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Abstract

Traditionally, the US has been the major trading and financial partner of Latin America. However, since 2000 it has lost its hegemony in the region due to China's growing influence. In particular, China has emerged as a source of capital for Latin America integrating financial markets and, in turn, paving the way for volatility transmission. Using Heterogeneous ARDL models for range volatility, we study volatility transmission from the US and China to six main Latin American stock markets at different horizons (short-run and long-run). Although the US volatility spillover has decreased over time, it is still more relevant than that of China. This finding remains after controlling for commodity price volatility. The dynamic patterns of both the US and Chinaâs volatility spillovers can help investors to make more informed portfolio management decisions, and policymakers to monitor financial stability in the region.

JEL Classification	:	C22, C58, F36, G15
Keywords	:	Volatility transmission, range volatility, ARDL models, China, Latin America.

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1 Introduction

The economic and financial linkages between the two major global economies, the US and China, and Latin America have changed notoriously since 2000. Not only China has become the main trade partner of several Latin American countries, but it has also emerged as an important source of external funding to the region. Chinese financial flows take many forms, namely, foreign direct investment, portfolio investment, cross-border bank allocations, and official loans to governments (Horn et al., 2021). Such exchanges have an integrating effect between the financial markets of the Asian juggernaut and Latin American countries, that in turn tends to increase the exposition of these emerging markets to Chinese financial shocks. Thus, in this context of integration, it is important for investors, portfolio managers, and policymakers to know whether the volatility is transmitted from China to Latin America, and whether it is stronger than that originated in the US. Furthermore, it is also worth inquiring whether this transmission of volatility to the region's stock exchanges happens all at once or manifests itself sluggishly over time. These questions are the main focus of our study.

In the financial literature, spillovers are understood as the relation between returns or volatilities and information flows. That is, how specific information from one market changes the return or volatility of an asset in another market (Fleming et al., 1998). The nature of the process through which information propagates is referred to as channels of transmission. According to the IMF (2019), there are mainly three such channels to emerging markets such as Latin America. The first one is trade as the US and China are key trading partners for the region (see Saldarriaga and Winkelried, 2013). Since Latin American economies rely heavily on commodity exports, and the US and China are the largest consumers of commodities, the second channel is commodity prices (see Gauvin and Rebillard, 2018). The last one is financial flows, which we believe has not been sufficiently studied in the literature. Thus, our goal is to help bridging this gap with an exploration of the volatility transmission from the US and Chinese stock markets to the Latin American's.

To that end, we compute price range volatility estimators for the stock market indices of the US, China, and the main Latin American economies (Argentina, Brazil, Chile, Colombia, Mexico, and Peru), and then estimate dynamic equations to unveil how volatility transmits from the large markets to the smaller ones.[1] Methodologically, we follow Corsi (2009) and Jung and Maderitsch (2014) to propose a Heterogeneous Autoregressive Distributed Lag (HARDL) model of volatility series to explore volatility spillover effects at different time horizons (daily, weekly, and monthly). In particular, we are interested in heterogeneous short-run and long-run effects that can be easily tackled in our setup, but are difficult to implement in other methods used in the literature such as the multivariate GARCH models or the Diebold and Yilmaz (2009) approach (see section 2 below). Our sample includes two global shocks – the Global Financial Crisis (GFC) and the outbreak of the COVID-19 pandemic – and two local shocks with potential global consequences – the Chinese stock market crash in 2015 and the US presidential election in 2016. Thus, we pay special attention to the dynamics of volatility spillovers during these events.

We contribute to the growing literature on volatility spillovers from major economies to emerging markets in three ways. First, although previous literature has investigated volatility spillovers from

1 Degiannakis and Livada (2013) show that range measures of volatility are superior to realized volatility at a relatively low sampling frequency (for instance, daily). One of the most popular explanation is that market microstructure noise produces biased estimates of realized volatility (Martens and Van Dijk, 2007).

either the US or China to emerging markets (see section 2), their simultaneous effects on Latin America have not been studied yet. Second, due to the different degrees of interconnection between Latin American economies and the US and China, we provide a comparison of volatility spillovers in both the short-run and long-run. By formally decoupling volatility transmission into short-term and long-term factors, we show commonalities of risk contagion during global shocks (periods of high uncertainty). Finally, while there is evidence of volatility transmission from the US to the region in the past (see, *inter alia*, Chen et al., 2002), the recent evidence is limited.

We provide evidence that the US stock market volatility passes through the volatility in Latin American stock markets quickly and strongly. This is not true for the Chinese stock market volatility, even though we do find some significant short-run effects for some of the countries in our sample. Another interesting finding is related to the cumulative effects of volatility transmission. We find significant long-run volatility transmission from the US, especially over periods of turmoil such as the GFC. On the contrary, the evidence of long-run volatility transmission from China is weak.

Our results suggest that even though China's financial ties to Latin America has strengthened, stock price fluctuations from China are not strongly transmitted to the region yet. Indeed, the US remains a much more important player than China for financial stability in Latin America. Hence, local policymakers should monitor the dynamics of the US stock market volatility since it amplifies volatility risk in the region. Moreover, the heterogeneous propagation of volatility shocks from the US and China has clear practical implications for portfolio diversification decisions, and futures and options pricing. For instance, large swings in American equity prices can increase the volatility of a diversified portfolio composed of only Latin American stock markets. A similar argument can be made for China's short-run price fluctuations.

The remainder of this paper is organized as follows. Section 2 reviews the related literature on the economic and financial linkages between China and Latin America, and on the measurement of financial contagion and interdependence. Section 3 discusses methodologies issues on the computation of volatility from stock market data, and describes the HARDL model. Section 4 presents the data, the estimation results and our main findings, along with some robustness checks. Section 5 concludes and discusses some topics for future research.

2 Related literature

This section presents a bird's eye view of the literature on the topics of interest for this study: the economic and financial linkages between China and Latin America, and the methods used to assess financial contagion.

2.1 China and Latin America

The first two decades of the century witnessed the reallocation of world output and demand from industrial countries to emerging markets, along with the redirection of world savings, providing international resources to emerging economies. In this context, China emerged as a relevant actor in the global scene.

The China influences Latin American markets mainly through three channels. The first one is trade. It has been widely documented (see, *inter alia*, Cesa-Bianchi et al., 2012; Feldkircher and Korhonen,

2014) that China has become the main export destination for countries such as Brazil, Chile and Peru, and a quite relevant trade partner for the rest of the region, displacing traditional partners such as Japan and several European countries. As a result, a shock to Chinese output transmits strongly and relatively fast to Latin America GDP growth.

The second channel is commodity prices, which is related and reinforces the trade channel. China's demand for international commodities is capable of producing commodity prices super-cycles, i.e., sustaining high prices above their trends for decades (see Winkelried, 2018). The latter helps to synchronize the business cycle among emerging economies, especially commodity exporter countries. Saldarriaga and Winkelried (2013) show that whereas business cycles in Latin America and China have become increasingly correlated, they appear to have decoupled from those of advanced countries, a process that was particularly notorious with the fast recovery of the region after the GFC.

The third channel is financial. Initially, the academic interest was on whether China as a recipient of resources crowded out other emerging markets (see Resmini and Siedschlag, 2013). Now, however, the interest has shifted to the influence of China as an investor or creditor. As stressed by Wise (2020), since the GFC, the presence of Chinese capital in the region has increased considerably following a strategic vision of the Chinese government and investors for relevance and collaboration with Latin America. At the same time, Chinese resources give Latin American countries more leverage when negotiating with traditional partners, such as the US or the European Union, or multilateral organizations.

Avendano et al. (2017) and ECLAC (2021) provide a detailed account of one of the main means of Chinese financial involvement in the region: foreign direct investment (FDI). This type of investment has been done mostly through mergers and acquisitions, but also through the development of new projects, construction contracts and concessions. The largest investments have been made in mining, energy and transport infrastructure, though a recent interest in sectors related to the development of technology is apparent. Furthermore, the Chinese companies investing most heavily in the region are state-owned and under the supervision of the State-owned Assets Supervision and Administration Commission of the State Council (SASAC). It is estimated that by the early 2020s between 3 to 5 percent of the total FDI inflows to Latin America came from China.[2]

On the other hand, Horn et al. (2021) argue that China is nowadays the largest official bilateral creditor in the world and its presence is particularly strong in low-income countries, where Chinese lending flows can exceed those from multilateral creditors. According to Gallagher and Myers (2022), loans from Chinaâs policy banks – mainly, the China Development Bank and China Export-Import Bank –, to Latin American and Caribbean governments and state-owned enterprises have amounted to US$ 130 billion (US$ 75 billion excluding Venezuela) from 2005 to 2021, out of US$ 300 billion globally. Contrary to other official lending, the authors state that this type of China's funding has mainly political motivation, which in turn offers different interest rate and maturity. Kaplan (2021)

2 Estimations of the Chinese FDI flows to Latin America vary widely from source to source. Sadly, not all countries in the region register the country of origin of their FDI, and according to Avendano et al. (2017) and Wise (2020) there is a large under-reporting of the Chinese official data. Many Chinese firms make their investments overseas through other financial centers (Hong Kong, Macao, Cayman Islands or British Virgin Islands) and the share of Chinaâs investment entering the region through tax havens can be as high as 80 percent. See Dussel Peters (2021) for valuable resources and data on this matter.

offers a detailed account on the latter topic and its influence in the public finance of the debtor countries.

