined in the PWT v7.1. For exports and imports data we used the data from the Correlates of War Project (COW).

FIGURE 3. Volatility and Openness in Latin American Countries without TTO



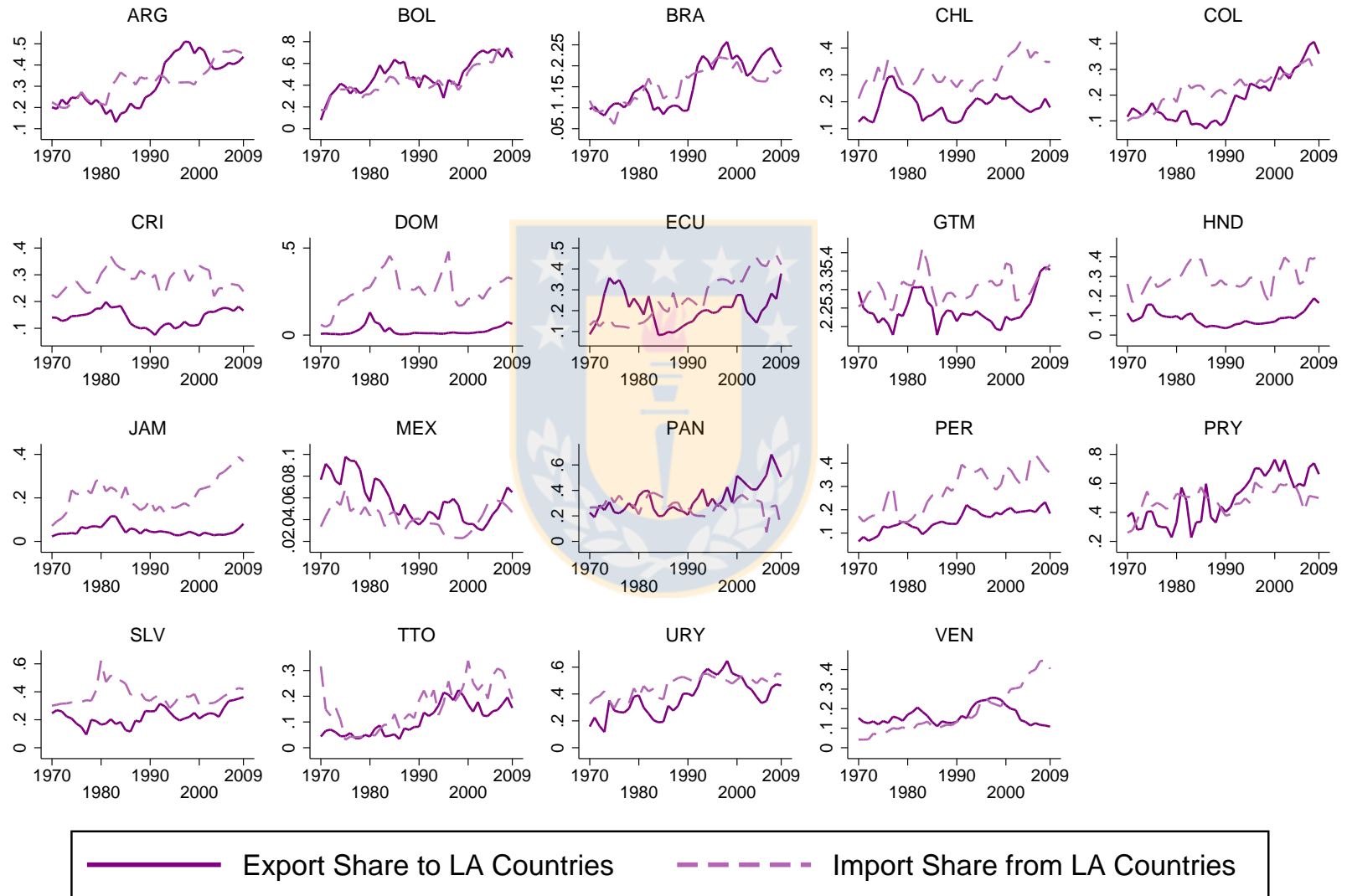
Note: GDP series correspond to the *tcgdp* series defined in the PWT v7.1. For exports and imports data we used the data from the Correlates of War Project (COW).

