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"The Prices in the Cycle of Emerging Market Economies with Independent Central Banks"

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Thesis for Master in Economics

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Abstract

In this paper, I compare the price cycle in emerging market economies (EMEs) and advanced economies (AEs), conditioned on the existence of an independent and transparent central bank. Firstly, through correlation analysis and estimation of a Dynamic Factor Model (DFM), I find that the price cycle is not the same. In EMEs, unlike in AEs, positive price cycles do not occur simultaneously nor are they preceded by positive output cycles. Additionally, inflation in EMEs exhibits more idiosyncratic behavior. Secondly, I estimate a Structural Vector Autoregression (SVAR), and I find that these differences are explained by three particularities of EMEs. The first is that the Nominal Effective Exchange Rate (NEER) is more relevant, as it explained 30% of the price cycle in EMEs compared to only 13% in AEs. The second is that only in EMEs does the NEER depreciate due to decreases in the prices of exported commodities as well as increases in sovereign spreads. The third is that in EMEs, the Global Financial Cycle (GFC) has an amplifying mechanism: when global uncertainty rises, the NEER depreciates; simultaneously, increased uncertainty decreases commodity prices and increases spreads, further depreciating the exchange rate. Due to these depreciations, a GFC recession generates inflationary pressures in EMEs but deflationary pressures in AEs. Overall, these three characteristics imply that the NEER appreciations are procyclical in EMEs, leading to deflationary pressures when output is high. In contrast, in AEs, the NEER is acyclical, and this phenomenon does not occur.

Resumen

En este trabajo, comparo el ciclo de precios en economías emergentes (EMEs) y economías desarrolladas (AEs), condicionando a la existencia de un banco central independiente y transparente. En primer lugar, mediante un análisis de correlaciones y la estimación de un Dynamic Factor Model (DFM), encuentro que el ciclo de los precios no es igual. En EMEs, a diferencia de en AEs, los ciclos positivos de los precios no ocurren de manera simultánea ni son precedidos por ciclos positivos del producto. Además, la inflación en EMEs tiene un comportamiento más idiosincrático. En segundo lugar, estimo un SVAR, y encuentro que estas diferencias se explican por tres particularidades de las EMEs. La primera, que el Tipo de Cambio Nominal Efectivo (NEER) es más relevante, dado que explicó un 30% del ciclo de los precios en EMEs y sólo un 13% en AEs. La segunda, que sólo en EMEs el NEER se deprecia tanto por bajas en los precios de *commodities* exportados como por subidas en los *spreads* soberanos. La tercera, que en EMEs, el Ciclo Financiero Global (GFC) tiene un mecanismo amplificador: cuando sube la incertidumbre global, se deprecia el NEER, a su vez, la mayor incertidumbre disminuye el precio de los *commodities* y aumenta los *spreads*, lo que deprecia aun más el tipo de cambio. Debido a estas depreciaciones, una recesión del GFC genera presiones inflacionarias en EMEs pero deflacionarias en AEs. En conjunto, estas tres características implican que, en EMEs, las apreciaciones del NEER son procíclicas, lo que genera presiones deflacionarias cuando el producto es alto. En AEs, el NEER es acíclico y este fenómeno no ocurre.

1 Introduction

Inflation has costs: it generates distortions in relative prices, uncertainty, income redistribution, and growth reduction (Ha et al., 2019). Therefore, since the 1990s, some emerging market economies (EMEs) adopted institutional frameworks to regulate monetary policy, such as independent central banks and inflation targeting. These economies successfully reduced inflation from the 2000s and experienced institutional convergence with advanced economies (AEs) (Neely & Rapach, 2011; Ha et al., 2019; Forbes, 2019).

Despite similar institutions, inflation can behave differently between AEs and EMEs for four reasons. First, I will focus on headline Consumer Price Index (CPI) inflation, typically measured as the rate of change in a basket of goods. This basket can vary within economies, and EMEs often have a higher percentage of volatile products, such as energy and food (IMF, 2011). Second, business cycles differ; output and consumption, which influence inflation, are more volatile in EMEs (Neumeyer & Perri, 2002; Uribe & Yue, 2002; Aguiar & Gopinath, 2007). Third, Exchange Rate Pass-Through (ERPT) to domestic prices is higher in EMEs (Ha et al., 2019). Fourth, the exchange rate is more volatile and more responsive to changes in the prices of main exports and international capital movements (Ha et al., 2019; Goda & Priewe, 2020; Agosin, 2023). Together, these differences may result in distinct price cycle behaviors in AEs and EMEs, and could affect the optimal monetary policy in EMEs.

This paper addresses two questions. First, whether the price cycle differs between EMEs and AEs when controlling for central bank independence and transparency. Second, the reasons for these differences. Previous studies have shown that inflation remains higher and more idiosyncratic in EMEs (Neely & Rapach, 2011; Ha et al., 2019). However, these results might be due to some EMEs still having weak regulatory frameworks that allow seigniorage-driven monetary issuance.

Therefore, I consider only economies with high scores on the Dincer and Eichengreen (2014) Index of Central Bank Independence and Transparency, from 2000Q1 to 2021Q4. After filtering, 12 EMEs and 24 AEs with low and controlled inflation remain. I find that within these economies, the price cycle differs between AEs and EMEs, primarily due to structural differences. These differences imply that in EMEs, price levels depend more on exchange rate shocks. Also, during positive output shocks, the exchange rate appreciates, creating a procyclical exchange rate not observed in AEs.