To get a sense of magnitude, Figure 1 shows the evolution of two indicators of closeness between China and our sampled Latin American countries. Panel (a) of Figure 1 shows the trade interlinkages between China and Latin America, which is calculated as the sum of exports to China and imports from China, as a percentage of GDP. These commercial ties have increased from 2000 to 2020 in all countries, although in a heterogeneous manner. For instance, the trade closeness measure has increased ten times in Colombia and 5 times in Brazil. Moreover, during the 2015-2020 period, this indicator is almost 10 percent in Peru, while it is about 14 percent in Chile. These are the underlying developments behind the increased Chinese influence thorough the trade channel in studies such as Feldkircher and Korhonen (2014).

On the other hand, panel (b) of Figure 1 refers to financial closeness as measured by the turnover of the Chinese companies in the recipient countries, which is a proxy on the profitability of the Chinese foreign direct investment in these countries, scaled by the total gross capital formation. The increase in this measure is also pervasive and heterogeneous: threefold in Peru, sixfold in Chile and fifteen fold in Brazil. Arguably, despite the growth, the absolute values of the ratios by the end of the period are not always economically significant, with Peru and Chile being possible exceptions. We enquire whether these links are in practice strong enough to open a channel of volatility transmission from the Chinese to the Latin American financial markets. To the best of our knowledge, we are the first study to perform this task.

2.2 Contagion and interdependence

Financial market interdependence – i.e., how financial markets interact with each other, how they respond to common news or how one influences the other – is a hot topic in international finance that has been widely studied on theoretical and empirical grounds. The interest in concepts such as contagion or interconnections often renews after a financial crises, so the most important recent developments bulk around the early 2000s, after the burst of the dot-com bubble, and after the GFC.

Curiously, there is no consensus on important definitions such as contagion. For instance, Allen and Gale (2000) defined the phenomenon as the spread of small shocks originating from one market to another market.

Another definition is based on the dynamics of the correlation coefficient and, therefore, the terms “interlinkages”, “relations” and “interdependence” can be used interchangeably. The seminal papers of Baig and Goldfajn (1999) and Calvo and Mendoza (2000) consider contagion as a significant increase in the correlation between two stock market returns. Forbes and Rigobon (2002) stated that the co-movement between two markets is different under extreme conditions (market turmoil) compared with in normal times, and is considered a contagion only if the correlation rises significantly after controlling for variances; the so-called shift-contagion. Recently, Kallberg and Pasquariello (2008), Bekaert et al. (2009), and Baele and Inghelbrecht (2010), defined contagion as excess correlations; that is, when the correlation coefficient is above what economic fundamentals predict.

Another strand of the literature defines contagion in terms of volatility transmission or volatility spillovers among financial markets. For instance, Dimpfl and Jung (2012) provide evidence that volatility spillovers among the Dow Jones Euro Stoxx 50, the Standard & Poorâs 500 and the Nikkei

225 are more pronounced and persistent. Likewise, Jung and Maderitsch (2014) find that volatility spillovers among stock markets in Hong Kong, Europe and the US experienced structural breaks. In a similar vein, Buncic and Gisler (2016) show that US stock market volatility information improves the out-of-sample forecasts of realized volatility in 17 foreign stock markets.

Within the empirical literature, multivariate GARCH models have become popular among the methods to assess financial contagion, both in developed and emerging markets. For instance, Chiang et al. (2007) study nine Asian stock markets and find two phases during the Asian crisis: in the first, there was evidence of shift-contagion, while in the second the high correlation indicates herding behavior. Using a similar multivariate framework, Celık (2012) tests the existence of financial contagion between foreign exchange markets during the GFC and unveils contagion effects on most of the emerging and developed markets. By the same token, Hwang et al. (2013) study the comovements of stock markets among the US and ten emerging economies also during the GFC. They find that Korea, Taiwan, and Thailand exhibited three distinctive phases of crisis spillover (contagion, herding, and post-crisis adjustment), while the other markets showed different phases of crisis spillover. Likewise, Hemche et al. (2016) find an increase in dynamic correlations for most of the ten developed and emerging stock markets (France, Italy, UK, Japan, China, Argentina, Mexico, Tunisia, Morocco, and Egypt) with respect to the US market. More recently, Tilfani et al. (2021) provide evidence of shift-contagion between the US and eight economies: the correlations between the US stock index and the other stock indices were relatively low before the GFC, but they significantly increased thereafter.

Regarding Latin America, Cardona et al. (2017) also estimate GARCH models over the 1993-2013 period and find strong evidence of volatility transmission from the US to Argentina, Brazil, Chile, Colombia, Mexico and Peru, but not in the opposite direction. Applying the same technique, Yousaf et al. (2020) examine return and volatility spillovers between two big global markets (the US and China) and four Latin American stock markets during the GFC and the Chinese stock market crash in 2015. They find bidirectional volatility transmission between the US and the Chilean and Mexican stock markets during the GFC, whereas they provide evidence of bidirectional volatility transmission between the US and Mexican stock markets during the Chinese crash.

Another popular method to assess contagion is advanced in Diebold and Yilmaz (2009, 2012) and does not rely on GARCH methods; instead, it uses simple linear models applied to previous estimates of volatility. Gamba-Santamaria et al. (2017) explore volatility transmission between the US and and four Latin American stock markets, and identify Brazil as a net volatility transmitter, and Chile, Colombia and Mexico as net receivers. Similarly, McIver and Kang (2020) find that, following the beginning of the GFC, the US, Brazilian, and Chinese markets are net volatility transmitters, whereas the Russian, Indian, and South African markets are net recipients. Li (2021) studies the asymmetry in volatility spillovers among the US, Japan, Germany, the UK, France, Italy, Canada, China, India, and Brazil from 2009 to 2020. The author finds that developed markets are the main risk transmitters, whereas emerging markets are the main risk receivers. Similarly, Li et al. (2021) examine the impact of the COVID-19 pandemic on G20 stock markets, and find that developed markets are the main spillover transmitters, and emerging markets are the main spillover receivers.

Other less popular methods have been applied to study volatility spillovers. For instance, Chen et al. (2002) use error correction models to examine the dynamic interdependence of the major Latin American stock markets in the late 1990s. See also Diamandis (2009).

3 Methodological discussion

This section describes the methods to compute daily volatility from various realizations of the stock market indices within a given trading day. Then, it focuses on the framework for dynamic regression equations and, therefore, on the causal inference procedures to assess volatility transmission across international stock markets.

3.1 Range volatility

Return volatility is a non-observable risk measure of asset prices that plays an important role in risk management decisions and asset allocation, and is also a key parameter for pricing financial derivatives. Stock market volatility can be measured using information from the maximum and minimum values of the stock market indices reported within a day in a stock exchange. As discussed in Garman and Klass (1980) and more recently in Alizadeh et al. (2002), Molnár (2012) and Chou et al. (2015), apart from simplicity, range volatility (RV) methods can render more accurate and considerably more efficient ex-post estimates of the daily return variation than alternative approaches based exclusively on closing prices. The underlying assumption is that volatility is fixed within a day but can vary across days.

Consider the opening (O_t), highest (H_t), lowest (L_t), and closing (C_t) levels of a stock exchange index in day t, and define the logarithm of these indices normalized by the opening level as $h_t = \ln(H_t/O_t)$, $l_t = \ln(L_t/O_t)$ and $c_t = \ln(C_t/O_t)$. The simplest range estimator of volatility is $V_t = (h_t - l_t)^2/(4\ln(2))$, and the so-called Garman and Klass (1980) estimator is:

$$V_t = 0.511(h_t - l_t)^2 - 0.019[c_t(h_t + l_t) - 2h_t l_t] - 0.383(c_t)^2 . \tag{1}$$

This is our preferred measured of volatility, expressed in annualized terms (multiplied by 252, the number of trading days in a year).

3.2 Autoregressive distributed lag models, estimation and inference

To study the transmission of volatility from the US and Chinese stock markets to the Latin American stock markets, we estimate transfers functions within an autoregressive distributed lags (ARDL) model, as advanced in Pesaran and Shin (1999), surveyed in Hassler and Wolters (2006) and used in Jung and Maderitsch (2014) to study volatility spillovers.

Let y_t be a measure of volatility in one Latin American stock market, and x_t be a vector that includes the volatility of the US and Chinese stock markets. An ARDL model of y_t and x_t is a dynamic equation in which the effects of the regressors x_t on y_t manifest themselves over time:

$$y_t = \alpha_1 y_{t-1} + \alpha_2 y_{t-2} + \ldots + \alpha_p y_{t-p} + \beta_0 x_t + \beta_1 x_{t-1} + \beta_2 x_{t-2} + \ldots + \beta_q x_{t-q} + \varepsilon_t , \tag{2}$$

where $p, q \geq 0$ and ε_t is a serially uncorrelated white noise. Equation (2) may include an unrestricted intercept that we omit to ease the notation.

Let L be the lag operator such that $L^k y_t = y_{t-k}$ for $k = 0, 1, 2, \ldots$. Define the polynomials $A(z) = 1 - \alpha_1 z - \alpha_2 z^2 - \ldots - \alpha_p z^p$ and $B(z) = \beta_0 + \beta_1 z + \beta_2 z^2 + \ldots + \beta_q z^q$, so the ARDL model in equation (2) can be rewritten compactly as $A(L)\, y_t = B(L) x_t + \varepsilon_t$. The transfer function of the ARDL is given by the (coefficients of the) polynomial $B(L)/A(L)$ and captures all the dynamics features of this model.

For brevity, we will focus on the ends of this function, namely the effect on impact $B(0)/A(0) = \beta_0$ and the so-called long-run multiplier, LRM = $B(1)/A(1) = (\beta_0 + \beta_1 + \cdots + \beta_q)/(1 - \alpha_1 - \cdots - \alpha_p)$. Since news transmit quickly from one financial market to the other, both quantities provide a good summary of the entire transfer function for our empirical application below. The standard error for the long-run multiplier can be computed using the delta method.

