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Government policies and manufacturing production during the COVID-19 pandemic

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Abstract

This paper evaluates the impact of government support and containment measures on the manufacturing production cycle (MPC) of 39 countries during the COVID-19 pandemic. To the best of our knowledge, the effects of these variables on the MPC have not been studied. To obtain reliable evidence, we resort to two complementary econometric techniques: the Arellano-Bond Generalized Method of Moments (GMMs) and the Arellano-Bover GMMs. The evidence is consistent across econometric methods in showing that: 1) Closure and containment measures have been recessionary, 2) Income support measures and interest rate cuts have been effective in raising manufacturing production, and 3) Real exchange rate depreciations do not stimulate (and could even discourage) manufacturing production, presumably because they make imported intermediate inputs more expensive. Therefore, raising consumption through higher income and investment through lower interest rates can alleviate the recessionary effects of closure and containment policies, whereas depreciating the currency may not be effective to boost manufacturing production amid falling world trade and disrupted global supply chains, which could interact with a weaker currency to make imported intermediate inputs even more costly.

JEL Classification: C33, E21, E22, E43, F62, I18.

Keywords: Manufacturing production cycle, government support policies, close and containment measures, dynamic panel data models, generalized method of moments.

Políticas gubernamentales y producción manufacturera durante la pandemia de COVID-19

Resumen

Este trabajo evalúa el impacto de las medidas de reactivación económica y de contención de la pandemia de COVID-19 en el ciclo de la producción manufacturera (CPM) de 39 naciones. El impacto de estas variables en el CPM no ha sido estudiado. Para obtener evidencia robusta, se emplea el Método Generalizado de Momentos en dos versiones: la Arellano-Bond y la Arellano-Bover. La evidencia indica que: 1) Las medidas de cierre y contención han sido recesivas, 2) Las medidas de apoyo al ingreso y los recortes de tasas de interés han reactivado la producción manufacturera, y 3) Las depreciaciones cambiarias reales no estimulan (e incluso podrían desalentar) la producción manufacturera al encarecer los insumos intermedios importados. Esto implica que los efectos recesivos de las medidas de contención pueden efectivamente atenuarse mediante recortes de tasas de interés para incentivar la inversión y mediante apoyo a los ingresos para elevar el consumo. Asimismo, las depreciaciones cambiarias pueden no estimular la producción con un comercio mundial en caída y cadenas globales de valor interrumpidas, que tienden a encarecer todavía más los insumos intermedios importados.

Clasificación JEL: C33, E21, E22, E43, F62, I18.

Palabras clave: ciclo de la producción manufacturera, políticas gubernamentales de apoyo, medidas de cierre y contención, modelos dinámicos de datos en panel, método generalizado de momentos.

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1. Introduction

This paper investigates the effects of government support and containment measures on the manufacturing production cycle of 39 nations, including Mexico, during the COVID-19 pandemic. To capture the impact of closure and containment measures as well as vaccination endeavors on the manufacturing output cycle, we make use of the containment and health index (CHI). Such an index comprises the actions undertaken by governments in 13 different areas, such as school and workplace closing, restrictions on traveling and internal movements, testing and contact tracing policies, vaccination funding, and emergency health care investments (Hale *et al*., 2021). Moreover, government support measures are captured by three key indicators:

1) The income support index, which reflects the extent to which the government of a given country is reacting to the pandemic by: 1.1) Making direct cash payments to the unemployed and other people in need, 1.2) Granting temporary subsidies to private enterprises to prevent job losses, and 1.3) Providing financial aid to households or firms.
2) The index of debt/contract relief for households. This index captures to what degree a government is implementing temporary measures such as: 2.1) Delaying tax payments, 2.2) Freezing mortgages and other loan repayments to private banks, 2.3) Stopping evictions, and 2.4) Ensuring the provision of services like water and electricity regardless of payment (Government Response Tracker (OxCGRT) Coding Interpretation Guide, 2022).
3) To reflect the impact of monetary policy actions on the manufacturing production cycle (MPC, hereafter), we make use of the real policy-related interest rate.
4) To account for the external sector, we employ the real effective (or multilateral) exchange rate based on consumer price indices.[2]

To the best of our knowledge, the impact of this set of variables on the MPC has not been studied, so we attempt to fill this gap in the empirical literature. The analysis of the MPC and its determinants is relevant not only because the manufacturing sector is a major source of job creation, but also because it generates more learning by doing activities (LBD), greater positive externalities, and better prospects for export expansion and for attracting foreign direct investment (FDI) than other sectors of the economy (Sachs and Warner, 1995; Gylfason and Zoega, 2006). Our econometric work relies on a dynamic panel data model, which comprises 39 nations and monthly data from January 2020 through December 2021. The number of cross-section units (or nations) is restricted because some countries provide insufficient data (or not data at all) for at least one of the variables of the model. Given that the econometric methods employed here require a sufficiently large number of cross-section units (*i.e.*, countries), for reasons of data availability our 39-nation group consists of 28 high-income countries and 11 upper-middle-income countries. Mexico, of course, belongs to the upper-middle-income country subgroup. Appendix 1 contains the complete list of nations.

[2] More details about these variables are provided below.

To increase the robustness of the findings, we make use of two versions of the Generalized Method of Moments (GMMs) to estimate the panel data model: 1) The Arellano-Bond GMMs (1991), and 2) The Arellano-Bover GMMs (1995). When the number of cross-section units (N) exceeds the number of time periods (T), the Arellano-Bond GMMs is not only consistent but also robust to endogeneity problems, and these properties hold regardless of the behavior of the error term (Arellano and Bond, 1991; Ahn and Schmidt, 1995; Baltagi, 2008, pp. 147-155). So, when N>T and the sample is large, the Arellano-Bond GMMs estimator basically requires no information as to the behavior of the model residuals. In this study, N(=39)>T(=24) and there is a fairly large number of observations: 858 for each variable after adjusting for the loss of data caused by the presence of a lagged dependent variable and a set of instrumental variables. Nonetheless, we also resort to the Arellano-Bover GMMs estimator, which in relatively small samples tends to yield smaller standard deviations and even lower biases than the Arellano-Bond GMMs estimator (Hayakawa, 2009). Moreover, to further improve the efficiency of the estimations in a finite-sample setting, we include some remedial measures for residual heteroscedasticity and correlation.