I begin studying the variance, autocorrelation, and correlation of the price cycle with the cycles of expenditure components and nominal variables. I follow methodologies like those of Neumeyer and Perri (2005), Aguiar and Gopinath (2007), and Schmitt-Grohé and Uribe (2017) for studying business cycles in EMEs. The difference is that I also consider prices. I find that in EMEs, the price cycle is more pronounced. In fact, its variance is more than twice as high. Secondly, contrary to what occurs in AEs and what economic theory predict[1], there is no contemporaneous correlation between the price cycle and the output cycle in EMEs. Moreover, quarters characterized by high price levels are not preceded by quarters with levels of output above the trend. Additionally, this result holds for all expenditure components except government spending. In other words, I observe an apparent disconnect between prices and domestic variables. Thirdly, in emerging economies,

[1] There exists an extensive literature linking inflation with output. As early as 1958, Phillips identified a positive relationship between inflation and domestic slack, later coined as the Phillips curve, which continues to be used today to explain inflation in both developed and emerging economies. More recent models document a relationship between inflation and the output gap (see King, 2000, for a brief history of its evolution). Although this study focuses on the price and output cycles, they are closely related concepts, and therefore, some level of correlation between them is expected.

quarters of high prices cycles are preceded and often coincide with quarters of depreciation in the effective nominal exchange rate (NEER). While this dynamic also exists in AEs, it is less pronounced.

Next, I estimate a Dynamic Factor Model (DFM) to study the co-movements of inflation in EMEs and AEs with global inflation. Specifically, I decompose each country's inflation into three components: common, group-specific, and idiosyncratic. This method has been used in various studies (Neely & Rapach, 2011; Ha et al., 2019; Forbes, 2019) but without differentiating economies based on central bank characteristics. From this estimation, I find a fourth difference: the idiosyncratic inflation factor is significantly more relevant in EMEs. In EMEs, 55.6% of inflation variance is due to idiosyncratic factors, compared to only 39% in AEs.

I then seek to explain these differences by focusing on the causes of inflation in EMEs and AEs. Using a Structural Vector Autoregressive (SVAR) model, I compute Impulse Response Functions (IRFs) and variance decompositions. This allows me to identify the magnitude and direction of shocks on prices and the percentage of the price cycle explained by each shock. This methodology has also been used to study real variable cycles in EMEs (Uribe & Yue, 2006; Akinci, 2013; Fernández et al., 2017; Schmitt-Grohé & Uribe, 2017), but without analyzing prices. I find that the differences between emerging and developed economies are explained by three particularities of EMEs. Together, these factors imply that (almost) anything that reduces the output cycle, depreciates the exchange rate, and, through this channel, generates inflationary pressures.

The first peculiarity is that in EMEs, the NEER is more relevant in the price cycle. Prediction error variance decompositions show that 30% of the price cycle in EMEs is explained by exchange rate innovations, compared to only 13% in AEs. This is consistent with both a higher ERPT to domestic prices and more volatile exchange rates in EMEs (Ha et al., 2019).

The second is the NEER's response to sovereign spread shocks and commodity price changes. In EMEs, a higher sovereign spread depreciates the exchange rate. This happens because as country risk increases, foreign investors tend to withdraw their investments, leading to capital flight and currency depreciation (Carrera et al., 2021). However, this phenomenon does not occur in AEs. On the other hand, a negative shock in the prices of exported commodities causes a greater NEER depreciation in EMEs than in AEs. This aligns with the idea that EMEs concentrate their exports in a few products, often commodities. Therefore, in EMEs, both shocks reduce output and depreciate the NEER.

The third is that a recession in the Global Financial Cycle (GFC) depreciates the NEER more in EMEs due to an amplifying mechanism. This amplifier has two stages. First, increases in global risk perception, measured as VIX rises—a proxy for the GFC—depreciate the NEER more in EMEs than in AEs. This is consistent with previous studies finding that when risk rises, global investors withdraw their capital from emerging markets, seeking refuge in developed economies (Carrera et al., 2021). The second stage occurs because VIX increases lead to higher sovereign spreads and lower commodity prices. As mentioned earlier, both effects further depreciate the exchange rate in EMEs, which does not happen in AEs. The result is that GFC recessions generate inflationary pressures in EMEs but deflationary pressures in AEs through the exchange rate (the opposite occurs during a boom).

These three characteristics help explain the differences between AEs and EMEs. First, they imply that in EMEs, output is not irrelevant, but periods of high growth often coincide with exchange rate appreciations. This occurs because three types of shocks that increase output—increases in exported commodity prices, lower sovereign spreads, and VIX declines—appreciate the NEER in EMEs. Given the higher ERPT, they generate acyclical prices. Second, they imply that the larger idiosyncratic factor of inflation observed in EMEs is due to the reactions of their exchange rates to internal and external shocks. Since the NEER in EMEs tends to depreciate when global inflation rises, it creates deflationary pressures while other countries experience high inflation (i.e., a higher idiosyncratic behavior).

The structure of this paper is as follows. Section 2 describes the data and explains the sample selection process. The subsequent two sections aim to identify differences between the price cycles of AEs and EMEs. In Section 3, the correlation of the price cycle with other relevant variables is analyzed. Subsequently, in Section 4, a DFM is estimated to compare the idiosyncratic factor of inflation between AEs and EMEs. Then, in Section 5, an SVAR is estimated, and IRFs and variance decompositions are computed. The objective in this section is to study the causes of the price cycle in EMEs. Finally, in Section 6, conclusions are drawn.

1.1 Literature Review

Firstly, this work is connected to the literature that examines bussines cycles in various countries and has identified empirical regularities (some classic papers include Kydland & Prescott, 1982; Backus & Kehoe, 1992; Mendoza, 1991). Although initially focused on developed countries, more recently, other authors have become interested in stylized facts of cycles in EMEs (Neumeyer & Perri, 2002; Uribe & Yue, 2006; Aguiar & Gopinath, 2007; Akinci, 2013; Fernández et al. 2017; Schmitt-Grohé & Uribe, 2017; Schmitt-Grohé & Uribe, 2018). These investigations have primarily centered on the behavior of real variables, leaving aside the analysis of prices, which is precisely the focus of this study.