As discussed in Pesaran and Shin (1999), the OLS estimator of the coefficients in equation (2) is consistent under two conditions. First, x_t should be exogenous in the sense that cov $(\varepsilon_t, x_s) = 0$ for $t \geq s$, i.e,. the determination of y_t does not feedback into the determination of x_t. This assumption seems uncontroversial in this study as we do not expect news in the Latin American stock markets to affect systematically and significantly the volatility of larger stock markets - those of the US and China.[3] An additional implication of this condition is that the single equation approach based on equation (2) renders estimators as efficient as those based on a multiple equation setup. The second condition is that the ARDL equation is dynamically well-specified, i.e., p and q are chosen such that the residuals mimic the behaviour of the white noise ε_t, which can be tested with residual adequacy tests for the absence of serial correlation.

Oftentimes, stock market volatility tends to be persistent and may contain unit roots (see, *inter aia*, Wright, 1999; Gavala et al., 2006). Hence, it is worth enquiring whether such nonstationarity affects the properties of the standard inferential procedures based on the OLS estimation of equation (2) and the asymptotic normal approximation of the estimators. Pesaran et al. (2001) develop a bound tests to answer such a question. They consider the t-statistic of the null hypothesis $H_0 : A(1) = 0$ and show that if it is higher (in absolute value) than an upper bound, then the standard procedures apply regardless of whether the series in the ARDL model are integrated or not. The bounds provided by Pesaran et al. (2001, Table CII, Case III, p. 303) are stringent: at a 1% (2.5%) confidence level, it is 4.10 (3.80) when x_t contains two regressors and 4.37 (4.05) when x_t contains three regressors.[4]

3.3 Parsimony and heterogeneous effects through time

We follow Jung and Maderitsch (2014) and incorporate a clever device advanced in Corsi (2009) to render a parsimonious, more transparent and easier to interpret ARDL model. In particular, to model the autoregressive behavior of persistent volatility series, Corsi (2009) proposes an additive cascade of partial volatilities from high frequencies (usually one day) to low frequencies (usually one month). The multiple components in the volatility structure can be motivated by institutional structures, information flow, differences in agentsâ risk profiles, or differences in temporal investment horizons. As volatility components are defined over different time horizons, the approach is referred to as Heterogeneous Autoregressive (HAR) model of volatility.

3 Due to time zone differences, the interpretation of the impact multiplier may change slightly. Since the US shares the same time zone with most of Latin America, β_0 is readily interpreted as an immediate, simultaneous effect. On the other hand, stock exchanges in China close before those in the Western Hemisphere open, so β_0 is a lagged effect but with a lag of less than a day, still interpretable as a short run effect. In any case, the weak exogeneity of the regressors remains a reasonable assumption. See Jung and Maderitsch (2014) for further discussion of time zone effects.

4 Pesaran et al. (2001) also discuss an F-test for $H_0 : B(1) = 0$. We do not report the results of this test here since they did not contradict in any case the conclusions of the t test.

Define the averages:

$$Y_t^h = \frac{1}{n_h}\sum_{i=0}^{n_h-1} y_{t-i} \qquad \text{and} \qquad X_t^h = \frac{1}{n_h}\sum_{i=0}^{n_h-1} x_{t-i}. \tag{3}$$

The index h defines the horizons: $h = d$ is daily, $n_d = 1$ and $Y_t^d = y_t$ trivially (similarly with x_t); $h = w$ is weekly with $n_w = 5$ trading days; and $h = m$ is monthly with $n_m = 21$ trading days. Based on these definitions, we consider the Heterogeneous ARDL (HARDL) model:

$$y_t = \alpha_d Y^d_{t-1} + \alpha_w Y^w_{t-1} + \alpha_m Y^m_{t-1} + \beta_0 x_t + \beta_d X^d_{t-1} + \beta_w X^w_{t-1} + \beta_m X^m_{t-1} + \varepsilon_t. \tag{4}$$

Note that the HARDL model is a rather rich ARDL model of the $A(L)y_t = B(L)x_t + \varepsilon_t$, with $p = q = n_m = 21$ and:

$$A(z) = 1 - \alpha_d z - \alpha_w \left(\frac{1}{n_w}\sum_{i=1}^{n_w} z^i\right) - \alpha_m \left(\frac{1}{n_m}\sum_{i=1}^{n_m} z^i\right). \tag{5a}$$

$$B(z) = \beta_0 + \beta_d z + \beta_w \left(\frac{1}{n_w}\sum_{i=1}^{n_w} z^i\right) + \beta_m \left(\frac{1}{n_m}\sum_{i=1}^{n_m} z^i\right). \tag{5b}$$

Despite the large lag lengths, parsimony is achieved by restricting the coefficients in (2) to be equal within a window (weekly or monthly). The latter implies that the coefficients in the polynomials $A(z)$ and $B(z)$ are step functions of z.[5] Yet the transfer function can still adopt a wide range of forms, so little flexibility is lost with the added parsimony.

Of course, our previous discussion on estimation and statistical inference applies to the HARDL model. The impact effect is still $B(0)/A(0) = \beta_0$ and the long-run multiplier simplifies to LRM $= B(1)/A(1) = (\beta_0 + \beta_d + \beta_w + \beta_m)/(1 - \alpha_d - \alpha_w - \alpha_m)$.

In sum, for the purpose of our study we propose dynamic equations in the spirit of Corsi (2009), Jung and Maderitsch (2014) and Buncic and Gisler (2016) to assess volatility spillovers from the US and Chinese stock markets to Latin American stock markets, at different horizons. We seek to examine the cascade effect, and the short-term and long-term impact of volatility series from the two world giants to the region. There are other techniques to study contagion, such as the Diebold and Yilmaz method or multivariate GARCH models, but they are not aligned with the purposes of this study as they do not offer the cascade effect analysis as needed.

4 Empirical analysis

This section shows the results of the paper. We first describe the data used in our empirical work. Then, we present baseline results on the estimation of the HARDL model of volatility transmission across stock markets. Next, we study and discuss the stability of the estimated coefficients, that is, the stability of volatility spillovers. Finally, we present the dynamics of volatility transmission and some robustness checks.

5 Consider the polynominal $B(L)$ in (2) and in (4). The treatment for $A(L)$ is similar. The coefficient β_0 is the same in both equations, $\beta_1 = \beta_d + \beta_w / n_w + \beta_m / n_w$, $\beta_i = \beta_w / n_w + \beta_m / n_m$ for $i = 2, \ldots, n_w$ and $\beta_i = \beta_m / n_m$ for $i = n_w + 1, \ldots, n_m$.

4.1 Data

The dataset consists of indices for the American, Chinese and Latin American stock markets, all of them extracted from the Bloomberg database. The selected indices are: Mercado de Valores (MERVAL) for Argentina, Bolsa de Valores, Mercadorias & Futuros de Sao Paulo (BOVEPSA) for Brazil, Indice de Precio Selectivo de Acciones (IPSA) for Chile, Indice de la Bolsa de Valores (COLCAP) for Colombia, Indice de Precio y Cotizaciones (IPC) for Mexico, Indice General de la Bolsa de Valores de Lima (IGBVL) for Peru, the Standard & Poorâs 500 index (SP500) for the US, and the Shanghai Composite Index (SHCOMP) for China. Commodity prices or indices were also sourced from Bloomberg: soybean oil (BCOMBO), iron ore (IOE1), copper (LMCADS03), and oil (CL1).

We use intraday data for each stock index from January 4, 2000 to December 30, 2020: open, close, high, and low. With the exception of Colombia, the data spans a 20-year window that contains, after accounting for non-trading days, about 5,218 observations. In the Colombian case, the COLCAP index was inaugurated on January 5, 2008, which reduces the number of observations reduces to 3,380.

The Latin American stock markets studied in this document are the most liquid and largest in terms of market capitalization in the region. As of December 2021, all these markets represent 98% of the total market capitalization in Latin America and the Caribbean.

4.2 Baseline results

Consider range-based volatility estimators as described in equation (1). In particular, we use $y_t = \log(V_t)$, which is a common transformation, so the HARDL models are log-linear equations and the dynamic multipliers can be interpreted as elasticities. The treatment for x_t is similar. We entertain an alternative transformation of V_t later in section 4.5.

Table 1 shows the results of the OLS estimates of equation (4). The equations have a good fit, with the adjusted R^2 ranging from 0.35 to 0.50, and display no first-order serial correlation in the residuals: the Breusch-Godfrey statistic (line “BG”) is in all cases comfortably less than its asymptotic critical value of 3.84. Other testing procedures confirm this conclusion, which is no surprising as the HARDL model has an extensive structure from a dynamic viewpoint.

The autoregressive coefficients (daily α_d, weekly α_w, and monthly α_m), which are also the coefficients of the heterogeneous own-volatility components, are very precisely estimated, i.e., significant at a 1% confidence level, for all instances. This explains the lack of correlation in the residuals. More importantly, the estimates of $A(1)$ are also statistically different from zero ($H_0 : A(1) = 0$), with large t-statistics for all equations: Argentina (6.46), Brazil (9.06), Chile (8.15), Colombia (8.28), Mexico (8.07), and Peru (8.43). All these values are well above the bound of 4.10 provided by Pesaran et al. (2001), so we conclude that the inference based on the normal approximation of the OLS estimator will be valid regardless of whether y_t or x_t contain a unit root.