As we shall see, the evidence is very consistent across econometric methods and remedial measures. Broadly speaking, the evidence shows that closure and containment measures are recessionary, just as expected. Moreover, income support measures, debt relief measures, and expansionary monetary policies are effective in boosting manufacturing production. Lastly, real exchange rate depreciation may not encourage manufacturing production and could even discourage it in the short term. Put differently, it could even exert a negative influence on the MPC. As we shall see, there are four reasons behind this finding, one of them being that real currency depreciation raises the domestic currency costs of a range of imported intermediate inputs, which are used intensively in manufacturing production.

The rest of this paper is organized as follows. Section 2 is a brief review of the empirical literature. Section 3 describes the empirical model, the estimation methods, and the variables involved. Section 4 presents the empirical evidence. Finally, as part of the conclusions, we summarize the findings and discuss their policy implications.

2. Literature review

2.1 The negative impacts of containment and closure

While partial and full lockdowns were useful to cope with the virus, they caused a myriad of factories to either close or drastically cut back working hours, thus generating supply-side disruptions across countries. In some cases, lockdowns interacted with a growing critical mass of people getting infected to impair a bulk of services, which were critical to the normal functioning of the economy. Although demand- and supply-side forces were both behind the global economic downturn, global supply chains (GSCs) concentrated most of the impact of pandemic-related policies (Maital and Barzani, 2020). Along these lines, the bottlenecks in industries like semiconductors and electronic equipment have been a major concern across the world, given that those components are widely used in the medium- and high-technology sectors responsible for providing durable goods to households, in addition to machinery and equipment to enterprises (Akbulaev, Mammadov and Aliyev, 2020).

On the demand side, restrains on international traveling and domestic movements, coupled with public places closings, have had a crushing effect on the service sector, mainly in hotels, restaurants, land and air transportation services, entertainment and recreation activities, and wholesale and retail commerce (Yeh, 2021). Also, the closing of commercial shopping centers, office buildings, restaurants, coffee shops, and bars, coupled with the abandonment of flats in residential areas, dragged down the real estate markets (Balemi, Füss and Weigand, 2021). In this context, residential and, to a much greater degree, commercial real estate experienced hard times (Balemi, Füss, and Weigand, 2021). In the countless cases where factories had to shut down for good, even industrial real estate battled to remain afloat. Amid soaring vacancy rates, residential, commercial, and industrial property sales went down, so developers and other investors incurred sizeable losses. Furthermore, with rising unemployment rates, landlords struggled to collect rents or even faced rent moratoriums, whereas mortgage defaults rates rose. The resulting increase in mortgage foreclosures brought down house prices which, in turn, led to new rounds of foreclosures (Capponi, Jia, and Rios, 2021).

Broadly speaking, closure and containment policies slowed down the propagation of the virus, saved lives, and lessened the burden on national health systems, but they also caused supply-side disruptions and delivery problems which, ultimately, put many micro, small and medium-sized enterprises (MSMEs) out of business (Makin and Layton, 2021; Susskind and Vines, 2020; Antonescu, 2020). MSMEs have been vulnerable to partial and full lockdowns, especially the ones operating within the tourism, entertainment, and recreation industry. In the face of falling sales and revenues, MSMEs frequently lack the financial resources to pay wages, banking debts, rents, utilities, and taxes (Antonescu, 2020). These firms can even run out of input supplies due to liquidity problems.

Analyzing the impact of the COVID-19 pandemic on MSMEs, Antonescu (2020), Kurmann, Lalé, and Ta (2020), and Shafi, Liu, and Ren (2020), highlight the greater likelihood of bankruptcies and layoffs in this sector. In this context, increasing business failures, climbing unemployment, and lower private agents' confidence, induced households to purchase fewer durable goods and producers to delay investment decisions, so demand for capital goods also dropped. As a result of the second-order effects stemming from unemployment hikes, business liquidations, and lower confidence among consumers and producers, aggregate demand continued to fall. With consumer demand and private investment plummeting worldwide, and with global supply chains seriously affected, international trade basically collapsed (Barlow, van Schalkwyk, McKee, Labonté, and Stuckler, 2021). Declining economic activity and lower international trade had a negative impact on government revenues,[3] making it more difficult for developed and developing nations to maintain social safety nets (Barlow, van Schalkwyk, McKee, Labonté, and Stuckler, 2021). As industrial production declined all over the world, so did imports of intermediate inputs and raw materials, including oil. Regarding the financial sector, as firms in the hardest-hit industries failed to pay their loans and unemployed people defaulted on mortgages, banks' delinquency rates increased. Therefore, the financial situation of banks across the world began to deteriorate as well (Balemi, Füss, and Weigand, 2021).

[3] Given that consumption, income, and trade taxes fell. In some countries, emergency economic packages allowed firms to delay tax payments, which caused a further reduction in governments' room for maneuvering.

In times of economic hardship, most industries lose but a few can win. During the worst episode of the pandemic, food delivery businesses and internet services were among the winners (Akbulaev, Mammadov, and Aliyev, 2020). With the booming demand for remote work services (mainly, online teaching and home office), the information-and-communication-technology industry gained substantially. Such an industry also gained because of soaring online purchases. Moreover, demand for medical supplies, all kinds of drugs, cleaning and sanitation products, and hospital equipment (such as ventilators) skyrocketed (Economic Commission for Latin America and the Caribbean (ECLAC, 2020)). The big pharmaceutical companies profited from increasing purchases of medications, treatments, and COVID-19 tests, as well as from government subsidies in support of vaccines development efforts (Ayati, Saiyarsarai, and Nikfar, 2020).

In many nations, the winning group also included food markets and the overall agricultural industry. According to Perez *et al.* (2021), during the COVID-19 pandemic, not only did governments exempt the agricultural sector and the food distribution system from pandemic-related restrictions, but they prioritized food production given the need of preventing further deterioration of household welfare. Lastly, the health sector has also been marked as a winner, given that its infrastructure was significantly enhanced during the pandemic (ECLAC, 2020). In the case of private health care providers, their profits surged together with the demand for their services.