Secondly, it is related to the extensive literature examining the relationship between inflation and output, namely the Phillips curve. In particular, with studies focusing on the Phillips curve in EMEs (Nugent & Glezakos, 1982; Céspedes et al., 2005; Jasová et al., 2020; Kamber et al., 2020). Some of these studies have documented a strong relationship between inflation and domestic output (Bems et al., 2018), while others have observed weakening of this relationship in recent decades (Carney, 2017; Borio & Filardo, 2017; Forbes, 2019). Although this study does not aim to estimate the Phillips curve, it does examine the relationship between the price cycle and domestic variables in a different manner: by combining correlation analysis with the estimation of econometric models such as SVAR and DFM.

Thirdly, this study is linked to the literature on the GFC and how it partially determines economic cycles, particularly those of EMEs (Akinci, 2013; Rey, 2013; Obstfeld, 2018; Carrera et al., 2021; Miranda-Agrippino & Rey, 2020). This body of literature has focused on how the GFC affects global output and capital flows but has overlooked its effects on the Consumer Price Index (CPI). Therefore, this study aims to analyze the effects and transmission channels of the GFC on local prices.

Fourthly, this work is connected to research on the co-movement of local inflations with global inflation (Ho & McCauley, 2003; Aizenman et al., 2008; Neely & Rapach, 2011; Ha et al., 2019; Ha et al., 2023). These investigations estimate DFMs and subsequently compare idiosyncratic inflation factors across groups of countries. The novelty of this study lies in the sample selection (i.e., economies with transparent central banks) and the timeframe considered (i.e., from 2000 to 2021).

2 Data and Sample Selection

The price data is sourced from Ha et al. (2019) and Ha et al. (2023)[2]. According to the authors, this constitutes the most comprehensive database available on prices, encompassing price and inflation information for 209 countries spanning from 1970 to 2022, and incorporating various price metrics. The dataset comprises both annual and quarterly frequency data.

The national accounts data are sourced from the International Financial Statistics of the International Monetary Fund (IMF)[3]. This database provides information on Gross Domestic Product (Y), consumption (C), investment (I), government expenditure (G), imports (M), and exports (X) for 96 countries spanning from 1960 to 2023. The data is available at both annual and quarterly frequencies. It is noteworthy that these national accounts are computed at constant prices, with the base year potentially varying by country; they are expressed in local currency and have not undergone seasonal adjustment. Additionally, I also extract data on broad money, Nominal Effective Exchange Rate (NEER), and sovereign bond rates from the International Financial Statistics.

From Ha et al. (2019), I have also extracted information regarding the independence and transparency of central banks and the classification of countries into developed, emerging, and poor categories. For the former variable, the authors extrapolate data from Dincer and Eichengreen (2014), who construct the Central Bank Independence and Transparency Index. This index rates the central banks of each country on a scale of 1 to 15 and provides data for 108 countries from 1998 to 2014. On the other hand, for the latter variable, the authors rely on categorizations from the World Bank and IMF. Thus, they classify 175 countries into developed, emerging, and poor categories.

Finally, population data is sourced from the World Development Indicators of the World Bank[4]. This series is available for 266 countries from 1970 to 2022 and is provided at an annual frequency. The Commodities Export Price Index (CEPI) data is obtained from Gruss and Kebhaj (2019), with quarterly information covering 182 economies from 1962 to 2022[5]. The Chicago Board Options Exchange Market Volatility Index (VIX) is extracted from the Federal Reserve Bank of St. Louis (FRED)[6]. Lastly, the classification of exchange rate regimes is sourced from Ilzetzki et al. (2019, 2021)[7].

Four methodological clarifications are pertinent. Firstly, the data regarding expenditure components and broad money are not provided on a per capita basis, requiring division by population. To accomplish this, population data from the World Development Indicators is utilized. Given that population data is available annually, it is necessary to assume that population growth from one year to the next occurs uniformly across each quarter. In other words, if the annual increase is 1 million people, it is assumed that the population increases by 250 thousand people each quarter.

The second clarification is that neither the national accounts data from the IMF nor the price level data from Ha et al. (2019) are seasonally adjusted, hence requiring this adjustment. Otherwise, the cyclical differences could be attributed to seasonal components rather than structural characteristics of AEs and EMEs. To accomplish this, I employed Seasonal and Trend decomposition using Loess (STL).

[2]These data were utilized for their book '*Inflation in Emerging and Developing Economies: Evolution, Drivers, and Policies*,' an extension of their previous work '*One-stop source: A global database of inflation*,' published two years earlier. The dataset is accessible via the following link.

[3]Link.

[4]Link

[5]Link

[6]Link

[7]Link

The third is that the Sovereign Spread variable is computed as the difference between the local 10-year sovereign bond rate in dollars and the sovereign bond rate of the United States in dollars.

The final clarification is that, for conducting price comparisons across economies, only the Consumer Price Index (CPI) with volatiles is considered. Ha et al. (2019) also provide data on CPI without volatiles, Producer Price Indices (PPI), and GDP Deflator Indices. However, while all of these are insightful price measures, the focus will be solely on the CPI with volatiles, as it is the most representative measure of the prices paid by a country's population. Henceforth, this index will be referred to simply as the price level.

2.1 Sample Characterization

Almost all macroeconomic time series can be adequately decomposed into a cyclical and a trend component. This holds true for variables such as GDP, other expenditure components, interest rates, among others. Indeed, the vast majority of studies on business cycles in EMEs tend to perform this decomposition and then focus solely on the cyclical component of the variables (see, for example: Neumeyer & Perri, 2002; Uribe & Yue, 2002; Aguiar & Gopinath, 2007; Akinci, 2013; Fernández et al., 2017; Schmitt-Grohé & Uribe, 2017; Schmitt-Grohé & Uribe, 2018).