Moving to the β coefficients, we first focus on the contagion from the SP500 to Latin America. It comes at no surprise that the American market exerts a significant and systematic influence on Latin American markets. An interesting pattern arise in all cases: the impact effect (US β_0) is positive whereas the monthly impact (US β_m) is negative, both estimated very precisely. This combination produces a positive and significant long-run multiplier (US LRM) of the same order of magnitude as the impact effect. The immediate volatility transmission is about 0.30 for Brazil and Mexico, and about 0.20 for the rest of the countries. The long-run multiplier is greater but close to the impact multiplier (about 0.40 for Brazil and Mexico, and between 0.20 and 0.30 for the other countries), which suggests that the transmission of volatility from the US is rather fast.

On the contrary, the coefficients related to the transmission of volatility from the Chinese market are generally not significant, with some exceptions. At a lenient 5% level of confidence, in the case of Chile the impact multiplier (China β_0) is small (0.03, about a seventh of the US multiplier) and the lack of any other statistically significant coefficient suggests that it captures a transitory volatility spillover. On the other hand, in the case of Mexico and Peru the long-run multiplier (China LRM) appears significant; this, along with no other significant effect, points out to a permanent effect that manifests itself slowly. In the Mexican case, the Chinese multiplier (0.15) is half as large as the American, while in the Peruvian case (0.24) both are of comparable magnitude.

This set of results suggests that the transmission of volatility from China to Latin America is country-specific and limited, as opposed to the region-wide and systematic transmission of volatility from the US.

4.3 Subsample stability

It is worth asking whether the effects found in the previous section are robust to parameter instability concerns. Parameter stability is an indication of correct model specification, and seems to be particularly relevant in a sample that features major events such as 2007/2008 Global Financial Crisis (GFC), which produce turmoil and boosted volatility in global financial markets.

To study the impact of the GFC (global shock) on the HARDL model coefficients, we split the sample period into two subsamples. The first runs from January 4, 2000 to January 4, 2010, including the GFC. The second covers the period from January 4, 2010 to December 30, 2020.

We do find evidence of parameter instability. The line "Stability" in Table 1 shows the F-statistic of this Chow-type test. It provides strong evidence of parameter instability for Brazil, Chile, Mexico, and Peru. However, the hypothesis of parameter stability cannot be rejected for Argentina and Colombia. The inability to reject the null hypothesis for Colombia could be explained by the low power of the small number of observations in the first subsample.

Table 2 presents the HARDL model estimates for both subsamples. The fit of these equations, as measured by the adjusted R^2, ranges from 0.4 (Peru) to 0.5 (Argentina). In addition, there is no evidence of serial correlation in the residuals. Similar to the full sample results, the null hypotheses $H_0 : A(1) = 0$ are strongly rejected. Note that, for Colombia, H_0 is only rejected at the 5% level of significance.

The case of Argentina is special since it is the only country in the sample where volatility has been arguably dominated by country-specific factors related to poor sovereign debt management (frequent debt renegotiations) and macroeconomic instability (high inflation and low growth). As a result, the transmission of volatility from China is not statistically significant in any subsample. In terms of volatility transmission from the US, the impact effect (US β_0) is similar between subsamples. Contrary to the full sample results, the US long-run multiplier is not statistically significant in any subsample at the 5% level.

For Brazil and Colombia, we do not find statistical evidence of volatility transmission from China in any subsample. On the contrary, we show that the impact effect from the US is positive and statistically significant in both subsamples. The US impact effect is slightly lower in the aftermath of the GFC. Moreover, there is statistical evidence of the US long-run effect for Brazil in both subsamples and for Colombia in the second subsample.

Similar to the full sample results, some influence from the Chinese market can be detected in Table 2 for Chile, Mexico and Peru. The long-run multiplier from China is large and statistically significant before the GFC, but drops considerably and looses significance after the GFC. Thus, the full sample results for Mexico and Peru regarding these multipliers are driven by the pre-GFC behavior. After the GFC, the impact multiplier (China β_0) remains significant only in the Chilean equation, although the corresponding US multiplier is two and a half times larger.

4.4 Rolling windows estimates

We can also investigate the extent of parameter instability in the HARDL models of volatility transmission through a moving window estimation exercise. We consider a window size of $T = 500$ observations (about a tenth of the total sample size) so first the equations are estimated with the sample that runs from $t = 1$ to $t = T$. Then, the regressions are estimated again with the sample that runs from $t = 2$ to $t = T + 1$, then from $t = 3$ to $t = T + 2$, and so on until the last observation of the full sample is reached.[6]

At each iteration, the coefficient β_0 and the sum $\beta_0 + \beta_d + \beta_w + \beta_m$ are stored along with their 95% confidence intervals. Since the sample size in each iteration is much smaller than the full sample size, or even the subsample sizes in section 4.3, the behavior of the estimates may be more erratic and also their standard errors can be considerably larger.

Figure 2 shows the evolution of β_0 for the US (solid red line in a shaded area) and for China (solid blue line within dashed lines) and their 95% confidence intervals. It is quite apparent that the impact effect from the US in the transmission of volatility to Latin American markets is much higher that from China over the whole sample period. It is interesting that US β_0 generally shows a hump-shaped pattern that allows us to identify three periods of increase in the volatility transmission. In order of magnitude: during the GFC in 2007/2008, after the US presidential election in 2016, and during the COVID-19 pandemic.

On the contrary, we find weak evidence of current volatility transmission from China to Latin American markets. For instance, China β_0 appears positive and statistically significant at the 5% level (the confidence interval does not contain zero) for a very brief period in Argentina (around early 2020) and Mexico (by 2018), and somehow longer in Chile (from mid 2016 onwards). The latter effect is also present in Table 2. In fact, impact linkages between the Chinese and Chilean stock markets are the largest.

6 It is worth mentioning that the results of this section were not very sensitive to the window size T, so the qualitative conclusions remain for different values of T. In addition, in this section we consider a restricted, more parsimonious HARDL model that imposes $\beta_d = \beta_w = 0$ as these coefficients were most of the times not statistically significant. The estimation results of this restricted model are reported in the Appendix (Tables A1 and A2) and are very similar to those in Tables 1 and 2.

The dynamics of the cumulative impact, $\beta_0+\beta_d+\beta_w+\beta_m$, from the US and China on Latin America are depicted in Figure 3. Despite being quite erratic, we can identify various instances of positive significant effects from the US that, in most cases, also coincide with the GFC, the US election and the outbreak of the COVID-19 pandemic. Conversely, it is difficult to find long periods of statistical significance in the cumulative impacts from China. Thus, we conclude that these effects are very limited, which is the same conclusion reached in Table 2.

Overall, our results highlight the fact that during the period of the GFC, the volatility spillovers from the US are positive and statistically significant to all countries. It could be argued that Latin American stock markets received volatility from the SP500 in a non-trivial manner. In this sense, this result is in line with Chen et al. (2002) and Gamba-Santamaria et al. (2017).

In addition, the current and long-term impact from the US to Latin America has been more substantial during the subprime crisis than during the pandemic. In this sense, our findings are in line with Bazán-Palomino and Winkelried (2021), who find that volatility spillovers during the COVID-19 pandemic were relatively moderate.

4.5 Further results

Next we perform two robustness checks to our previous results. We follow the approach of section 4.3 and present estimations for the subsamples before and after the GFC.[7]

First, as mentioned in the motivation, one important channel of influence of the dynamics of the Chinese economy on Latin American economies is through the international commodity markets. Thus, we augment the HARDL models with the volatility components (impact, daily, weekly, monthly) of the international price of the main primary export for each country: Soybean for Argentina, Iron ore for Brazil, Copper for Chile and Peru, and Oil for Colombia and Mexico. This exercise allows us to disentangle direct from indirect effects in the transmission of volatility to Latin American markets.

The results are shown in Table 3. In the subsample before the GFC, the introduction of the volatility of commodity prices reduces the magnitude of the transfer coefficients from the US and Chinese stock markets (except in the case of US LRM in Argentina and the China LRM in Colombia). This does not qualitatively alter the significance of the estimated coefficients associated to US, but it causes the China LRM estimates for Chile, Mexico and Peru to loose some statistically significance even though they remain significant at a 5% confidence level (Mexico and Peru) or at a lax 10% confidence level (Chile). This finding indicates that part of the effect reported in the baseline results can be attributed to the indirect effect these large stock markets, especially the Chinese, on the international commodity markets.

In the subsample after the GFC, no significant effect is lost. For instance, the impact term from China remains highly significant for Chile and loosely significant for Mexico. As before, although the magnitude of the US volatility spillover coefficients decreases, their statistical significance is not altered. Furthermore, after the crisis commodity prices volatility seems to be a relevant short-run determinant of the stock market volatility in Latin America, with the exception of Argentina, as revealed by statistically significant coefficients "Com β_0" (although they are generally smaller than

7 The full sample results of this robusteness checks are reported in an Online Supplement (Tables A3 and A4).

the corresponding effect from the US stock exchange). All these effects are transitory, except in Colombia where a significant long-run multiplier of the volatility of oil prices emerged.

On the other hand, as a second robustness check we estimate the basic HARDL models using $y_t = \sqrt{V_t}$ as a measure of volatility. Thus, the models are now dynamic linear equations on the daily standard deviations. The results are reported in Table 4 and the most important finding is that the qualitative conclusions about the transmission of volatility are the same than those in Table 2. The significance and magnitude of the effects remain relatively unchanged: US volatility spillovers are more important than that of China's volatility spillovers at both medium and low frequencies. The only important exception would be the Peruvian case before the GFC, where the impact effect from the Chinese market (China β_0) and the long-run effect from the American market (US LRM) are more precisely estimated. Yet, the lower influence of China along with a greater influence of the US after the GFC also appears in the new estimations.