2.2 The countermeasures and their effectiveness

Many nations implemented economic support programs to alleviate the effects of the crisis on firms, especially MSMEs, and households. Among other things, those programs sought to protect production capacities and workers' expertise, mainly to avert a permanent rise in unemployment rates. Broadly speaking, economic aid packages involved income support measures and debt/contract relief measures, which were complemented by expansionary monetary policies. Income support measures involved: 1) Direct cash transfers (or subsidies) to the hardest-hit industries, such as hotels, restaurants, land and air transportation services, entertainment and recreation activities, and wholesale and retail commerce,[4] 2) In some cases, financial assistance was also granted to big private corporations facing working capital problems in exchange for employment retention programs, 3) Direct financial support to self-employed people as well as other citizens in need, 4) Broader coverage of the unemployment compensation programs, and 5) Interest-free loans (Akbulaev, Mammadov and Aliyev, 2020; Makin and Layton, 2021; The International Monetary Fund (IMF) Policy Tracker).

The debt/relief programs consisted of: 1) Deferment of some tax and social fees payments, 2) Grace periods or temporary reductions in rents and utilities, 3) Freezing mortgages and other loan repayments to private banks, and 4) Stopping evictions for a given period (Akbulaev, Mammadov and Aliyev, 2020; Makin and Layton, 2021; The IMF Policy Tracker). Finally, to stimulate interest-sensitive consumption spending as well as private investment, many central banks resorted to lowering their policy-related interest rates (Maital and Barzani, 2020). To further increase liquidity, the monetary authorities reduced legal reserve requirements and supplied assistance to financial institutions through the money market (ECLAC, 2020).

[4] To further protect jobs, financial aid was in some cases applied to cover the payrolls.

Among the empirical papers devoted to studying the effects of fiscal and monetary policies on real variables during the COVID-19 pandemic, the following stand out. Chudik, Mohaddes and Raissi (2021) resort to a threshold-augmented Vector-Autoregression technique to assess the impact of fiscal policy in a sample of 33 countries. In this context, they show that expansionary fiscal policies were useful to reduce output losses during the pandemic, not only in advanced economies but also in emerging and developing economies.

For their part, Barišić and Kovač (2022) evaluate the impact of fiscal policy measures in 26 (out of the 27) European Union economies. Using regression analysis and Okun's law, they show that the fiscal policy actions undertaken during the second quarter of 2020 were generally effective in lowering short-term unemployment. Over the long-term horizon, these authors provide some (counterfactual) evidence that, in the absence of a fiscal stimulus, the pandemic would have had a stronger negative effect on potential GDP growth.

Rather than analyzing a large group of nations, some empirical works focus on one or two nations. In the case of Thailand and Vietnam, Bui, Dräger, Hayo, and Nghiem (2022) assess the effects of fiscal policy measures on households during the pandemic. Based on consumer surveys, they provide evidence that, during 2020, government support to households strengthened consumer confidence, raised consumer spending on durable goods, and improved the general economic outlook. Using a general equilibrium model for the Chinese economy, Liu *et al.* (2021) produce evidence that fiscal and monetary policies were effective in counteracting the effects of the pandemic on economic activity and unemployment. Nonetheless, these authors highlight two drawbacks of fiscal and monetary expansion in the Chinese economy, namely higher inflation and lower exports.

To analyze the impact of taxes, transfers, and subsidies on Italy's Gross Domestic Product (GDP) during the great lockdown, Di Pietro, Marattin and Minetti (2020) resort to a calibrated macroeconomic model. In this context, they show that the Italian fiscal package softened to a certain degree the negative impact of the pandemic on GDP, whereas a hypothetical stronger fiscal boost would have been more effective but at the expense of compromising government finances. Along the same lines, Romer (2021) argues that the significant US fiscal expansion, coupled with the increased private saving rate associated with the pandemic, will generate economic growth in the long term, with the caveat that the resulting increase in government debt (as a share of GDP) may reduce the scope for future fiscal maneuver. As to the role played by US monetary policy, Feldkircher, Huber and Pfarrhofer (2021) make use of the VAR technique to demonstrate that monetary expansion caused output growth as well as a depreciation of the dollar amid the pandemic.

Against this backdrop, our research evaluates the effects of fiscal and monetary countermeasures on the MPC, which is something that, to the best of our knowledge, has not been done. Moreover, we weigh fiscal and monetary actions against closure and containment measures.

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3. Model specification, data issues, and econometric methodologies

The next task is to specify the determinants of the MPC, describe the variables involved and the treatment of the data, and explain the pros and cons of the econometric methodologies employed. The selection of explanatory variables is consistent with economic theory and allows us to assess the role played by closure and containment measures, fiscal and monetary policy actions, and real multilateral exchange rate fluctuations. However, the larger the number of countries included in the panel, the smaller the set of variables for which complete statistical series are available. Given this tradeoff and the fact that the dependent variable is not manufacturing production itself but the manufacturing production cycle, we put forward the following model:

$$MPC_{it} = \gamma MPC_{it-1} + \beta_1 CHI_{it} + \beta_2 IS_{it} + \beta_3 DR_{it} + \beta_4 R_{it} + \beta_5 Q_{it} + \mu_i + v_{it} \quad (1)$$

where the subscripts i and t denote the country and the year, and MPC_{it} is the manufacturing production cycle. The MPC was calculated by applying the Hodrick-Prescott (1997) filter to the manufacturing production index, going several years back to properly derive the manufacturing output gap for the period January 2020-December 2021. The model is dynamic as it includes a lagged dependent variable, MPC_{it-1}, which means that the impact of the other regressors depends on the past behavior of the manufacturing production cycle. Under the standard specification suggested by Arellano and Bond (1991, p. 280) and Baltagi (2008, p. 147), all the regressors are current variables except for the lagged dependent variable, which is MPC_{it-1} in this case. The rationale behind this is to capture the predetermined or inertial component of the dependent variable, so that one can assess to what degree the other explanatory variables can change its current trajectory. Regarding the rest of regressors, we point out that:

1) CHI_{it} is the containment and health index. Such an index measures the extent to which the different countries have been enforcing the following 13 policy areas to cope with the COVID-19 pandemic at different points in time: on-line teaching rather than in-person teaching, remote work, bans on public events, limitations on the number of people that can gather, public transportation stoppage, stay-at-home mandates, domestic travel protocols and limitations, international travel protocols and limitations, public information efforts to create awareness, massive testing campaigns, contact tracing endeavors to break the virus propagation channels, mandatory use of masks, and vaccination campaigns (Hale *et al*., 2021, p. 530). In this context, the CHI gauges the intensity and scope of the government interventions in these 13 areas.
2) IS_{it} stands for the income support index, which is designed to reflect the degree to which governments are counteracting the effects of the pandemic through cash transfers to unemployed people and informal workers (such as roadside vendors affected by the lockdown), or through food rations to vulnerable population groups. This index also covers temporary financial support to either households or private sector enterprises. In the case of

firms, the financial aid is usually aimed at preventing firms from firing workers during the pandemic (OxCGRT Coding Interpretation Guide, 2022; Hale *et al*., 2021).[5]