FIGURE 4. Trade Openness in Latin American Countries 1970-2009



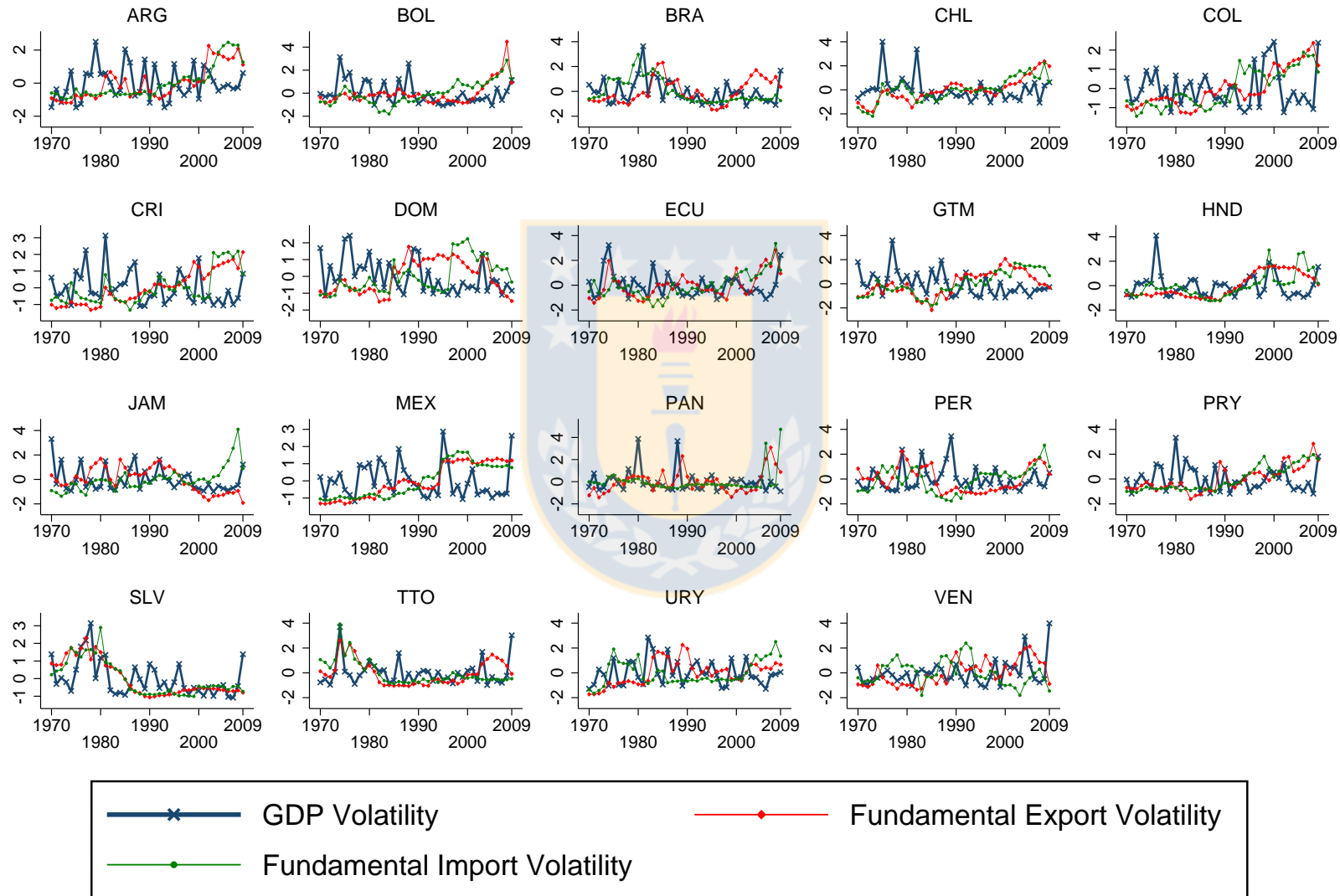
Note: Data for exports and imports were obtained from the Correlates of War Project (COW). GDP data was obtained from the PWT v7.1.