4.6 Economic implications

Very little was found in the previous literature on volatility spillovers from the US and China to Latin America. In the previous section, we have provided evidence that the US volatility transmission to the region is more relevant than that of China. In other words, although Chinaâs financial ties to Latin America has strengthened, stock price fluctuations from China are not strongly transmitted to the region.

We also have uncovered strong time-variation in volatility transmission during the GFC. In addition, the rolling window estimates allowed us to unveil a synchronization of the contagion from the US to the region. In particular, the synchronization of short-run contagion is more pronounced during the two global shocks (GFC and the COVID pandemic) as expected. During a crisis or period of high uncertainty in stock markets, volatility risk coming from the US spreads to other markets, including Latin American countries. Nevertheless, our results point to lower cross-market linkages between the US and Latin America, especially in the short-run. The dynamics of β_0 provided by the rolling window analysis support this claim.

As mentioned before, China is currently Latin Americaâs top trading partner, after the United States. Latin American exports to China are mainly soybeans, copper, petroleum, oil, and other raw materials. By using commodity prices as controls, our results argue in favor of an indirect effect of a raw material trade channel. Our HARDL setup sheds new light on the process of volatility transmission from commodity prices to the region.

5 Closing remarks

China has increased significantly its trade and financial ties with Latin America since the turn of the century. In this study we enquire the extent to which this closer relation exposes the stock markets in the region to the Chinese stock market volatility. Using an Heterogeneous ARDL model to assess volatility transmission from the US and China, we find that the Chinese stock market volatility does not represent a source of concern for the region, as news affecting Chinese markets locally would not transmit to Latin American exchanges. On the contrary, the US continues to be the main volatility transmitter to the region. Thus, negative events related to the US stock market still pose a risk for financial instability in the region.

Our analysis points to a number of promising avenues for future research. First, understanding the reasons behind the high volatility transmission from the US along with a low transmission from China seems to be relevant for investors, portfolio managers, and policymakers. A sectoral approach could show whether China's volatility is weakly transmitted to Latin America. For instance, Chinese investments are prominent in mining and energy, and one would expect some volatility transmission in these sectors. In other words, some industry volatility spillovers may be hidden due to aggregation – our analysis was done at the stock market level.

Second, Chinese news may not have the global and pervasive impacts of US news, but still may find their way to pass-through to Latin American markets. Specifically, the finding of significant volatility transmission from commodity prices suggests that China shocks may have important *indirect* spillovers in the region through its increasing influence on this markets, despite our finding of weak direct spillovers.

Finally, it would be interesting to replicate our analysis to other regions with tighter financial connections with China. For instance, countries under a greater influence of the Belt and Road initiative. It may be the case that our results are reflecting the fact that, despite the greater integration, Latin America remains a relatively distant partner of China. Future studies might use our HARDL setup to further explore volatility spillovers between other major economies and emerging markets.

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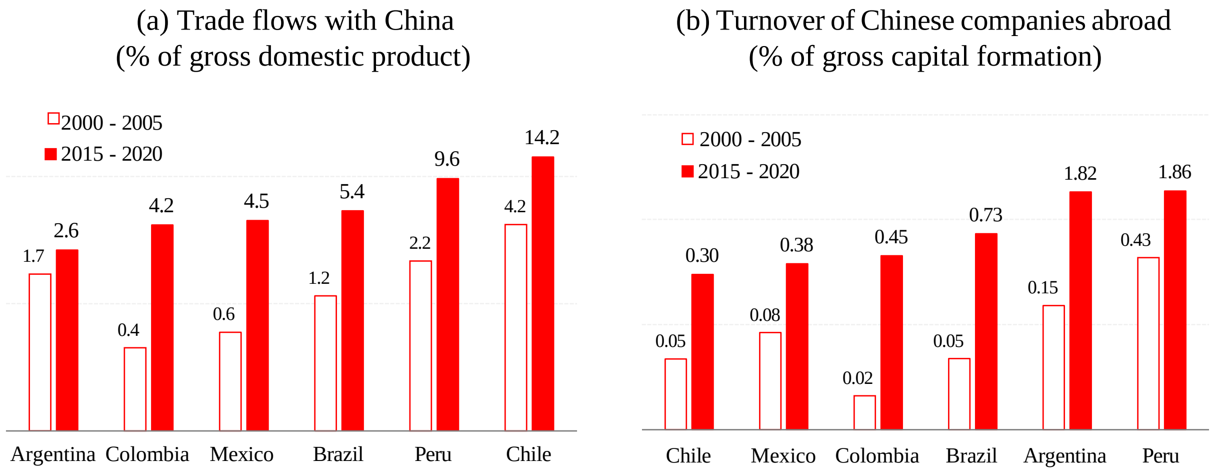
Tables and figures

Figure 1. *Economic closeness between China and Latin American countries*



Notes: The graphs shows the averages of the ratios over the indicated years, in logarithmic scale. Countries are sorted in ascending order by the value of the ratio between 2015 and 2020. Trade flows is the sum of exports and imports.

Sources: National Bureau of Statistics of China and World Development Indicators.

Table 1. *Estimation results: Full sample*

	Argentina	Brazil	Chile	Colombia	Mexico	Peru
α_d	0.253***	0.197***	0.228***	0.246***	0.163***	0.198***
	(0.016)	(0.016)	(0.016)	(0.019)	(0.016)	(0.016)
α_w	0.283***	0.276***	0.300***	0.276***	0.206***	0.330***
	(0.032)	(0.033)	(0.032)	(0.040)	(0.036)	(0.032)
α_m	0.364***	0.315***	0.307***	0.249***	0.443***	0.295***
	(0.031)	(0.037)	(0.034)	(0.043)	(0.039)	(0.035)
$A(1)$	0.100***	0.212***	0.166***	0.229***	0.189***	0.177***
	(0.015)	(0.023)	(0.020)	(0.028)	(0.023)	(0.021)
China β_0	0.025*	0.016	0.030**	0.010	0.017	0.020
	(0.015)	(0.013)	(0.015)	(0.019)	(0.014)	(0.017)
China β_d	0.002	0.011	0.018	0.016	0.031*	0.019
	(0.017)	(0.015)	(0.018)	(0.022)	(0.016)	(0.020)
China β_w	0.017	−0.050*	−0.026	−0.001	−0.025	−0.022
	(0.034)	(0.029)	(0.034)	(0.045)	(0.031)	(0.038)
China β_m	−0.054*	0.034	−0.014	0.005	0.006	0.024
	(0.031)	(0.027)	(0.032)	(0.040)	(0.029)	(0.036)
China LRM	−0.101	0.056	0.052	0.135	0.150**	0.238**
	(0.146)	(0.059)	(0.089)	(0.087)	(0.072)	(0.093)
US β_0	0.233***	0.302***	0.204***	0.214***	0.312***	0.180***
	(0.014)	(0.012)	(0.014)	(0.017)	(0.013)	(0.016)
US β_d	−0.011	−0.002	0.024	−0.008	0.017	0.031*
	(0.017)	(0.015)	(0.017)	(0.021)	(0.016)	(0.019)
US β_w	−0.068**	−0.006	−0.009	−0.015	−0.013	−0.028
	(0.032)	(0.030)	(0.033)	(0.038)	(0.032)	(0.036)
US β_m	−0.130***	−0.201***	−0.171***	−0.135***	−0.238***	−0.144***
	(0.030)	(0.029)	(0.031)	(0.036)	(0.031)	(0.033)
US LRM	0.253**	0.436***	0.291***	0.250***	0.414***	0.223***
	(0.128)	(0.051)	(0.077)	(0.076)	(0.063)	(0.081)
Observations	5,218	5,218	5,218	3,380	5,214	5,218
Adjusted R^2	0.493	0.463	0.399	0.388	0.449	0.361
BG	0.719	0.623	0.504	0.197	0.169	0.481
Stability	17.3	23.4**	42.2***	12.1	53.6***	35.0***

Notes: OLS estimates of the HARDL model for selected Latin American markets. The dependent variable and regressors are the logarithms of the range estimates of daily variance. The equations include an unreported intercept. Standard errors in parenthesis. *, **, and *** indicate statistical significance at the 10%, 5% and 1% confidence levels, respectively. Recall that $A(1) = 1 - \alpha_d - \alpha_w - \alpha_m$ and LRM $= (\beta_0 + \beta_d + \beta_w + \beta_m)/A(1)$, their standard errors computed with the delta method. BG is the Breusch-Godfrey statistic of the null hypothesis of first-order autocorrelation in the residuals (critical value is 3.84).