3) DR_{it} is the index of debt/contract relief for households, which records the government's efforts to alleviate the financial situation of homeowners by: 3.1) Delaying tax payments, 3.2) Temporarily lowering or freezing residential mortgage payments to private banks, 3.3) Extending soft loans backed by the government, 3.4) Banning evictions for a given period, and 3.5) Ensuring the provision of basic services such as water, electricity, and primary health care (OxCGRT Coding Interpretation Guide, 2022; Hale *et al*., 2021).
4) R_{it} is the real policy-related interest rate, which was calculated by subtracting the inflation rate (based on the consumer price index) from the nominal policy-related interest rate. In the case of only three countries,[6] we made use of the real lending rate as there was little or no data regarding the policy interest rate. The rationale behind this is that policy interest rates are supposed to influence other interest rates, such as the lending rate.
5) Q_{it} is the real effective (or multilateral) exchange rate based on consumer price indices. This variable is incorporated to estimate how real exchange rate fluctuations affect the manufacturing production cycle in times of pandemic.
6) Finally, μ_i denotes a cross-section disturbance term that captures the heterogeneity of nations, whereas v_{it} is a combined disturbance term changing from one nation to another and over time.

In this context, Equation (1) is estimated by two econometric methods: 1) The Arellano-Bond GMMs (1991), and the Arellano-Bover GMMs (1995). Broadly speaking, the Arellano-Bond GMMs takes care of the following potential problems: First, the dependent variable (MPC_{it}) is influenced by the cross-section error term (μ_i), which means that the lagged dependent variable (MPC_{it-1}) and μ_i could be correlated. Secondly, the lagged dependent variable and the combined error term (v_{it}) could be correlated as well. Thirdly, any of the explanatory variables (CHI_{it}, IS_{it},DR_{it}, R_{it}, and Q_{it}) could be correlated with the combined error term due to endogeneity problems. All these three problems give rise to biased estimations and thus must be solved. The first step to address these problems is to first-difference all the variables of Equation (1):

$$\Delta MPC_{it} = \gamma \Delta MPC_{it-1} + \beta_1 \Delta CHI_{it} + \beta_2 \Delta IS_{it} + \beta_3 \Delta DR_{it} + \beta_4 \Delta R_{it} + \beta_5 \Delta Q_{it} + \Delta v_{it} \tag{2}$$

By first-differencing the data, the cross-section error term (μ_i) is eliminated and, therefore, its potential correlation with the lagged dependent variable. The potential correlation between the regressors of Equation (2) and the new combined error term (Δv_{it}) is solved by "internal" instrumental variables estimation. The instruments are internal because they are provided by the appropriate lags of the independent variables "in levels"; that is, by the appropriate lags of MC_{it-1},

[5] For instance, in some cases the subsidies compensate private employers for allowing workers to enjoy full pay while undergoing the 14-day mandatory isolation period after testing positive for COVID-19 or after returning from another country. However, this must be a nationwide policy to be accounted for by the OxCGRT.
[6] See Appendix 2 for details.

CHI_{it}, IS_{it}, DR_{it}, R_{it}, and Q_{it}.[7] The instruments generated in this fashion fulfill two requirements: 1) They are highly correlated with the regressors of Equation (2), which are in first differences, and 2) They are uncorrelated with the combined error term, so that the endogeneity problem is properly solved (Arellano and Bond, 1991).

The next step is to address serial correlation and heteroscedasticity by combining this set of instruments with a sequential Generalized Least Squares (GLS) procedure, which gives rise to the Arellano-Bond first-, second-, and n-step consistent estimators. In this context, it has been shown that when the number of cross-section units (N) in the panel is greater than the number of periods (T), the Arellano-Bond GMMs has three advantages: 1) It is free of endogeneity problems, 2) It is consistent, and 3) It is reliable regardless of the initial behavior of the error term (Arellano and Bond, 1991; Ahn and Schmidt, 1995; Baltagi, 2008, pp. 147-155). In fact, the first- and second-step consistent estimators are equivalent in large samples when, from the start, the model residuals are homoscedastic and uncorrelated (Baltagi, 2008, p. 150).

As we have shown, the Arellano-Bond (1991) GMMs transforms the data by taking first differences. In contrast, the Arellano-Bover (1995) GMMs makes use of what is known as forward orthogonal deviations (FODs). Both procedures are useful to eliminate the cross-section error term (μ_i), which as we explained tends to be correlated with the lagged dependent variable (MPC_{it-1}), thereby generating biased estimations. As with the first-differencing procedure, the FODs procedure applies to all the variables of the model, including the two disturbance terms (μ_i and v_{it}). Let us assume that $\hat{X}_{it}$ is the variable transformed by the FODs procedure and that X_{it} is the original variable in levels. As explained by Abdul-Karim, Azman-Saini, and Abdul-Karim (2011), the relationship between $\hat{X}_{it}$ and X_{it} is given by the following mathematical expression:

$$\hat{X}_{it} = \left(\frac{T_{it}}{T_{it}+1}\right)^{1/2} \left[X_{it} - \frac{1}{T_{it}}(X_{it+1}+\ldots+X_{iT})\right] \qquad \text{for t=1, 2,..., T-1,} \tag{3}$$

where T_{it} denotes the number of periods for the ith country. Put differently, first we get the difference between a given observation and the mean of all future observations, and then we multiply that difference by the scale factor $\left(\frac{T_{it}}{T_{it}+1}\right)^{1/2}$. Using Monte Carlo simulation, Hayakawa (2009) and Phillips (2019) study the performance of the Arellano-Bond GMMs, based on first differencing, and the Arellano-Bover GMMs, based on FODs. In this context, both authors conclude that the Arellano-Bover GMMs tends to yield more efficient and less biased estimations when working with small samples. Along these lines, although the panel data models estimated here involve a fairly large number of observations, we decided to employ both estimation procedures.