FIGURE 5. Evolution of Trade between Latin American Countries



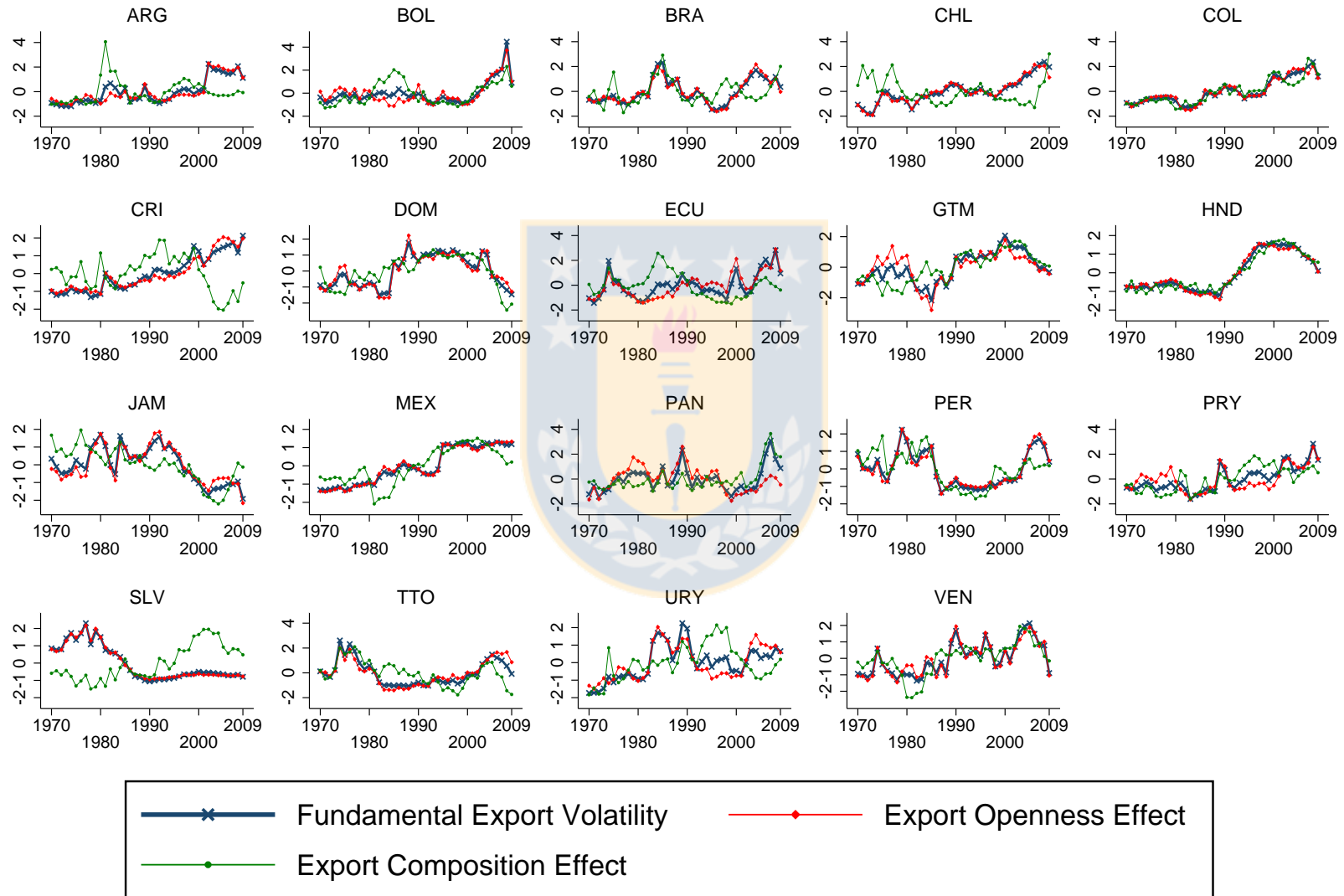
Note: Data was obtained from the Correlates of War Project (COW).