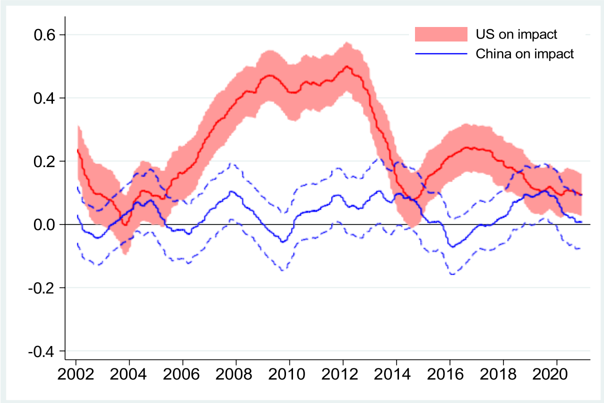
Table 2. *Estimation results: Subsamples*

	Argentina	Brazil	Chile	Colombia	Mexico	Peru
			Before the Global Financial Crisis			
$A(1)$	0.098***	0.285***	0.254***	0.236***	0.190***	0.163***
	(0.023)	(0.041)	(0.038)	(0.059)	(0.034)	(0.030)
China β_0	0.018	−0.004	−0.022	0.040	−0.002	0.021
	(0.022)	(0.020)	(0.024)	(0.055)	(0.021)	(0.025)
China LRM	−0.186	0.011	0.305***	0.497	0.321***	0.419***
	(0.214)	(0.065)	(0.088)	(0.319)	(0.107)	(0.149)
US β_0	0.251***	0.331***	0.233***	0.292***	0.396***	0.167***
	(0.022)	(0.019)	(0.023)	(0.054)	(0.021)	(0.025)
US LRM	0.340*	0.441***	0.325***	−0.019	0.463***	0.202
	(0.187)	(0.056)	(0.076)	(0.220)	(0.093)	(0.126)
Observations	2,348	2,348	2,348	512	2,344	2,348
Adjusted R^2	0.545	0.432	0.390	0.398	0.503	0.449
BG	0.205	0.376	0.241	0.121	0.042	0.603
			After the Global Financial Crisis			
$A(1)$	0.110***	0.182***	0.153***	0.253***	0.238***	0.239***
	(0.022)	(0.029)	(0.027)	(0.033)	(0.037)	(0.035)
China β_0	0.032	0.030*	0.076***	0.007	0.031*	0.017
	(0.020)	(0.017)	(0.019)	(0.020)	(0.018)	(0.023)
China LRM	0.039	0.053	−0.126	0.142	−0.044	0.038
	(0.204)	(0.101)	(0.139)	(0.088)	(0.083)	(0.106)
US β_0	0.228***	0.286***	0.191***	0.205***	0.260***	0.193***
	(0.018)	(0.015)	(0.017)	(0.018)	(0.016)	(0.020)
US LRM	0.165	0.389***	0.408***	0.362***	0.423***	0.328***
	(0.178)	(0.088)	(0.122)	(0.077)	(0.072)	(0.092)
Observations	2,870	2,870	2,870	2,868	2,870	2,870
Adjusted R^2	0.444	0.437	0.415	0.370	0.359	0.262
BG	0.641	0.293	0.257	0.060	0.084	0.065

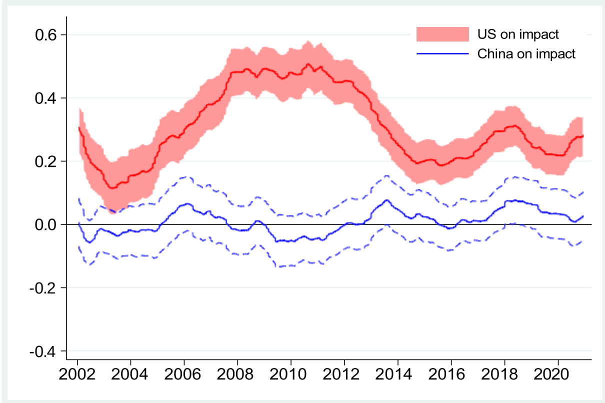
Notes: The splitting point for both subsamples is the first trading day of 2010. See notes to Table 1.

Figure 2. *Impact effect from the US and China on volatility in Latin American stock markets*

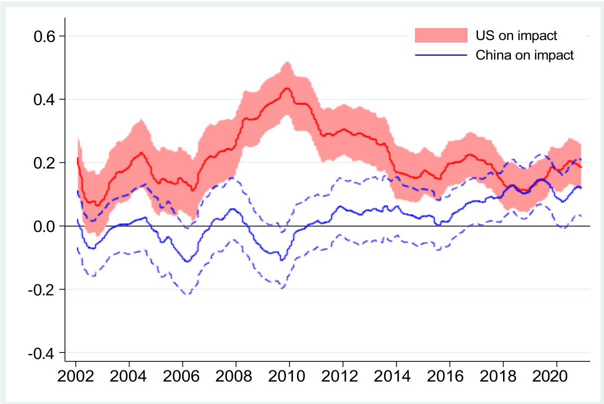
(a) Argentina



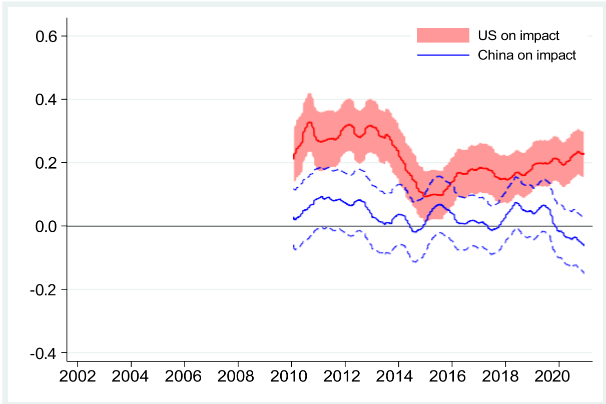
(b) Brazil



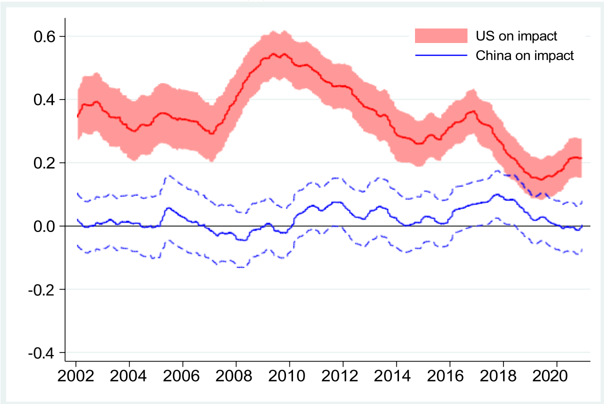
(c) Chile



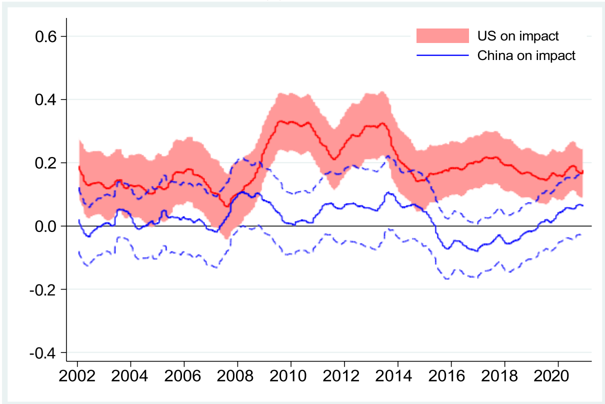
(d) Colombia



(e) Mexico

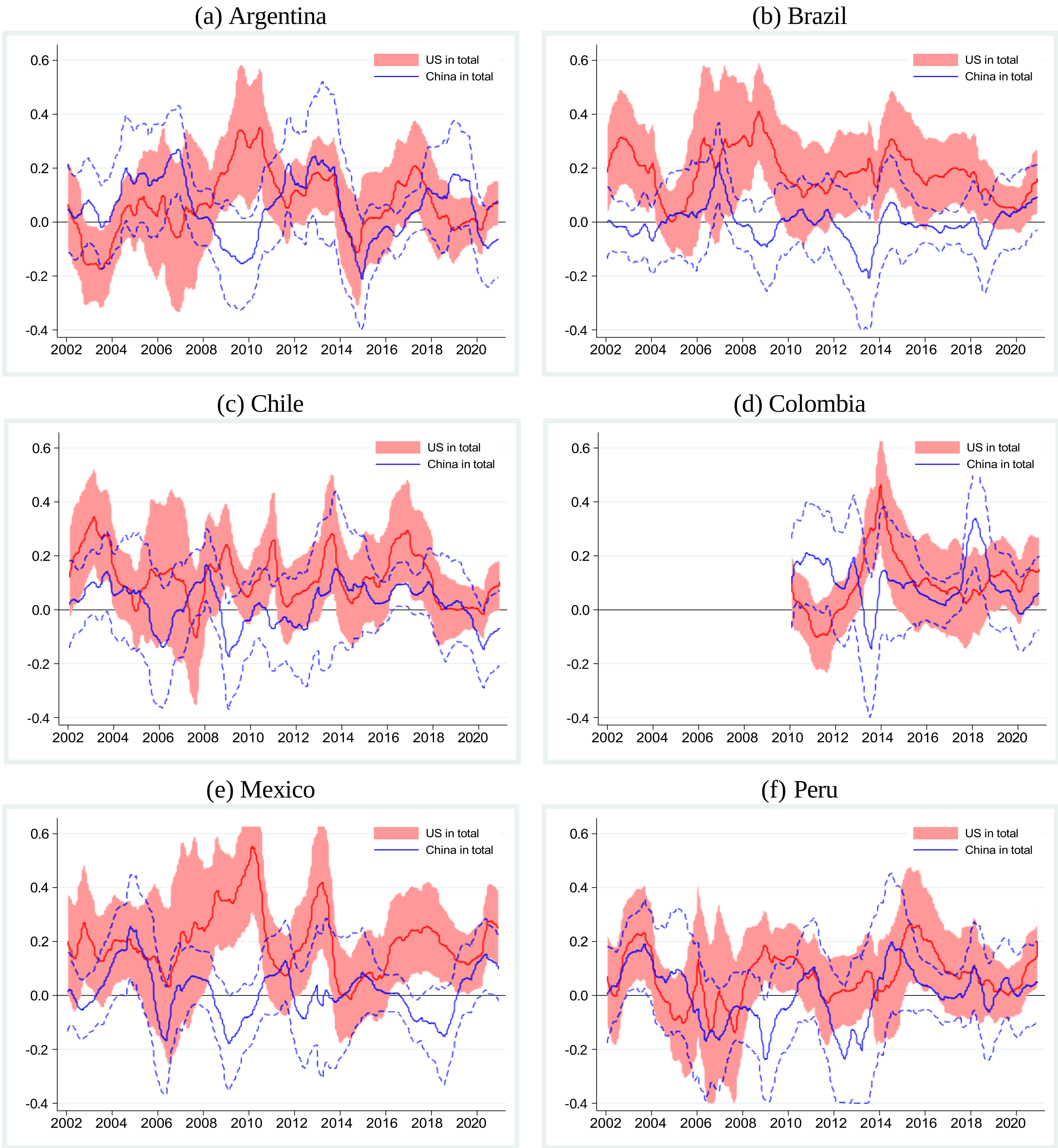


(f) Peru



Notes: Rolling window estimates, with a fixed window length of 500 days, of the transfer on impact (β_0) in the HARDL models for the logarithms of range volatility and their 95% confidence intervals. The horizontal axis shows the end of each subsample. To ease visualization, exponentially smoothed averages are displayed.