While it is reasonable to assume that variables such as GDP can be decomposed in such a manner, the challenge arises when considering the study of price levels. Logically, prices are influenced significantly by institutional factors, meaning that their cyclical and/or trend components may be driven more by the decisions of monetary authorities at the time rather than by structural features of the economies. Therefore, in an economy where the central bank issues money recklessly, studying the cyclical component of its prices simply becomes nonsensical.

Furthermore, since high or uncontrolled money emissions due to seigniorage motives are more common in EMEs than in AEs, comparing the cyclical component also becomes meaningless. Indeed, the results would be trivial, as the price cycle would be much more pronounced in EMEs, with a variance that would be thousands or even millions of times greater. Moreover, the price cycle would be less correlated with other cyclical components, given that inflation would be explained almost entirely by excessive monetary issuance and not, for example, by what happens with aggregate demand. In other words, the price cycle would be different, but it would not be possible to determine whether it is due to differences in central bank behavior or due to structural differences between AEs and EMEs.

For these reasons, the analysis can only be conducted by considering emerging and developed economies that have similar monetary policy institutions and regulations. With this aim in mind, I only consider data from 2000Q1 to 2021Q4 for economies that have received a score of five or higher on the Central Bank Independence and Transparency Index in all years from 2000 onwards.

The reason for the temporal restriction is that since the 1990s, emerging economies have adopted institutional frameworks and regulations similar to those of developed economies, such as independent central banks and inflation targets. The result has been a significant decrease in inflation from 2000 onwards in these economies and a convergence of monetary policies in response to the same shocks (Forbes, 2019; Ha et al., 2019).

The reason for the second restriction is that economies with a consistently well-evaluated central bank should have low and controlled inflation rates. Figure 11 (Appendix) displays the distribution of annual inflation, segmented by their score on the index. It can be observed that the distributions shift to the left as the index improves. In other words, economies with higher scores are able to control their inflation rates.

Both restrictions, considered together rather than individually, allow for the inclusion of only

AEs and EMEs with controlled inflation rates. Table 1 (Appendix) presents descriptive statistics on annual inflation for developed economies, EMEs, and filtered EMEs. It can be observed that for the period 1970-2021, there are countries with hyperinflation in all three groups, which affects the means and variances. However, from 2000 to 2021, the means and variances decrease, and there are no longer hyperinflations in either developed economies or filtered emerging economies.

It is worth noting that the Central Bank Independence and Transparency Index cannot assign scores to countries in the Eurozone. However, I have chosen to include the 11 founding economies of the monetary union to encompass more developed countries. On the other hand, I have excluded all major world economies: France, Germany, Japan, the United Kingdom, and the United States. The reason for this is that otherwise, the group of developed economies would include larger countries than the emerging ones. Thus, after applying the filter, there are 12 EMEs with independent and transparent central banks (just EMEs from now on) and 24 developed economies, the composition of which is described in Table 2 (Appendix).

2.2 Descriptive Statistics

Some interesting observations can be directly drawn from Figure 12 (Appendix), specifically through a simple comparison of inflation between emerging and developed economies. The first finding reveals that inflation remains higher in EMEs. From 2000 to 2021, emerging economies had an annualized average inflation rate of 4.3%, more than double that of developed countries, which stood at 2.03%. It can also be observed that the average inflation in emerging economies is higher in all years and, in fact, seems to consistently surpass inflation in developed economies by approximately two percentage points.

Inflation is also more volatile in emerging economies. The variance of annualized inflation was three times higher in emerging economies for the period in question. In Figure 12 (Appendix), it can be observed that the fluctuations of average inflation are greater in emerging economies. Additionally, this graph illustrates that the interquartile range is always wider in emerging economies, suggesting greater variability among EMEs than among AEs. In other words, the former would constitute a more heterogeneous group.

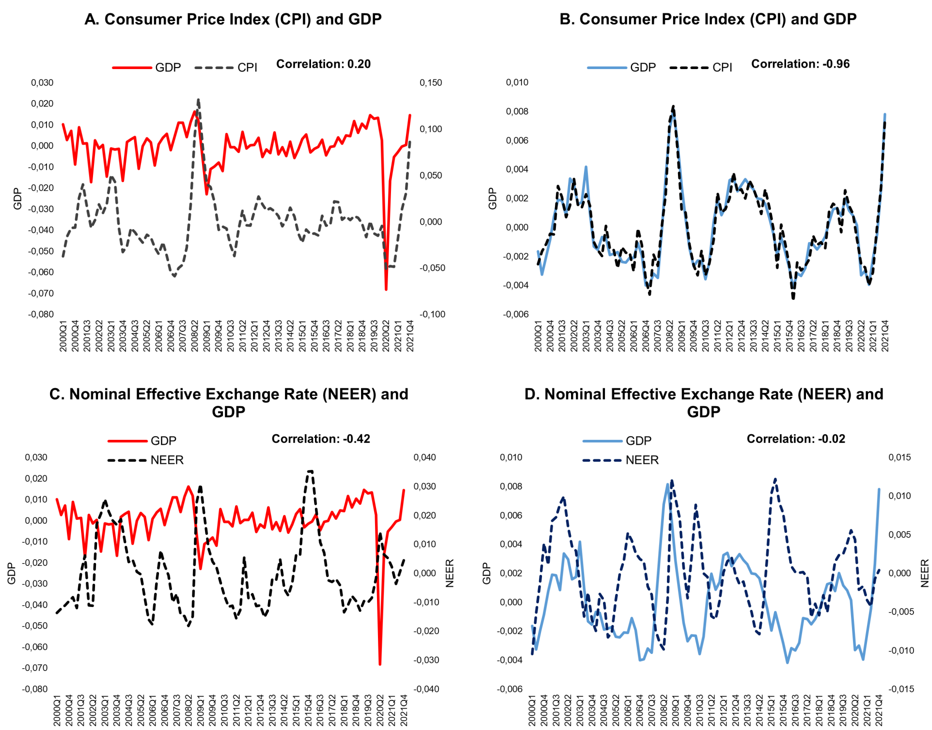
It is also noteworthy that developed countries consistently receive higher scores in the central bank index, which could have implications for conditional analysis. However, the scores of emerging economies show an upward trend in all years until 2014, where the index concludes, gradually closing the gap with more developed countries.