FIGURE 6. Fundamental Volatility and Volatility



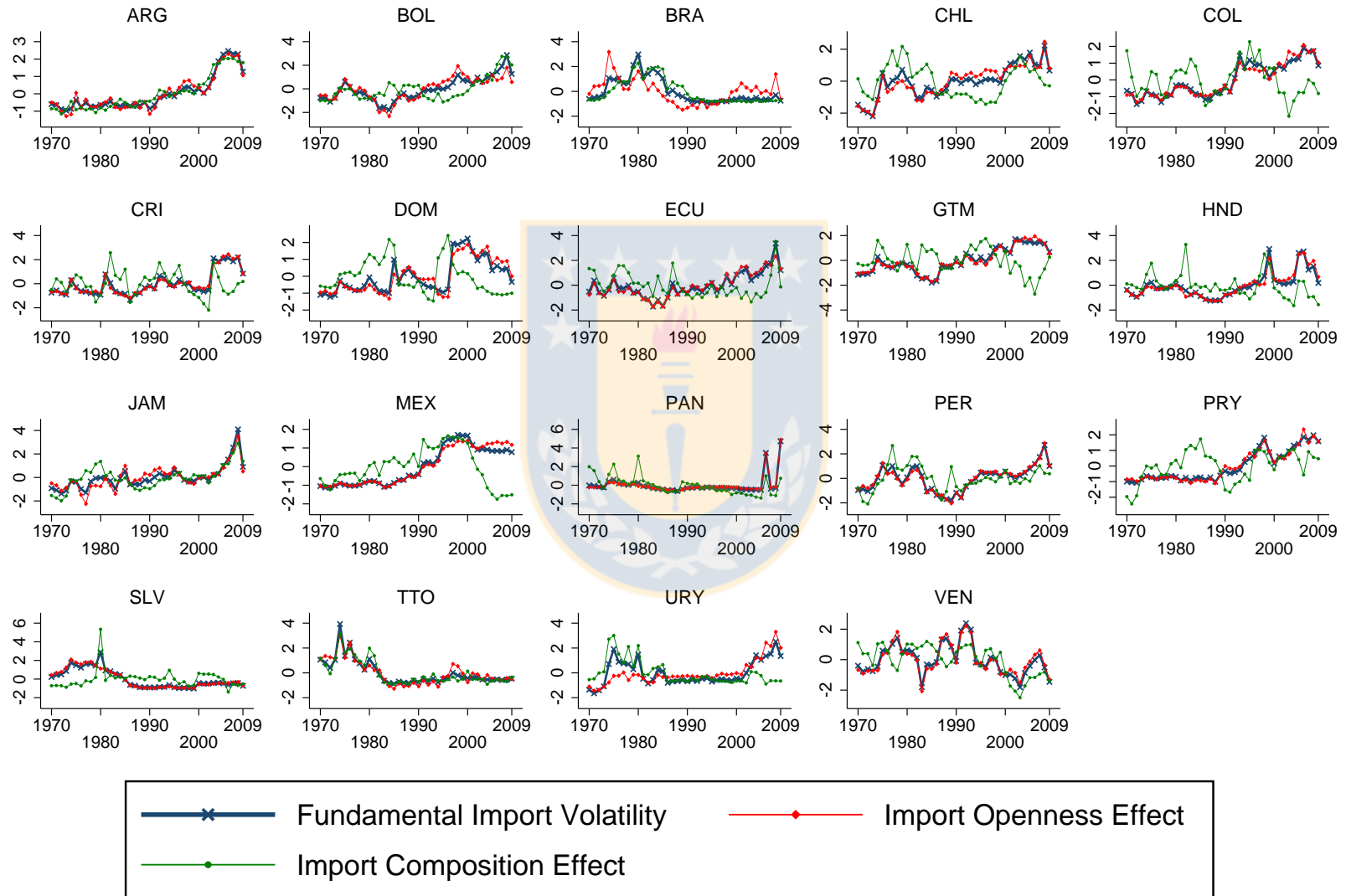
Note: Data for exports and imports were obtained from the Correlates of War Project (COW). GDP data was extracted from the PWT v7.1. GDP Volatility is presented as the standard deviation of the GDP growth rate. All variables are standardized with zero mean and unit standard deviation.