For each variable of the model, we gathered monthly data from January 2020 to December 2021 for the 39 countries of the sample. As stated before, this means that there are 858 observations for each variable, once we have adjusted for the loss of data due to the presence of a lagged dependent variable and a set of instrumental variables. Appendix 1 contains the list of the 39 the countries

[7] The number of instruments depends on the number of cross-sections units and the number of periods in the panel, which are counted from t=3 to the last observation of the series. So, there will be a matrix of instruments for each cross-section unit.

involved in the analysis, whereas Appendix 2 explains the measurement units and data sources for each variable.

4. Empirical evidence

As is well known, when working with time-series equations, there are basically two types of problems with the model's residuals that compromise efficiency: correlation and heteroscedasticity across time. However, when working with panel equations there are four types of problems: time-series correlation and heteroscedasticity, on the one hand, and cross-section correlation and heteroscedasticity, on the other. We deal with these four problems in three ways:

1) By making use of two robust estimation methods: the Arellano-Bond GMMs and the Arellano-Bover GMMs. When N>T and the sample is large, as in this case, the Arellano-Bond GMMs is consistent, robust to endogeneity problems, and basically requires no information concerning the behavior of the residuals (Arellano and Bond, 1991; Ahn and Schmidt, 1995; Baltagi, 2008, pp. 147-155). Considering the value of T and N, and the loss of data due to the use of a lagged dependent variable and a set of instrumental variables, we have 858 observations for each variable, which is quite reasonable. Nonetheless, we also make use of the Arellano-Bover GMMs, which in relatively small samples is proven to yield even lower standard deviations and biases (Hayakawa, 2009).
2) We make use of a white period instrument weighting matrix under both econometric methods: the Arellano-Bond GMMs and the Arellano-Bover GMMs. The white period instrument weighting matrix is a good remedial measure for serial correlation.
3) We also resort to coefficients' white period standard errors and covariance, which is a coefficients variance-covariance method that is robust not only to serial correlation, but also to heteroscedasticity across time. This coefficients covariance method is useful to further enhance efficiency and is available for the Arellano-Bover as well as for the Arellano-Bond estimator.

In this context, we estimate Equation (1) by the two econometric methodologies: the Arellano-Bond GMMs and the Arellano-Bover GMMs. In addition, we make use of the remedial measures previously mentioned: 1) The white period instrument weighting matrix, and 2) The white period standard errors and covariance. Table 1 displays the estimations results:

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Table 1. Dynamic panel data models

Econometric methods: The Arellano-Bond GMMs, based on first-difference transformation, and the Arellano-Bover GMMs, based on forward orthogonal deviations (FODs).

GMMs weights: White period instrument weighting matrix

Coefficients covariance method: White period standard errors and covariance (corrected for d.f).

The Arellano-Bond GMMs, which is based on first differencing.		The Arellano-Bover GMMs, which is based on forward orthogonal deviations.	
Dependent variable: ΔMPC_{it}		Dependent variable: $\widehat{MPC}_{it}$	
Explanatory variables	Coefficients	Explanatory variables	Coefficients
ΔMPC_{it-1}	0.579949***	$\widehat{MPC}_{it-1}$	0.592617***
ΔCHI_{it}	-0.139666***	$\widehat{CHI}_{it}$	-0.059990***
ΔIS_{it}	1.573109***	$\widehat{IS}_{it}$	1.339657***
ΔDR_{it}	3.038778***	$\widehat{DR}_{it}$	2.437481***
ΔR_{it}	-0.961637***	$\hat{R}_{it}$	-0.778582***
ΔQ_{it}	-0.093145*	$\hat{Q}_{it}$	-0.078896***

Notes:

1. Asterisks *, **, and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.
2. GMMs= Generalized Method of Moments.
3. Δ is the first difference operator, whereas the hat ∧ denotes the forward orthogonal deviations operator.
4. d.f.= Degrees of freedom.

Source: Authors' estimations based on information from the data sources depicted in Appendix 2 and the use of EViews 12.

The second column of Table 1 shows the estimation results under the Arellano-Bond GMMs estimator, whereas the fourth column shows the estimation results under the Arellano-Bover GMMs estimator. Before interpreting the signs and statistical significance of the parameter estimates, we will display the outcome of the Arellano-Bond test for serial correlation, which is useful only to detect first- and second-order autocorrelation. According to Arellano and Bond (1991), if the error term in Equation (1) is identically independently distributed, then the error term in Equation (2) should show two things: 1) Negative first-order autocorrelation, and 2) No second order autocorrelation. Along these lines, Table 2 shows that the probability values for the null hypotheses of first- and second-order autocorrelation are 0.1025 and 0.6046, respectively. Therefore, there is no second-order autocorrelation, but we fail to establish -in the margin, given that the probability value is slightly higher than 0.10- the presence of negative first-order autocorrelation in the underlying residuals as Arellano and Bond require. Although these results are reasonably good, we deemed appropriate to implement the remedial measures previously mentioned.

Table 2. Arellano-Bond (AB) test for autocorrelation

Null hypothesis	m-statistic	Probability value
Absence of first-order autocorrelation	-1.632784	0.1025
Absence of second-order autocorrelation	-0.517800	0.6046

Note: The AB autocorrelation test applies only to first- and second-order serial correlation.
Source: Authors' estimations based on information from the data sources depicted in Appendix 2 and the use of EViews 12.

Another important test available for the Arellano-Bond and the Arellano-Bover estimators is the test of exogeneity of the instruments. Put differently, in addition to being correlated with the regressors, the instruments must be uncorrelated with the error term (i.e., they must be exogenous). Table 3 shows the results of the test of exogeneity of the instruments under both econometric methods.

Table 3. *J*-test of exogeneity of the instruments

Null hypothesis: all the instruments are uncorrelated with the error term

Arellano-Bond GMMs		Arellano-Bover GMMs	
J-statistic	Probability value	*J*-statistic	Probability value
35.98523	0.330510	37.29138	0.278180

Note: GMMs= Generalized Method of Moments.
Source: Authors' estimations based on information from the data sources depicted in Appendix 2 and the use of EViews 12.

According to Table 3, the probability values for the null hypothesis that "all the instruments are uncorrelated with the error term" are 0.330510 for the Arellano-Bond GMMs and 0.278180 for the Arellano-Bover GMMs. This means that such a null hypothesis cannot be rejected and, therefore, the instruments are valid. In this context, the next step is to briefly summarize the findings displayed in Table 1:

1) The coefficient of the lagged dependent variable is statistically significant at the 1% level in the two cases. This means that the past behavior of the manufacturing production cycle (MPC) is a key driver of the current behavior. Therefore, the MPC involves an inertial (or predetermined) component. The stronger this inertial component is, the more difficult is for fiscal and monetary policies to influence the MPC.
2) The containment and health index (CHI) has a negative estimated coefficient, which is statistically significant at the 1% level under both econometric methods. As stated earlier, this is a comprehensive index encompassing 13 policy areas. So, broadly speaking, a negative coefficient in this case reflects the recessionary effects of the closure and containment measures previously described.