It is worth noting that there are some very high inflation rates in EMEs. Indeed, the highest was experienced by Sri Lanka in the first quarter of 2008, where inflation reached 23%. However, the filter appears to work for three reasons. First, because high inflation rates have also occurred within AEs, such as the case of Iceland with 16% in 2008Q1. Second, because over 96% of the recorded inflation rates in EMEs were of magnitudes lower than two digits. Lastly, because it is feasible to work with simple averages of inflation, whereas the literature often resorts to medians due to the presence of hyperinflations (see Ha et al., 2019; Ha et al., 2023).

If we focus on the simple average of the price cycle for emerging and developed economies, we can notice two differences. Figure 1 shows that the correlation between the price cycle and the product cycle is almost 1 in AEs. This means that when prices are above their trend level, the product is also above its trend. This correlation also exists in EMEs, but it is lower. In the same figure, it can also be seen that in developed economies, the product cycle does not correlate with the NEER cycle. On the contrary, in EMEs, this correlation is negative. In other words, when prices are above their trend level, the exchange rate tends to be depreciated.

Figure 1: Correlations of GDP, CPI, and NEER for AEs and EMEs.

The figure shows the correlations of the product cycle with the price cycle, measured as the Consumer Price Index (CPI), and the Nominal Effective Exchange Rate (NEER) cycle. The cycle of each variable for each group is the simple average of all cycles within the group. For example, the product cycle for AEs is the simple average of all product cycles for countries considered within the AEs. The other cycles are calculated analogously.



Notes: Quarterly price data is sourced from the CPI by Ha et al. (2019). GDP and NEER utilize quarterly frequency data from the International Monetary Fund. The temporal scope considered spans from 2000Q1 to 2021Q4. Data is seasonally adjusted using the STL method, followed by extraction of the cyclical component through the Hodrick-Prescott filter. The analysis encompasses a total of 12 Emerging Market Economies (EMEs) and 24 developed small and medium-size economies, as detailed in Table 2 (Appendix).

In the following sections, I will argue that the lower correlation of the product with prices in EMEs is precisely due to the correlation between the product and the NEER. As mentioned earlier, in these economies, some of the shocks that reduce the product also depreciate the exchange rate and, through this channel, generate inflationary pressures. The result is what is shown in Figure 1: in EMEs, when the product decreases, the NEER also tends to depreciate; at the same time, we cannot observe a strong correlation between the product and prices.

3 Cyclical Analysis

In this section, the correlations of the cyclical components of a set of relevant macroeconomic variables are computed for quarterly data spanning from 2000Q1 to 2021Q4. This approach has been widely employed in studies on business cycles in emerging economies (see Mendoza, 1991;

Neumeyer & Perri, 2002; Uribe & Yue, 2002; Aguiar & Gopinath, 2007) and primarily serves as an initial step for analysis. A key departure from prior studies is the focus on price dynamics.

Before comparing the business cycles between AEs and EMEs, we must inquire why they could differ if only considering economies whose central banks do not pursue seigniorage objectives. The rationale is that AEs and EMEs often exhibit structural differences, which could lead to distinct price cycles. These disparities can be summarized into three.

The first is that the business cycle is not identical in AEs and EMEs. Not only is output more volatile, but the cycle of other variables exhibits different dynamics as well. For instance, unlike in AEs, in EMEs consumption is more volatile than output, and both current accounts and interest rates are countercyclical (Neumeyer & Perri, 2002; Uribe & Yue, 2002; Aguiar & Gopinath, 2007). Additionally, the literature has found that shocks to commodity prices and sovereign spreads are more relevant to the output cycle in EMEs (Akinci, 2013; Fernández et al., 2017). Therefore, given the differing business cycles, price cycles could also diverge.

The second reason is that the price baskets, from which the CPI is constructed, are not the same in AEs and EMEs. One difference is that basic baskets in EMEs often have a higher percentage of food and energy products (IMF, 2011). This discrepancy is relevant because energy and food are the most volatile components of the CPI, and their prices tend to depend more on global phenomena than local ones. Therefore, the price cycle could be different in AEs and EMEs because the same products are not considered in their calculations.

The third reason is that EMEs exhibit a higher Exchange Rate Pass-Through (ERPT) to domestic prices, meaning that the price level is more responsive to nominal exchange rate changes (Ha et al., 2019). This phenomenon occurs for various reasons. For example, EMEs tend to have a higher proportion of imported goods in their baskets, along with a lower capacity to replace them with local products when their prices increase due to depreciation. Additionally, this occurs because currencies of EMEs are not typically used to set prices globally, leading to a higher ERPT to imported goods (Gopinath et al., 2007; Gopinath, 2015).

3.1 Methodology

The methodology is based on Schmitt-Grohé and Uribe (2017), with minor variations implemented. We can summarize the method in three fundamental steps[8]. The first step involves taking logarithms of the price level and other variables of interest. This allows us to define:

$$x_t \equiv \log X_t \tag{1}$$

Where X_t represents the variable of interest, which should be seasonally adjusted and, if necessary, expressed on a per capita basis. It is noteworthy that logarithms are not applied to variables that can take negative values, such as sovereign spreads.