FIGURE 7. Fundamental Export Volatility Decomposition



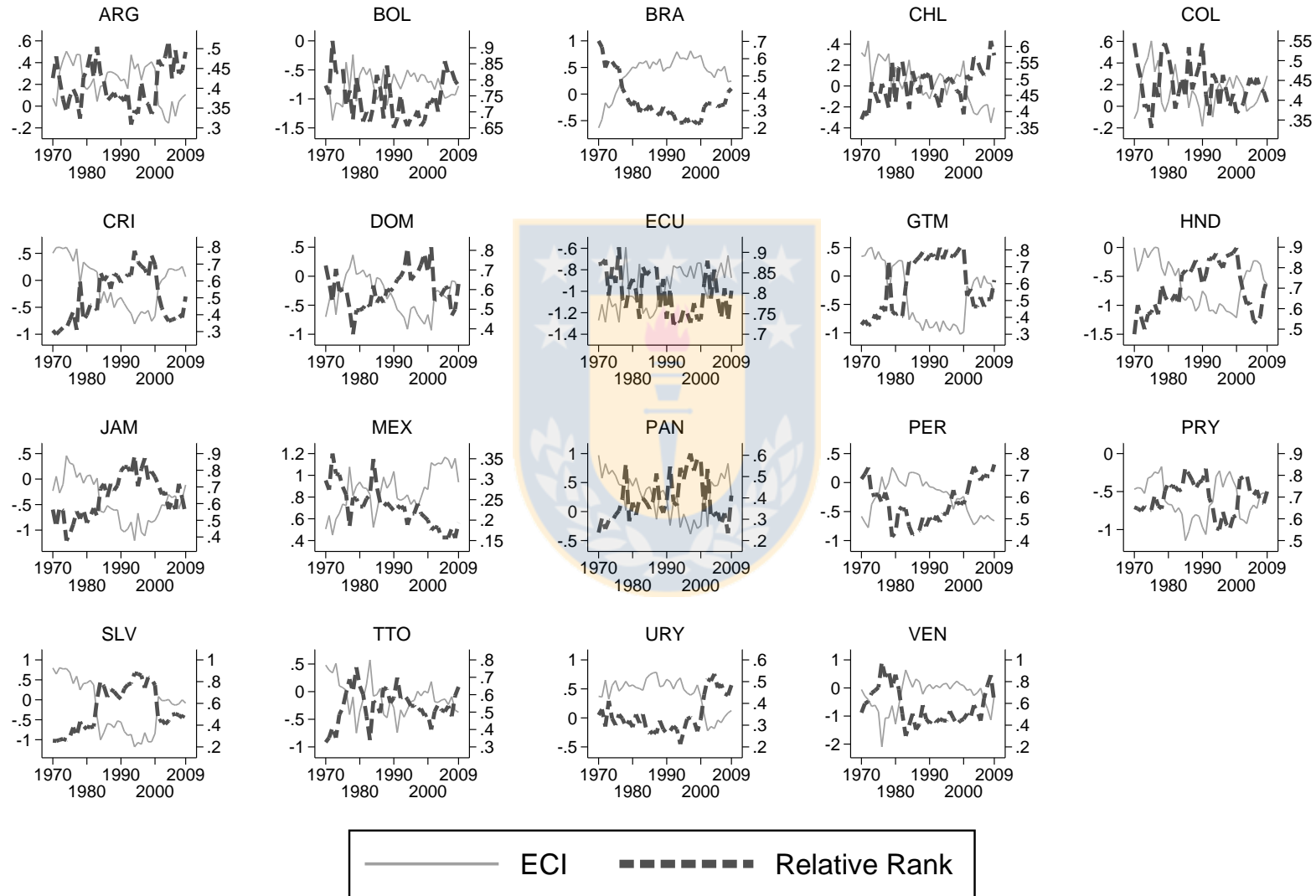
Note: Data for exports and imports were obtained from the Correlates of War Project. GDP data was extracted from the Penn World Table Database v7.1.

FIGURE 8. Fundamental Import Volatility Decomposition



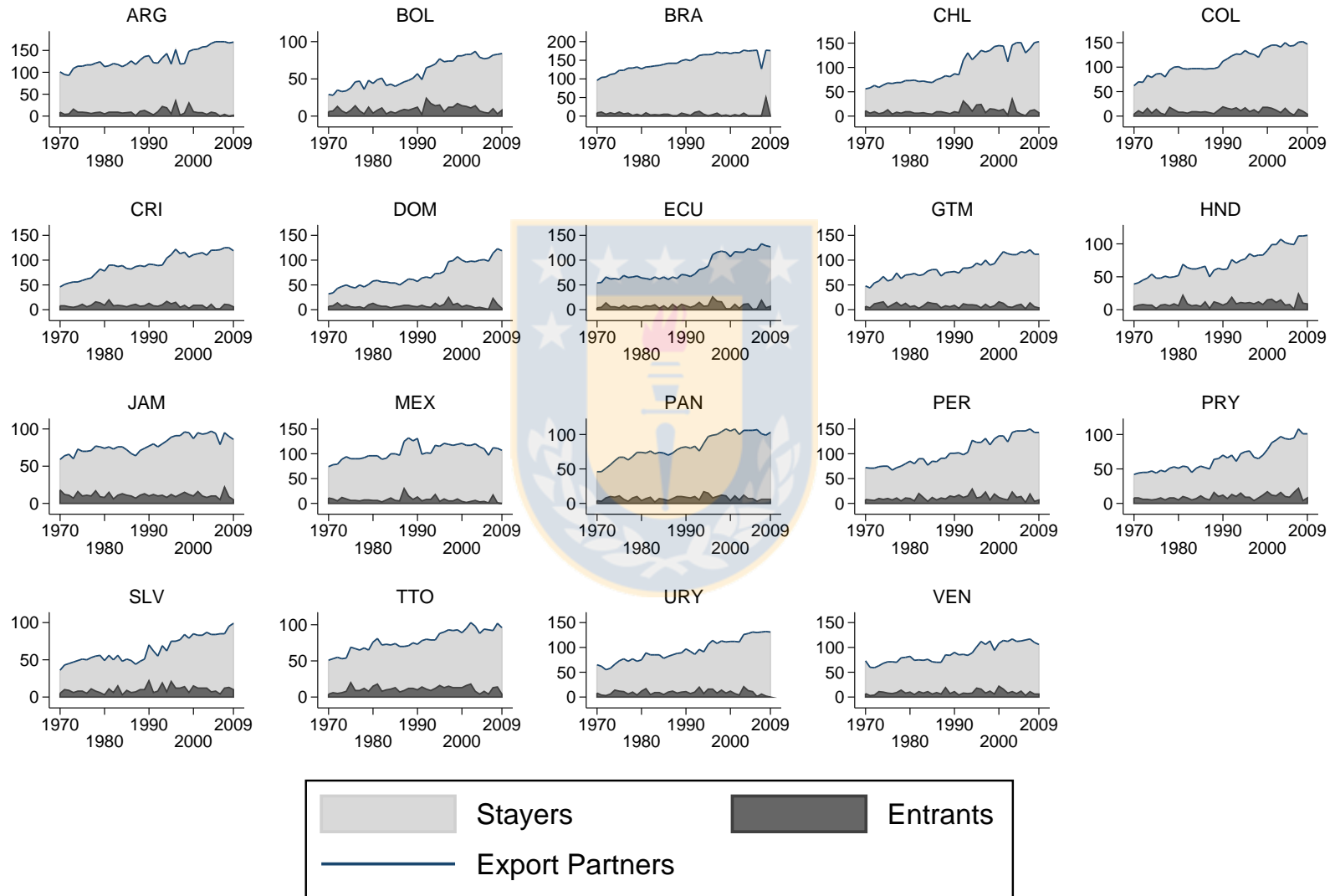
Note: Data for exports and imports were obtained from the Correlates of War Project. GDP data was extracted from the Penn World Table Database v7.1.