3) The parameter estimate associated with income support measures (IS) is positive and statistically significant at the 1% level in both regressions. And the same applies to the estimated coefficient of debt contract relief (DR). Therefore, countercyclical fiscal policies are effective in encouraging manufacturing output.
4) The estimated parameter of the real policy-related interest rate (R) is negative and statistically significant at the 1% level in both cases, which means that lower interest rates would boost manufacturing production.
5) The coefficient of the real multilateral exchange rate (Q) is negative and statistically significant at the 1% level under the Arellano-Bover GMMs and at the 10% level under the Arellano-Bond GMMs. Thus, as we argue below, real exchange rate depreciation lowers manufacturing output growth, at least in the short term.

5. Conclusions and policy implications

This paper relies on a dynamic panel data model involving 39 countries and monthly observations from January 2020 to December 2021. To enhance the robustness of the evidence, the model is estimated through two econometric methods. The first is the Arellano-Bond GMMs, which for N>T is consistent, free of endogeneity problems and basically requires no information regarding residual behavior (Arellano and Bond, 1991; Ahn and Schmidt, 1995; Baltagi, 2008, pp. 147-155). Although the number of observations for each variable is reasonably large (858), we also resort to the Arellano-Bover GMMs, which in finite samples performs even better in terms of standard deviations and biases (Hayakawa, 2009). Using the tools at hand for these econometric methods,[8] we further improve efficiency by implementing remedial measures for serial correlation and heteroscedasticity across time.

The evidence across econometric methods is very consistent in indicating that:

1) The MPC has a strong predetermined or inertial component, given the statistical significance of the coefficient linked to the lagged dependent variable. This means that a dynamic panel data model is a suitable specification and the effects of the exogenous regressors is contingent upon the past behavior of the MPC. Moreover, the stronger the inertial component of the MPC is, the more difficult is for fiscal and monetary policies to alter the course of the MPC.
2) Closure and containment measures, which are captured by the CHI, have been clearly recessionary. The deep negative impact on global economic activity must be explained not only by the nature and severity of these measures, but also by their worldwide implementation. Therefore, to normalize global production chains, reactivate consumption and investment, and generate positive spillover effects through international trade, there must also be a coordination of national economic policies (Susskind and Vines, 2020; McKibbin and Vines, 2020) addressing the demand- as well as the supply-side factors behind the crisis (Maital and Barzani, 2020). As the reader may recall, those factors were analyzed in the literature review.

[8] That is, the tools available in EViews 12.

3) Income support measures seem to be effective in raising manufacturing production, and the same conclusion applies to debt contract relief for households. Put differently, in times of crisis, enhancing consumption through higher income (i.e., direct financial support to the unemployed and other people in need) can be effective in raising manufacturing production and creating jobs. On the other hand, direct cash transfers to MSMEs and financial assistance to big corporations is key to preventing bankruptcies and thus preserving production capacities, so that workers can remain in the same job or industry. In this manner, the accumulated work experience can be protected insofar as workers won't have to shift from one job to another that requires a different set of skills (Akbulaev, Mammadov, and Aliyev, 2020).
4) An expansionary monetary policy in the form of interest rate cuts has clearly a positive impact on the MPC. This highlights the importance of cheaper credit to consumers and investors to stimulate manufacturing production. One caveat to this conclusion is that the implementation of expansionary fiscal and monetary policies must go through very gradual stages given the time it takes for global production chains to normalize even when proper supply-side policies are in place.

The real multilateral exchange rate is negatively related to the manufacturing production cycle, regardless of the econometric method employed. Put differently, our evidence is consistent in indicating that real currency depreciation discourages manufacturing output. This result holds at the 1% significance level under the Arellano-Bover estimator, and at the 10% significance level under the Arellano-Bond estimator. Nonetheless, as previously stated the Arellano-Bover estimator is more reliable when the sample size is not too large. Conventional economic theory suggests that exchange rate depreciation raises manufacturing output by boosting manufacturing sales abroad. Therefore, a plausible interpretation of our finding is that real currency depreciation influences manufacturing production through two channels working in opposite directions. The demand-side channel of currency depreciation stimulates manufacturing output by making manufacturing products abroad cheaper, whereas the supply-side channel of currency depreciation discourages manufacturing production by making imported intermediate inputs more expensive. In this manner, our result underlines the prevalence of the supply-side channel of currency depreciation over the demand-side channel, at least in the short term. There are several reasons behind this conclusion:

1) The increasing role of international production sharing has made manufacturing firms across the world more dependent on imported parts, components, and materials. Therefore, currency depreciation increases the local currency costs of all those imported intermediate inputs, which in turn tends to deteriorate manufacturing export performance. Along these lines, the higher the import content of manufacturing exports is, the stronger the supply-side effect of currency depreciation becomes.
2) By reducing manufacturing exports and production, exchange rate depreciation could result in scale contraction for many manufacturing firms, thereby reducing productivity levels. In this regard, Fung and Liu (2009) analyze the effect of exchange rate depreciation on

manufacturing domestic and foreign sales, value-added and even productivity. However, those authors highlight the demand-side effect of currency depreciation on Taiwanese manufacturers.

3) Closure and containment measures disrupted trade flows, investments, and international production sharing, giving rise to bottlenecks in the production of numerous critical parts and components for the manufacturing sector. In this context, during the great lockdown, currency depreciation interacted with production shortfalls to make all those inputs even more costly.
4) Exchange rate depreciation often entails higher exchange rate volatility, which also worsens the export growth prospects of manufacturing firms (Zia and Mahmood, 2013). This negative impact on export performance may be stronger for those manufacturing firms holding net liabilities in foreign currency, in addition to producing goods with a high import content. Higher exchange rate volatility could also reduce investment by raising uncertainty.
5) Regardless of the direction of minor exchange rate movements, manufacturing exports could hardly increase amid falling global demand and recession.