The second step involves decomposing each variable into a cyclical x_t^c and a trend x_t^{tr}component as follows:

$$x_t \equiv x_t^c + x_t^{tr} \tag{2}$$

For the decomposition, I use the Hodrick-Prescott filter for quarterly data. This is an arbitrary decision; however, it does not imply significant variations in the final results.
The third step involves studying x_t^c, focusing on the cyclical component of the price level p_t^c. In particular, one should analyze the variance, autocorrelation, and correlation of p_t^c with the cycles

[8]For a more detailed explanation, refer to the book '*Open Economy Macroeconomics*' by Schmitt-Grohé and Uribe.

of other variables. While this approach closely resembles that followed by the literature, it also examines the correlation of the price cycle with both lagged and future cycles of other variables. In other words, it investigates the correlation of p_t^c with x_{t+T}^c, where $T \in (-6, -5, -4, \ldots, 4, 5, 6)$. The relevance of this approach lies in the potential for prices to react with a delay to changes in other variables. For example, it is expected that inflation will respond to increases in the monetary policy rate, but not immediately—rather, after several quarters—and that effects may persist even after a year. Similarly, a business cycle expansion is expected to increase aggregate demand and create upward pressure on prices, but not instantaneously; rather, with some delay.

3.2 Price Volatility and Inertia

The price cycle is more pronounced in EMEs than in AEs. Indeed, the variance of the cyclical component of prices was 2.07 times higher in emerging economies. This result is expected, given that the business cycle is stronger in EMEs, and the cycles of variables such as output and consumption are also more volatile (Schmitt-Grohé & Uribe, 2017). It can also be explained by the greater presence of volatile components in the basic baskets of EMEs (IMF, 2011).

The inertia of prices does not vary according to the type of economy. Figure 13 (Appendix) shows the autocorrelation, from lag one to lag eight, of the cyclical component of the price level in AEs and EMEs. It can be observed that the level of autocorrelation is not statistically different for any period, indicating that prices are equally persistent. This result differs from what the literature typically finds, namely, that inflation is stickier in EMEs (Asfuroglu, 2021). Additionally, prices follow a similar dynamic, with the first autocorrelation being high and then decreasing until it becomes negative. This means that high levels of price cycles are often followed by similarly high prices in the following quarters, with a maximum horizon of one year. However, after one year, the correlation becomes negative, suggesting that both economies are capable of controlling their high inflation rates within a one-year horizon.

3.3 Prices and Aggregate Demand

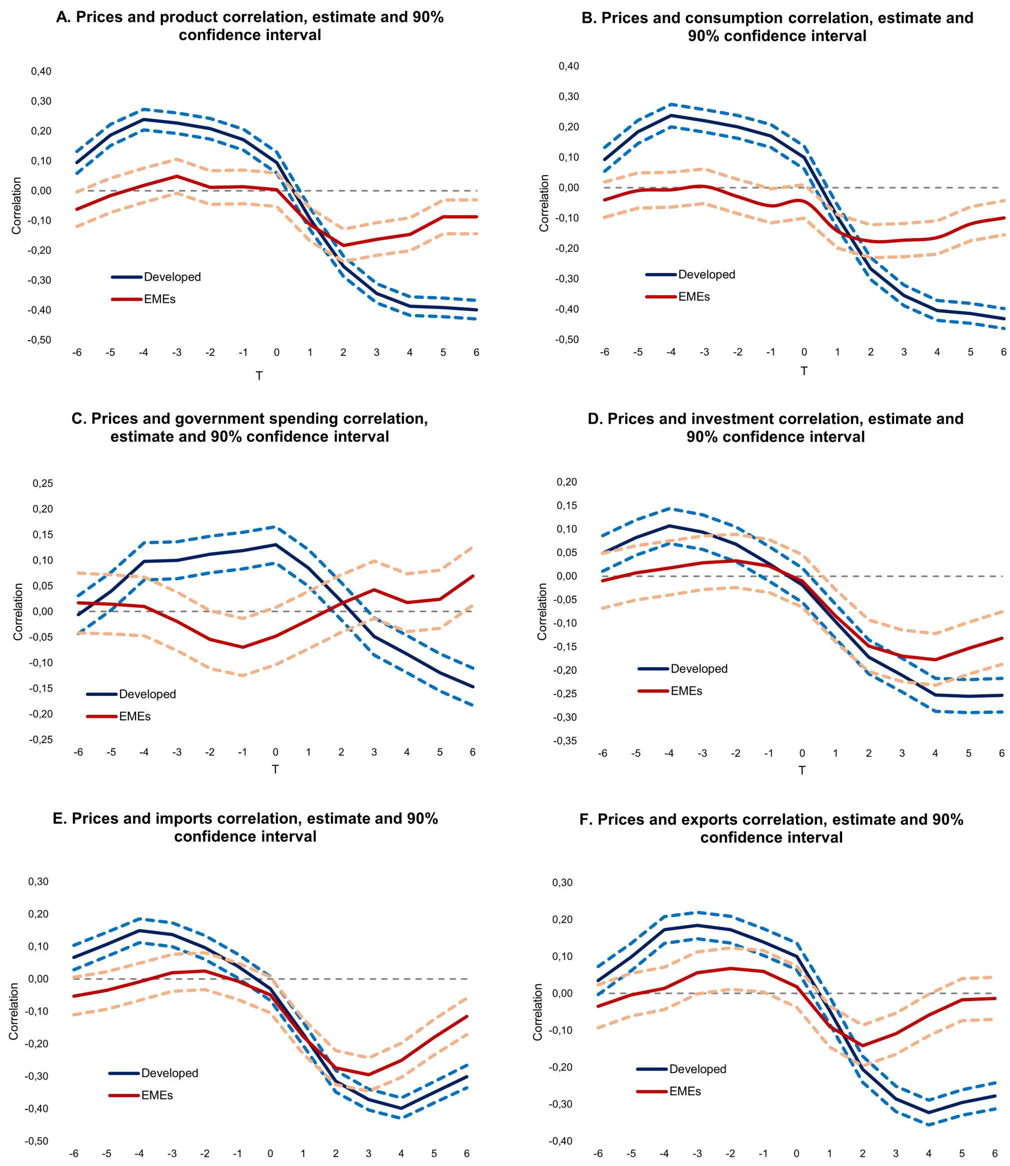
There exists an extensive literature linking inflation with output and components of aggregate demand. As early as 1958, Phillips identified a positive relationship between inflation and output, later coined as the Phillips curve. Although the curve has been subject to both criticism and theoretical advancements, it continues to be used today to explain inflation in both developed and emerging economies.