FIGURE 9. Economic Complexity Index and Relative Rank



Note: Data was extracted from the Observatory of Economic Complexity (OEC). Left axis correspond to the ECI scale, while the right axis belong to the relative rank.

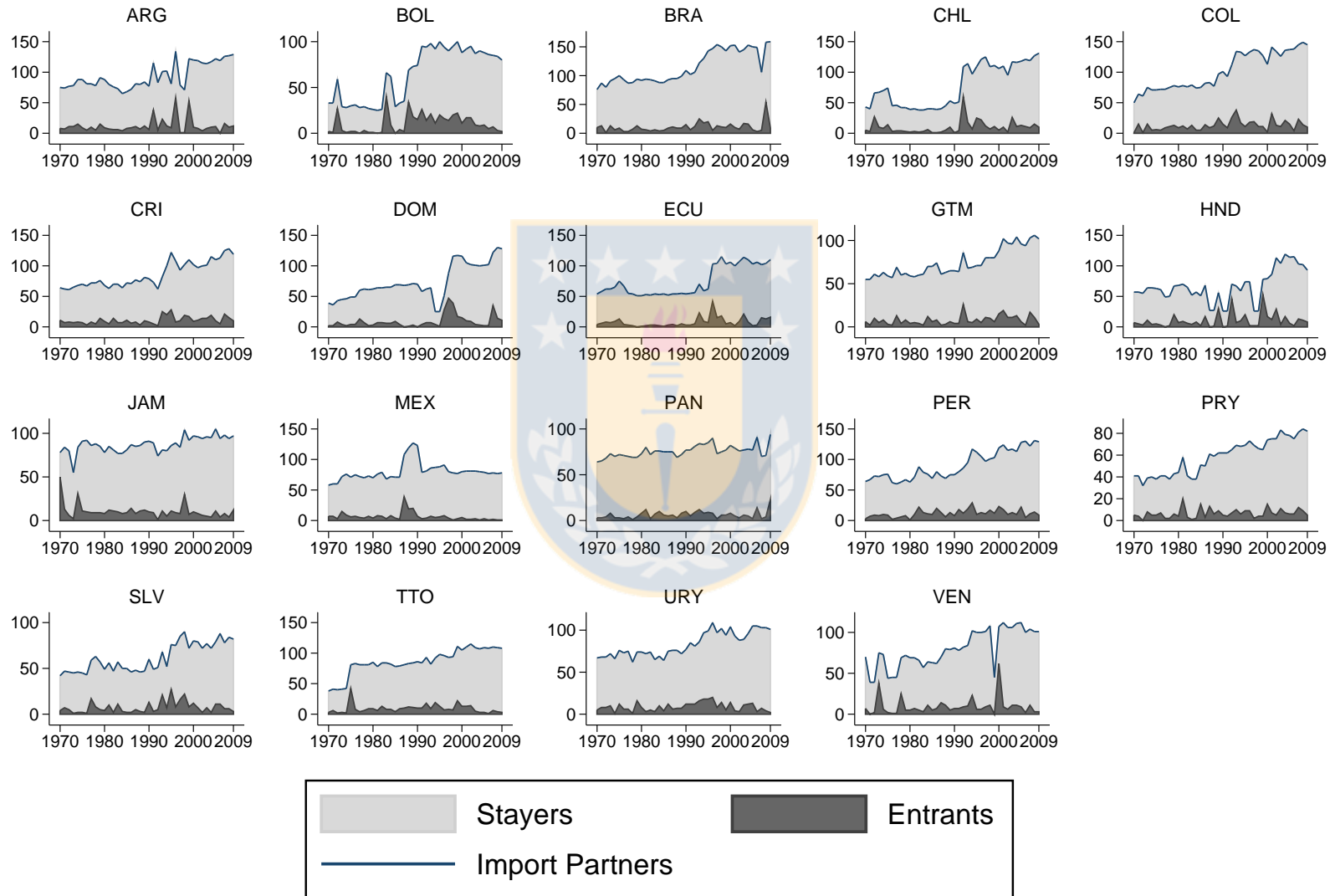
FIGURE 10. Export Partners and Composition