Disentangling the transmission channel through which real exchange rate depreciation could lower manufacturing output is beyond the scope of this investigation. However, the increasing role of global supply chains and processing trade is consistent with the view that the supply-side effect of exchange rate fluctuations is gaining force vis-à-vis the demand-side effect. In this context, weakening the domestic currency may not be the best alternative to raise manufacturing output, at least over the short-term horizon.

References

[1] Abdul Karim, Z., Azman-Saini, W. N. W., and Abdul Karim, B. (2011). Bank lending channel of monetary policy: Dynamic panel data study of Malaysia. *Journal of Asia-Pacific Business*, 12(3), 225-243. https://doi.org/10.1080/10599231.2011.570618

[2] Ahn, S. and Schmidt, P. (1995). Efficient estimation of models for dynamic panel data. *Journal of* Econometrics, 68(1). 5-27. https://doi.org/10.1016/0304-4076(94)01641-C

[3] Akbulaev, N., Mammadov, I., and Aliyev, V. (2020). Economic impact of COVID-19. *SYLWAN*, 164(5), 113-126. Available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3649813

[4] Antonescu, D. (2020). Supporting small and medium size enterprises through the COVID-19 crises in Romania. *Central European Journal of Geography and Sustainable Development*, 2(1), 38-57. Available at: https://doi.org/10.47246/cejgsd.2020.2.1.4

[5] Arellano, M. and Bond, S. (1991). Some test of specification for panel data: Monte Carlo evidence and an application to employment equations. *The Review of Economic Studies*, 58(2), 277-297. https://doi.org/10.2307/2297968

[6] Arellano, M., and Bover, O. (1995). Another look at the instrumental variable estimation of error-components models. *Journal of Econometrics*, 68(1), 29-51. https://doi.org/10.1016/0304-4076(94)01642-D

[7] Ayati, N., Saiyarsarai, P., and Nikfar, S. (2020). Short and long term impacts of COVID-19 on the pharmaceutical sector. *DARU Journal of Pharmaceutical Sciences*, 28, 799–805. https://doi.org/10.1007/s40199-020-00358-5

[8] Balemi, N., Füss, R., and Weigand, A. (2021). COVID-19's impact on real estate markets: Review and outlook. *Financial Markets and Portfolio Management*, 35(4), 495-513. https://doi.org/10.1007/s11408-021-00384-6

[9] Baltagi, B. (2008). *Econometric analysis of panel data*. Chichester, West Sussex: John Wiley & Sons Ltd.

[10] Barišić, P., and Kovač, T. (2022). The effectiveness of the fiscal policy response to COVID-19 through the lens of short and long-run labor market effects of COVID-19 measures. *Public Sector Economics*, 46(1), 43-81. https://doi.org/10.3326/pse.46.1.2

[11] Barlow, P., May CI van Schalkwyk, M., McKee, M., Labonté, R., and Stuckler, D. (2021). COVID-19 and the collapse of global trade: building an effective public health response. *The Lancet Planetary Health*, 5(2), 102-107. https://doi.org/10.1016/S2542-5196(20)30291-6

[12] Bui, D., Dräger, L., Hayo, B., and Nghiem, G. (2022). The effects of fiscal policy on households during the COVID-19 pandemic: Evidence from Thailand and Vietnam. *World Development*, *153*, 105828. https://doi.org/10.1016/j.worlddev.2022.105828

[13] Capponi, A., Jia, R., and Rios, D. (2021). Foreclosures, house prices growth, and refinancing in the COVID-19 period. Global Risk Institute. Downloaded from: https://globalriskinstitute.org/wp-content/uploads/2021/09/Mortgage_Forbearance__FinalReport-V6.pdf

[14] Economic Commission for Latin America and the Caribbean (ECLAC), U.N. (2020). Report on the economic impact of coronavirus disease (COVID-19) on Latin America and the Caribbean. Available at: https://doi.org/10.18356/497b1332-en

[15] Chudik, A., Mohaddes, K., and Raissi, M. (2021). Covid-19 fiscal support and its effectiveness. *Economics Letters*, *205*, 109939. https://doi.org/10.1016/j.econlet.2021.109939

[16] Di Pietro, M., Marattin, L., and Minetti, R. (2020). Fiscal policies amid a pandemic: The response of Italy to the COVID-19 crisis. *National Tax Journal*, 73(3), 927-950. Available at: https://doi.org/10.17310/ntj.2020.3.13

[17] Feldkircher, M., Huber, F., and Pfarrhofer, M. (2021). Measuring the effectiveness of US monetary policy during the COVID-19 recession. *Scottish Journal of Political Economy*, 68(3), 287-297. https://doi.org/10.1111/sjpe.12275

[18] Fung, L., and Liu, J. T. (2009). The impact of real exchange rate movements on firm performance: A case study of Taiwanese manufacturing firms. *Japan and the World Economy*, 21(1), 85-96. https://doi.org/10.1016/j.japwor.2007.11.002

[19] Hale, T., Angrist, N., Goldszmidt, R., Kira, B., Petherick, A., Phillips, T., Webster, S., Cameron-Blake, E., Hallas, L., Majumdar, S., and Tatlow, H. (2021). A global panel database of pandemic policies (Oxford COVID-19 Government Response Tracker). Nature Human Behaviour, 5, 529-538. https://doi.org/10.1038/s41562-021-01079-8

[20] Gylfason, T. and Zoega, G. (2006). Natural resources and economic growth: The role of investment. *The World Economy*, 29(8), 1091-1115. https://doi.org/10.1111/j.1467-9701.2006.00807.x

[21] Hayakawa, K. (2009). First difference or forward orthogonal deviation-which transformation should be used in dynamic panel data models?: A simulation study. *Economics Bulletin*, *29*(3), 2008-2017. Available at: https://www.researchgate.net/publication/46547299_First_Difference_or_Forward_Orthogonal_Deviation-_Which_Transformation_Should_be_Used_in_Dynamic_Panel_Data_Models_A_Simulation_Study

[22] Hodrick, R. J., and Prescott, E. C. (1997). Postwar U.S. business cycles: An empirical investigation. *Journal of Money, Credit, and Banking*, 29(1), 1-16. Available at: https://doi.org/10.2307/2953682

[23] Kurmann, A., Lalé, E., and Ta, L. (2020). *The Impact of COVID-19 on small business dynamics and employment: Real-time estimates with homebase data*. Working Paper, 2020-9, School of Management Sciences, University of Quebec. Available at: https://doi.org/10.2139/ssrn.3896299