The natural question arises as to whether there are differences in the relationship between inflation and domestic slack in emerging and developed economies. Figure 2 aims to provide an initial approach to answering this question. It contains the correlations of the cyclical component of prices with that of output and the components of expenditure[9]. These correlations are contemporaneous or up to 6 quarters ahead or behind.

[9]The Phillips curve depicts a relationship between inflation and the output gap; however, this study examines the cycles of prices and output, which are distinct concepts. Nevertheless, they are variables that are related. In fact, in Figure 14 (Appendix), it can be observed that the inflation cycle is very similar to the price cycle. Therefore, some kind of correlation between the price cycle and the output cycle should be observed, which indeed occurs in advanced economies. On the other hand, in Figure 14 (Appendix), it can also be noted that the findings of this section do not appear to vary significantly regardless of whether the price cycle or inflation is considered, suggesting that the main conclusions would remain unchanged. However, it is not possible to affirm that inflation is acyclical in emerging market economies, as prices are.

Figure 2: Correlation of the Cyclical Component of Prices with Expenditure Components.

The figure contains correlations of the cyclical component of prices with that of other relevant variables contemporaneously or T quarters forward or backward. For instance, the first graph illustrates the correlation between the cycle of prices and that of output. On the horizontal axis, we have T, as we calculate the value of $Corr(p_t^c, y_{t+T}^c)$ with $T \in (-6, -5, -4, \ldots, 4, 5, 6)$. Thus, the value on the vertical axis when T is equal to -6 represents the correlation of the cyclical component of prices with that of output from 6 quarters ago. The other graphs follow a similar pattern but consider different variables: investment, consumption, government spending, imports, and exports.



Notes: Quarterly price data is sourced from the Consumer Price Index (CPI) by Ha et al. (2019). Expenditure components utilize quarterly frequency data from the International Monetary Fund. The temporal scope considered spans from 2000Q1 to 2021Q4. Data is seasonally adjusted using the STL method, followed by extraction of the cyclical component through the Hodrick-Prescott filter. The analysis encompasses a total of 12 Emerging Market Economies (EMEs) and 24 developed small and medium-size economies, as detailed in Table 2 (Appendix).

From the first graph of Figure 2, it can be observed that contemporaneous correlations between prices and output are positive in AEs but not statistically different from zero in EMEs. Although it should be mentioned that the magnitude of the correlation is also low in rich economies, as it was 0.13, there is a relevant difference: prices are procyclical in AEs, while they are acyclical in EMEs. This discrepancy is further accentuated when considering correlations with lagged output, up to 6 quarters, as they are positive and of greater magnitude than the contemporaneous correlation in AEs. This implies that positive price cycles are often preceded by positive output cycles. This result is expected if we consider a Phillips curve since when output is very high, aggregate demand will rise, exerting upward pressure on prices. However, we cannot observe this dynamic in emerging economies, where the correlations in question are not statistically different from zero. That is, in these countries, periods of high price cycles do not usually occur after quarters with high product.

In Figure 2, it can also be seen that in both types of economies, positive price cycles are often followed by negative output cycles. Again, the result is consistent with simple economic logic since when prices are very high, the central bank will raise interest rates to control inflation, which in turn will lead to a decrease in output. Despite this, there are differences between emerging and developed economies, as in the former, the correlations in question are lower in absolute value—meaning less negative. In other words, in developed economies, periods of high prices are usually followed by periods of product even further below trend than in EMEs.

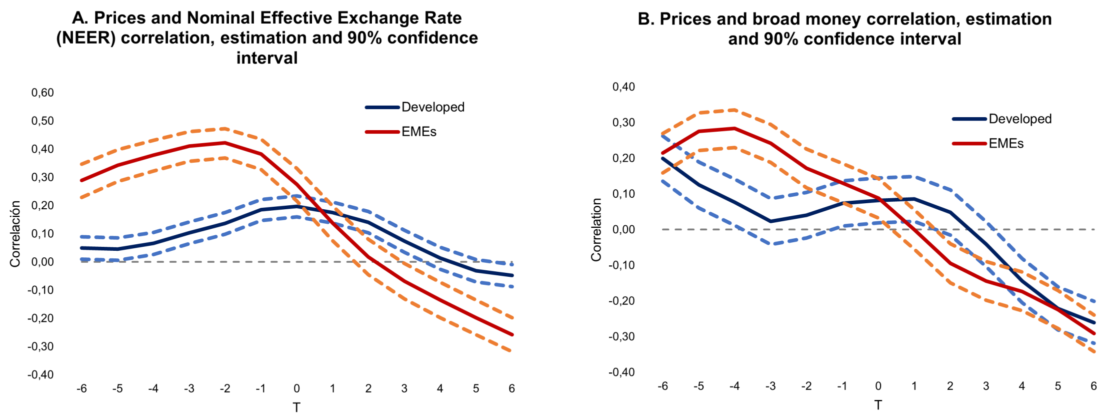
In the same figure, it is also possible to notice that the dynamics of prices and output in AEs and EMEs are replicated, to some extent, for consumption, investment, imports, and exports. Furthermore, in EMEs, the contemporaneous correlation of the price cycle with the cycles of all expenditure components is not statistically different from zero. That is, prices are completely acyclical. On the other hand, it can be observed that all graphs are similar to each other—except for the one considering government spending. This means that, for example, periods of high consumption in developed economies will be followed by periods of high price cycles, which, in turn, will be followed by periods of low consumption. This could again be explained by the aforementioned economic logic. Conversely, high prices in emerging economies are not usually preceded by quarters of high consumption. This dynamic is replicated, to a greater or lesser extent, for investment, imports, and exports as well.