43

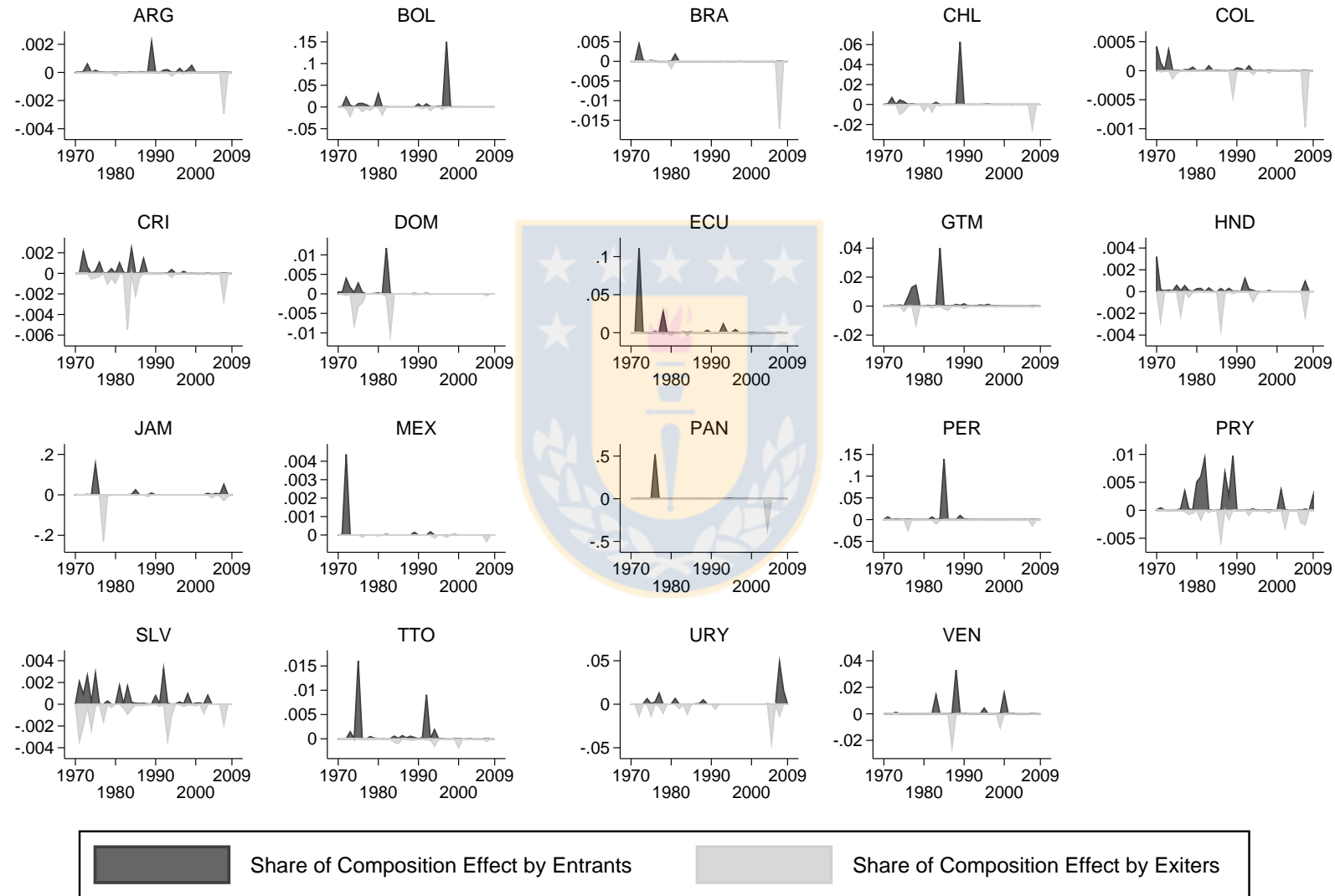
Note: Data for exports and imports were obtained from the Correlates of War Project (COW).