Figure 3. *Sum effect from the US and China on volatility in Latin American stock markets*



Notes: Rolling window estimates, with a fixed window length of 500 days, of the sum of coefficients ($\beta_0+\beta_d+\beta_w+\beta_m$) in the HARDL models for the logarithms of range volatility and their 95% confidence intervals. The horizontal axis shows the end of each subsample. To ease visualization, exponentially smoothed averages are displayed.

Table 3. *Commodity augmented volatility model: Subsamples*

	Argentina	Brazil	Chile	Colombia	Mexico	Peru
			Before the Global Financial Crisis			
$A(1)$	0.110***	0.282***	0.266***	0.283***	0.188***	0.185***
	(0.023)	(0.042)	(0.040)	(0.069)	(0.034)	(0.035)
China β_0	0.010	−0.006	−0.024	−0.004	0.001	0.022
	(0.022)	(0.020)	(0.024)	(0.056)	(0.021)	(0.026)
China LRM	0.029	0.002	0.206*	0.516*	0.254**	0.397**
	(0.024)	(0.018)	(0.031)	(0.080)	(0.024)	(0.032)
US β_0	0.245***	0.341***	0.219***	0.276***	0.381***	0.162***
	(0.022)	(0.020)	(0.025)	(0.058)	(0.021)	(0.027)
US LRM	0.410**	0.375***	0.333***	0.178	0.345***	0.195
	(0.022)	(0.027)	(0.025)	(0.101)	(0.029)	(0.024)
Com β_0	0.078***	0.052**	0.015	0.090	0.025	0.034***
	(0.022)	(0.023)	(0.009)	(0.065)	(0.025)	(0.010)
Com LRM	−0.218	0.155	0.107	−0.200	0.272	0.132
	(0.286)	(0.117)	(0.092)	(0.353)	(0.202)	(0.150)
Observations	2,180	2,172	2,154	478	2,172	2,154
Adjusted R^2	0.548	0.441	0.388	0.391	0.510	0.453
BG	0.395	0.680	0.275	0.343	0.015	0.254
			After the Global Financial Crisis			
$A(1)$	0.122***	0.207***	0.153***	0.300***	0.230***	0.240***
	(0.025)	(0.031)	(0.028)	(0.039)	(0.038)	(0.036)
China β_0	0.029	0.016	0.085***	0.003	0.035*	0.020
	(0.021)	(0.017)	(0.020)	(0.020)	(0.018)	(0.023)
China LRM	0.177	0.044	−0.036	0.124	−0.071	0.062
	(0.191)	(0.090)	(0.145)	(0.076)	(0.087)	(0.106)
US β_0	0.230***	0.266***	0.169***	0.182***	0.245***	0.164***
	(0.019)	(0.016)	(0.018)	(0.019)	(0.017)	(0.021)
US LRM	0.166	0.297***	0.298**	0.250***	0.401***	0.296***
	(0.169)	(0.094)	(0.140)	(0.079)	(0.091)	(0.101)
Com β_0	0.021	0.093***	0.037***	0.148***	0.051**	0.057***
	(0.20)	(0.020)	(0.012)	(0.024)	(0.022)	(0.014)
Com LRM	−0.178	0.089	0.288	0.223***	0.064	0.050
	(0.259)	(0.095)	(0.179)	(0.078)	(0.090)	(0.132)
Observations	2,654	2,671	2,663	2,669	2,671	2,663
Adjusted R^2	0.444	0.445	0.420	0.385	0.372	0.277
BG	0.963	0.523	0.010	0.005	0.540	0.079

Notes: OLS estimate of HARDL models augmented with the volatility components of the international prices of the following commodities (Com): Soybean for Argentina, Iron ore for Brazil, Copper for Chile and Peru, and Oil for Colombia and Mexico. See notes to Table 1.

Table 4. *Estimation results using standard deviation: Subsamples*

	Argentina	Brazil	Chile	Colombia	Mexico	Peru
			Before the Global Financial Crisis			
$A(1)$	0.088***	0.288***	0.268***	0.279***	0.212***	0.175***
	(0.021)	(0.043)	(0.038)	(0.058)	(0.037)	(0.030)
China β_0	−0.003	−0.025	−0.002	0.020	0.014	0.033**
	(0.027)	(0.022)	(0.013)	(0.032)	(0.015)	(0.016)
China LRM	−0.418	0.044	0.158***	0.095	0.229***	0.221**
	(0.351)	(0.086)	(0.056)	(0.186)	(0.080)	(0.105)
US β_0	0.392***	0.623***	0.263***	0.270***	0.532***	0.228***
	(0.036)	(0.029)	(0.017)	(0.037)	(0.020)	(0.021)
US LRM	0.420	0.752***	0.251***	0.211*	0.585***	0.310***
	(0.342)	(0.085)	(0.054)	(0.120)	(0.076)	(0.098)
Observations	2,348	2,348	2,348	512	2,348	2,348
Adjusted R^2	0.572	0.529	0.470	0.451	0.614	0.506
BG	1.505	0.191	0.621	0.436	0.051	1.493
			After the Global Financial Crisis			
$A(1)$	0.141***	0.198***	0.184***	0.245***	0.317***	0.251***
	(0.025)	(0.030)	(0.026)	(0.032)	(0.041)	(0.035)
China β_0	−0.019	−0.013	0.043***	−0.018	0.011	0.003
	(0.030)	(0.020)	(0.013)	(0.013)	(0.014)	(0.016)
China LRM	0.017	0.019	−0.087	0.034	−0.025	−0.005
	(0.213)	(0.102)	(0.073)	(0.055)	(0.044)	(0.065)
US β_0	0.442***	0.593***	0.216***	0.262***	0.400***	0.193***
	(0.040)	(0.027)	(0.018)	(0.018)	(0.018)	(0.021)
US LRM	0.723***	0.839***	0.662***	0.534***	0.574***	0.405***
	(0.276)	(0.133)	(0.094)	(0.071)	(0.056)	(0.083)
Observations	2,870	2,870	2,870	2,870	2,870	2,870
Adjusted R^2	0.420	0.534	0.554	0.463	0.427	0.274
BG	2.049	0.041	1.264	0.941	0.014	0.242

Notes: OLS estimates of the HARDL model for selected Latin American markets. The dependent variable and regressors are the square roots of the range estimates of daily variance. The equations include an unreported intercept. Standard errors in parenthesis. *, **, and *** indicate statistical significance at the 10%, 5% and 1% confidence levels, respectively. Recall that $A(1) = 1 - \alpha_d - \alpha_w - \alpha_m$ and LRM $= (\beta_0 + \beta_d + \beta_w + \beta_m)/A(1)$, their standard errors computed with the delta method. BG is the Breusch-Godfrey statistic of the null hypothesis of first-order autocorrelation in the residuals (critical value is 3.84).

Appendix

Table A1. *Estimation results for the restricted model: Full sample*

	Argentina	Brazil	Chile	Colombia	Mexico	Peru
α_d	0.251***	0.197***	0.232***	0.245***	0.168***	0.202***
	(0.015)	(0.015)	(0.015)	(0.019)	(0.015)	(0.016)
α_w	0.261***	0.267***	0.298***	0.270***	0.202***	0.325***
	(0.030)	(0.029)	(0.030)	(0.037)	(0.031)	(0.031)
α_m	0.386***	0.325***	0.303***	0.254***	0.442***	0.296***
	(0.030)	(0.034)	(0.032)	(0.041)	(0.036)	(0.034)
$A(1)$	0.101***	0.212***	0.167***	0.230***	0.189***	0.177***
	(0.015)	(0.023)	(0.020)	(0.028)	(0.023)	(0.021)
China β_0	0.025*	0.011	0.032**	0.014	0.023*	0.024
	(0.014)	(0.012)	(0.014)	(0.017)	(0.013)	(0.016)
China β_m	−0.037*	0.000	−0.024	0.017	0.005	0.018
	(0.019)	(0.015)	(0.019)	(0.025)	(0.018)	(0.022)
China LRM	−0.118	0.054	0.052	0.132	0.147**	0.237**
	(0.144)	(0.059)	(0.088)	(0.086)	(0.072)	(0.093)
US β_0	0.220***	0.300***	0.210***	0.210***	0.315***	0.185***
	(0.013)	(0.011)	(0.013)	(0.016)	(0.012)	(0.014)
US β_m	−0.194***	−0.207***	−0.162***	−0.152***	−0.237***	−0.146***
	(0.018)	(0.018)	(0.019)	(0.024)	(0.019)	(0.020)
US LRM	0.256**	0.439***	0.288***	0.250***	0.412***	0.220***
	(0.126)	(0.051)	(0.077)	(0.075)	(0.062)	(0.081)
Observations	5,218	5,218	5,218	3,380	5,214	5,218
Adjusted R^2	0.492	0.463	0.399	0.388	0.449	0.361
BG	0.189	0.483	1.014	0.101	0.590	0.963
Stability	7.9	17.3**	29.5***	8.6	48.2***	29.3***

Notes: OLS estimates of a restricted HARDL model that imposes $\beta_d = \beta_w = 0$. See notes to Table 1 in the main text.