[24] Liu, Y., Cui, Q., Liu, Y., Zhang, J., Zhou, M., Ali, T., Yang, L., Feng, K., Hubacek, K., and Li, X. (2021). Countermeasures against economic crisis from COVID-19 pandemic in China: An analysis of effectiveness and trade-offs. *Structural Change and Economic Dynamics*, *59*, 482-495. https://doi.org/10.1016/j.strueco.2021.09.017

[25] Maital, S., and Barzani, E. (2020). The global economic impact of COVID-19: A summary of research. *Samuel Neaman Institute for National Policy Research*, 1-12. Available at: https://www.neaman.org.il/EN/Files/Global%20Economic%20Impact%20of%20COVID-19_20200322163553.399.pdf

[26] Makin, A. J., and Layton, A. (2021). The global fiscal response to COVID-19: Risks and repercussions. *Economic Analysis and Policy*, 69, 340-349. https://doi.org/10.1016/j.eap.2020.12.016

[27] McKibbin, W., and Vines, D. (2020). Global macroeconomic cooperation in response to the COVID-19 pandemic: a roadmap for the G20 and the IMF. *Oxford Review of Economic Policy*, *36*(1), S297-S337. https://doi.org/10.1093/oxrep/graa032

[28] Oxford COVID-19 Government Response Tracker, Blavatnik School of Government, University of Oxford. Available at: https://www.bsg.ox.ac.uk/research/research-projects/covid-19-government-response-tracker

[29] Oxford COVID-19 Government Response Tracker Coding Interpretation Guide (2022), University of Oxford. Available at: https://github.com/OxCGRT/covid-policy-tracker/blob/master/documentation/interpretation_guide.md

[30] Perez, N. D., Kassim, Y., Ringler, C., Thomas, T. S., ElDidi, H., and Breisinger, C. (2021). *Climate-resilience policies and investments for Egypt's agriculture sector: Sustaining productivity and food security*. Washington, D. C.: International Food Policy Research Institute. Available at: https://doi.org/10.2499/9780896294189

[31] Phillips, R. F. (2019). A comparison of first-difference and forward orthogonal deviations GMM. *arXiv preprint arXiv:1907.12880*. Available at: https://arxiv.org/abs/1907.12880

[32] Romer, C. D. (2021). The Fiscal Policy Response to the Pandemic. *Brookings Papers on Economic Activity*, 89–110. Available at: https://doi.org/10.1353/eca.2021.0009

[33] Sachs, J., and Warner, A. (1995). Natural resource abundance and economic growth. National Bureau of Economic Research (NBER), Working Paper no. 5398, Cambridge, MA. Available at: https://doi.org/10.3386/w5398

[34] Shafi, M., Liu, J., and Ren, W. (2020). Impact of COVID-19 pandemic on micro, small, and medium-sized Enterprises operating in Pakistan. *Research in Globalization*, 2, 100018. https://doi.org/10.1016/j.resglo.2020.100018

[35] Susskind, D., and Vines, D. (2020). The economics of the COVID-19 pandemic: an assessment. *Oxford Review of Economic Policy*, 36(1), S1-S13. https://doi.org/10.1093/oxrep/graa036

[36] The International Monetary Fund (IMF) Policy Tracker. Available at: https://www.imf.org/en/Topics/imf-and-covid19/Policy-Responses-to-COVID-19.

[37] Yeh, S. S. (2021). Tourism recovery strategy against COVID-19 pandemic. *Tourism Recreation Research*, 46(2), 188-194. https://doi.org/10.1080/02508281.2020.1805933

[38] Zia, U., and Mahmood, Z. (2013). Exchange rate depreciation and export price competitiveness: the case of Pakistani manufacturing industries. *Journal of the Asia Pacific Economy*, 18(4), 529-542. https://doi.org/10.1080/13547860.2012.742722

Appendix 1. List of nations included in the analysis

1. Austria	11. Cyprus	21. Japan	31. Romania*
2, Belgium	12. Czechia	22. Latvia	32. Russia*
3. Brazil*	13. Denmark	23. Luxembourg	33. Slovakia
4. Bulgaria*	14. Finland	24. Malaysia*	34. South Africa*
5. Canada	15. France	25. Malta	35. Sweden
6. Chile	16. Germany	26. Mexico*	36. Switzerland
7. China*	17. Greece	27. Moldova*	37. The United Kingdom
8. Colombia*	18. Hungary	28. The Netherlands	38. The United States
9. Costa Rica*	19. Ireland	29. Norway	39. Uruguay
10. Croatia	20. Italy	30. Poland	

This Appendix lists, in alphabetical order, the 39 nations included in the empirical analysis. According to the Country Classification by Income Level proposed by the World Bank, 28 of those nations are high-income countries while 11 are upper-middle income counties. Mexico, of course, is among the upper-middle income countries, which are marked with an asterisk for the sake of clarity. To carry out this classification, the World Bank makes use of the Gross National Income (GNI) per capita for the fiscal year 2020/21.

Appendix 2. Description of variables, measurement units and data sources

Variable	Measurement units	Data sources
Manufacturing production cycle (MPC_{it})	Estimated by applying the Hodrick-Prescott (1997) filter to the manufacturing production index	United Nations Industrial Development Organization (UNIDO).
Containment and health index (CHI_{it})	This is a normalized index ranging from 0 to 100.	Oxford COVID-19 Government Response Tracker.
Income support index (IS_{it})	Ordinal indicator taking 3 possible values: 0, 1 and 2, which is the maximum value.	Oxford COVID-19 Government Response Tracker.
Debt/contract relief for households index (DR_{it})	Ordinal indicator taking 3 possible values: 0, 1 and 2.	Oxford COVID-19 Government Response Tracker.
Real policy-related interest rate (R_{it})	Nominal policy interest rate minus the rate of	International Financial Statistics of the

	increase in the consumer price index.	International Monetary Fund (IMF).
Real effective exchange rate index (Q_{it})	Calculated on the basis of consumer price indices.	International Financial Statistics of the IMF.

Appendix 2 contains a description of the variables included in the econometric model. The description includes the name of the variables, their measurement units, and their data sources. It is worth noting that, in the case of three nations (Bulgaria, China, and Uruguay), we utilized the real lending rate rather than the real policy rate. The real lending rate was calculated by subtracting the inflation rate (based on consumer prices) from the nominal lending rate, using data from the International Financial Statistics of the International Monetary Fund (IMF).