FIGURE 11. Import Partners and Composition



Note: Data for exports and imports were obtained from the Correlates of War Project (COW)

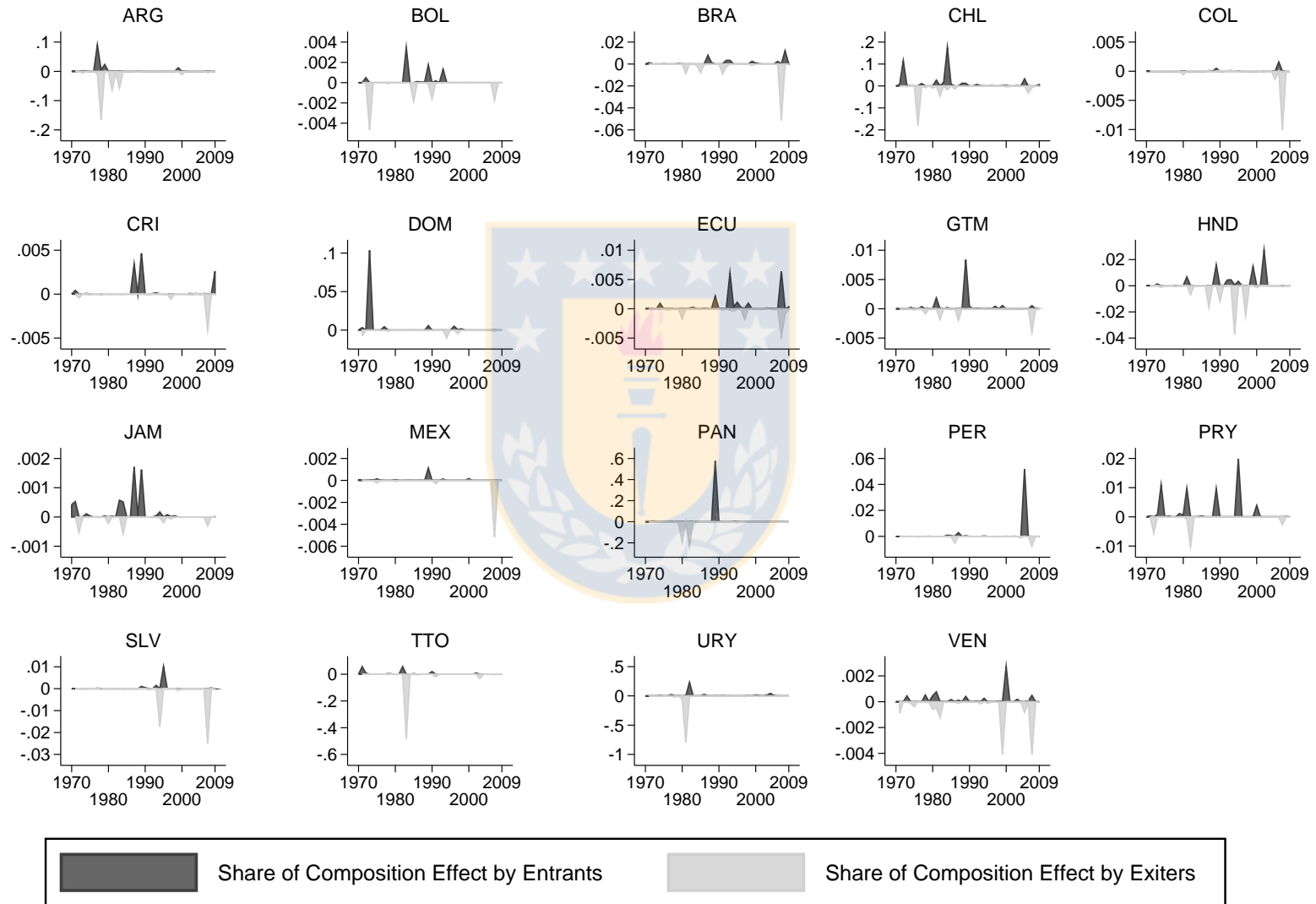
FIGURE 12. Share of Export Composition Effect by Entrant and Exiters



45

Note: Data for exports and imports were obtained from the Correlates of War Project. GDP data was extracted from the Penn World Table Database v7.1.

FIGURE 13. Share of Import Composition Effect by Entrant and Exiters



Note: Data for exports and imports were obtained from the Correlates of War Project. GDP data was extracted from the Penn World Table Database v7.1.