Table A2. *Estimation results for the restricted model: Subsamples*

	Argentina	Brazil	Chile	Colombia	Mexico	Peru
			Before the Global Financial Crisis			
$A(1)$	0.098***	0.285***	0.256***	0.242***	0.190***	0.164***
	(0.023)	(0.041)	(0.038)	(0.057)	(0.034)	(0.030)
China β_0	0.023	−0.010	−0.021	0.019	0.006	0.032
	(0.21)	(0.018)	(0.022)	(0.051)	(0.020)	(0.024)
China LRM	−0.187	0.019	0.310***	0.497	0.320***	0.429***
	(0.213)	(0.065)	(0.088)	(0.308)	(0.107)	(0.147)
US β_0	0.255***	0.339***	0.240***	0.280***	0.401***	0.178***
	(0.021)	(0.018)	(0.022)	(0.049)	(0.020)	(0.023)
US LRM	0.331*	0.443***	0.321***	−0.008	0.460***	0.197
	(0.187)	(0.056)	(0.075)	(0.214)	(0.093)	(0.125)
Observations	2,348	2,348	2,348	512	2,344	2,348
Adjusted R^2	0.545	0.432	0.389	0.401	0.504	0.449
BG	0.756	1.339	0.874	0.046	0.357	1.125
			After the Global Financial Crisis			
$A(1)$	0.111***	0.182***	0.153***	0.254***	0.239***	0.238***
	(0.022)	(0.029)	(0.027)	(0.033)	(0.037)	(0.035)
China β_0	0.028	0.027*	0.081***	0.015	0.037**	0.015
	(0.019)	(0.015)	(0.018)	(0.018)	(0.016)	(0.021)
China LRM	0.014	0.047	−0.131	0.138	−0.046	0.038
	(0.203)	(0.102)	(0.139)	(0.087)	(0.083)	(0.106)
US β_0	0.198***	0.275***	0.192***	0.202***	0.266***	0.195***
	(0.016)	(0.014)	(0.016)	(0.016)	(0.015)	(0.018)
US LRM	0.176	0.394***	0.408***	0.360***	0.420***	0.325***
	(0.177)	(0.088)	(0.121)	(0.077)	(0.072)	(0.092)
Observations	2,870	2,870	2,870	2,868	2,870	2,870
Adjusted R^2	0.442	0.437	0.415	0.370	0.359	0.262
BG	0.001	0.005	0.383	0.037	0.523	0.187

Notes: OLS estimates of a restricted HARDL model that imposes $\beta_d = \beta_w = 0$. See notes to Table 2 in the main text.

Table A3. *Commodity augmented volatility model: Full sample*

	Argentina	Brazil	Chile	Colombia	Mexico	Peru
α_d	0.254***	0.189***	0.221***	0.236***	0.171***	0.214***
	(0.016)	(0.016)	(0.016)	(0.020)	(0.016)	(0.016)
α_w	0.277***	0.268***	0.303***	0.277***	0.202***	0.309***
	(0.032)	(0.034)	(0.033)	(0.041)	(0.036)	(0.033)
α_m	0.357***	0.319***	0.289***	0.228***	0.440***	0.282***
	(0.032)	(0.038)	(0.036)	(0.045)	(0.040)	(0.038)
$A(1)$	0.112***	0.224***	0.187***	0.260***	0.187***	0.195***
	(0.016)	(0.025)	(0.022)	(0.030)	(0.024)	(0.024)
China β_0	0.019	0.007	0.032**	0.000	0.022	0.023
	(0.015)	(0.013)	(0.015)	(0.018)	(0.014)	(0.017)
China β_d	0.001	0.008	0.012	0.009	0.024	0.009
	(0.017)	(0.015)	(0.018)	(0.023)	(0.016)	(0.020)
China β_w	0.017	−0.033	−0.019	0.003	−0.020	−0.019
	(0.034)	(0.029)	(0.035)	(0.043)	(0.031)	(0.039)
China β_m	−0.027	0.031	−0.026	0.023	−0.001	0.028
	(0.033)	(0.027)	(0.033)	(0.041)	(0.028)	(0.037)
China LRM	0.085	0.057	−0.001	0.135*	0.132*	0.210**
	(0.145)	(0.057)	(0.086)	(0.079)	(0.074)	(0.091)
US β_0	0.232***	0.297***	0.190***	0.194***	0.300***	0.164***
	(0.014)	(0.012)	(0.015)	(0.018)	(0.013)	(0.016)
US β_d	−0.012	−0.011	0.026	−0.015	0.005	0.017
	(0.017)	(0.015)	(0.017)	(0.022)	(0.016)	(0.019)
US β_w	−0.059*	−0.017	0.004	0.001	−0.007	−0.003
	(0.033)	(0.031)	(0.034)	(0.043)	(0.034)	(0.038)
US β_m	−0.128***	−0.187***	−0.168***	−0.137***	−0.228***	−0.143***
	(0.031)	(0.030)	(0.032)	(0.041)	(0.033)	(0.034)
US LRM	0.297**	0.367***	0.272***	0.167**	0.368***	0.179**
	(0.120)	(0.058)	(0.074)	(0.085)	(0.076)	(0.078)
Com β_0	0.045***	0.071***	0.022***	0.140***	0.033**	0.041***
	(0.015)	(0.015)	(0.007)	(0.023)	(0.016)	(0.008)
Com β_d	0.003	0.025	0.001	0.042	−0.020	−0.014
	(0.017)	(0.018)	(0.008)	(0.027)	(0.019)	(0.009)
Com β_w	−0.019	0.005	0.020	−0.091	0.001	0.020
	(0.038)	(0.038)	(0.018)	(0.056)	(0.040)	(0.020)
Com β_m	−0.071*	−0.079**	−0.002	−0.048	0.008	−0.016
	(0.039)	(0.037)	(0.023)	(0.053)	(0.039)	(0.026)
Com LRM	−0.187	0.098	0.225**	0.168*	0.118	0.163*
	(0.181)	(0.075)	(0.089)	(0.088)	(0.096)	(0.098)
Observations	4,834	4,843	4,817	3,147	4,843	4,817
Adjusted R^2	0.494	0.471	0.401	0.397	0.461	0.372
BG	1.147	1.171	0.181	0.117	0.364	0.326
Stability	27.4**	33.3***	44.0***	24.5*	51.5***	33.6***

Notes: See notes to Table 3 in the main text.

Table A4. *Estimation results using standard deviation: Full sample*

	Argentina	Brazil	Chile	Colombia	Mexico	Peru
α_d	0.330***	0.187***	0.258***	0.171***	0.171***	0.278***
	(0.015)	(0.016)	(0.016)	(0.020)	(0.016)	(0.016)
α_w	0.182***	0.309***	0.369***	0.382***	0.205***	0.292***
	(0.030)	(0.034)	(0.030)	(0.041)	(0.036)	(0.030)
α_m	0.379***	0.273***	0.192***	0.212***	0.399***	0.238***
	(0.031)	(0.038)	(0.031)	(0.041)	(0.041)	(0.033)
$A(1)$	0.109***	0.231***	0.182***	0.235***	0.225***	0.192***
	(0.016)	(0.025)	(0.019)	(0.025)	(0.026)	(0.021)
China β_0	−0.009	−0.019	0.016*	−0.009	0.012	0.021*
	(0.020)	(0.015)	(0.009)	(0.012)	(0.010)	(0.011)
China β_d	−0.018	0.002	0.004	0.020	0.013	0.012
	(0.023)	(0.018)	(0.011)	(0.014)	(0.012)	(0.013)
China β_w	0.051	−0.017	−0.019	−0.030	−0.006	−0.065**
	(0.044)	(0.033)	(0.021)	(0.027)	(0.023)	(0.025)
China β_m	−0.044	0.047	−0.001	0.020	0.006	0.052**
	(0.042)	(0.031)	(0.019)	(0.025)	(0.021)	(0.024)
China LRM	−0.187	0.059	0.004	0.004	0.112**	0.107*
	(0.192)	(0.066)	(0.053)	(0.054)	(0.047)	(0.062)
US β_0	0.416***	0.607***	0.241***	0.266***	0.465***	0.209***
	(0.026)	(0.019)	(0.012)	(0.015)	(0.013)	(0.015)
US β_d	−0.054*	0.017	0.060***	0.039**	0.005	0.025
	(0.032)	(0.025)	(0.015)	(0.019)	(0.017)	(0.018)
US β_w	0.029	−0.094*	−0.034	−0.017	−0.059	−0.045
	(0.060)	(0.051)	(0.030)	(0.037)	(0.036)	(0.034)
US β_m	−0.330***	−0.345***	−0.201***	−0.207***	−0.278***	−0.122***
	(0.053)	(0.051)	(0.028)	(0.033)	(0.036)	(0.030)
US LRM	0.556***	0.798***	0.360***	0.341***	0.594***	0.349***
	(0.210)	(0.074)	(0.058)	(0.058)	(0.051)	(0.067)
Observations	5,218	5,218	5,218	3,382	5,218	5,218
Adjusted R^2	0.502	0.549	0.512	0.469	0.556	0.413
BG	3.589	0.267	1.870	1.690	0.056	1.804
Stability	5.7	10.0	27.8***	12.7	28.1***	24.3**

Notes: See notes to Table 4 in the main text.

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