In emerging markets, the correlation between the price cycle and the lagged or future government spending cycle is zero. In other words, there seems to be no relationship between prices and government spending. This result is surprising, given that government spending is a significant component of aggregate demand; however, it suggests once again that the considered emerging economies have central banks that do not print money to finance fiscal deficits. Otherwise, we would observe a positive correlation between the price cycle and lagged government spending. Indeed, this is precisely the dynamic observed in AEs, although the magnitude of the correlations is low.

Finally, Figure 17 (Appendix) shows that this analysis cannot be performed for EMEs with non-transparent central banks, i.e., those that do not pass the imposed filter. The figure in question is analogous to Figure 2 but only shows the correlation between prices and output. It is notable that there is no correlation between the price cycle and the output cycle for any value of T. This is expected since its behavior should be explained more by the arbitrary decisions of monetary authorities than by what happens with output.

Figure 3: Correlation of the Cyclical Component of Prices with Nominal Variables.

The figure contains the correlation of the cyclical component of prices with the cyclical component of the Nominal Effective Exchange Rate (NEER) (A) and broad money (B). The contemporary correlation and correlations T quarters backward or forward are displayed. For example, in graph A, it shows the correlation between prices and the NEER. On the horizontal axis, we have T, as we calculate the value of $\text{Corr}(p_t^c, xr_{t+T}^c)$ with $T \in (-6, -5, -4, \ldots, 4, 5, 6)$. Thus, the value on the vertical axis when T is equal to -6 represents the correlation of the cyclical component of prices with that of the NEER from 6 quarters ago.



Notes: Quarterly price data is sourced from the Consumer Price Index (CPI) by Ha et al. (2019). Nominal variables utilize quarterly frequency data from the International Monetary Fund. The temporal scope considered spans from 2000Q1 to 2021Q4. Data is seasonally adjusted using the STL method, followed by extraction of the cyclical component through the Hodrick-Prescott filter. The analysis encompasses a total of 12 Emerging Market Economies (EMEs) and 24 small and medium-size developed economies, as detailed in Table 2 (Appendix).

3.4 Prices and Nominal Variables

There are several studies that emphasize the importance of certain nominal variables in explaining inflation. Asfuroglu (2021) conducts a review of the inflation literature in EMEs and concludes that inflation remains a monetary phenomenon in these economies. Moreover, EMEs are more exposed to the influence of the exchange rate on inflation and focus their monetary policy more on controlling exchange rate fluctuations (Ho & McCauley, 2003; Aizenman et al., 2008; Ha et al., 2019). One reason for this is that, as mentioned earlier, EMEs would have a higher ERPT to domestic prices. Another nominal variable, the Monetary Policy Rate (MPR), is one of the primary tools of central banks to control inflation; however, its transmission to short-term rates could be imperfect in EMEs (De Leo et al., 2023).

Thus, it is also natural to inquire whether there are differences in the relationship between prices and nominal variables in AEs and EMEs. Figure 3 shows the correlation of the price cycle with the NEER and broad money. It can be noted that, in EMEs there is a positive contemporaneous correlation between the NEER and prices, implying that periods of exchange rate depreciation occur simultaneously with periods of high prices. Moreover, positive price cycles are preceded by quarters of exchange rate depreciation. This is expected and similar to findings in previous studies concluding the existence of greater ERPT in these economies. Additionally, the magnitudes of the correlations reach high levels, suggesting that the NEER is relevant in explaining inflation in EMEs. In contrast, in developed economies, although a similar dynamic is observed, the correlations are lower, indicating a weaker relationship.

It could be speculated that these differences stem from the presence of economies belonging to the eurozone within the group of wealthy countries, whereas no EMEs belong to a monetary union. However, Figure 15 (Appendix) presents the same analysis but without considering eurozone economies. It can be observed that the results are not sensitive to the decision to include or exclude these economies.

The Figure 3 also includes the correlation of prices with broad money. As expected, increases in money beyond its trend are followed by periods of high prices. However, there are no significant differences between the dynamics observed in EMEs and AEs. This, once again, suggests that the central bank's filter is effective.

Finally, Figure 16 (Appendix) illustrates the correlation of the price cycle with the dollar value and MPR. The relationship with the dollar value is similar to that with the NEER, but the correlations are of lower magnitude in both AEs and EMEs, suggesting that the NEER is more relevant than the dollar price in explaining price dynamics. On the other hand, high prices would be preceded by positive deviations from the trend of the MPR. However, this does not imply that the MPR is not useful in reducing inflation, but rather it is limited to displaying a correlation.

3.5 Prices, the Exchange Rate and the Global Financial Cycle (GFC)

The GFC refers to the co-movement in financial markets across different economies that are explained more by activity in global financial centers than by domestic factors. In particular, capital flows such as credit, portfolio investment, and foreign direct investment move jointly across countries and negatively correlate with the VIX, which is a measure of global uncertainty (Rey, 2013; Miranda-Agrippino & Rey, 2020). Indeed, it is common practice to use the VIX as a proxy for the GFC, a convention I will also adopt in this work.

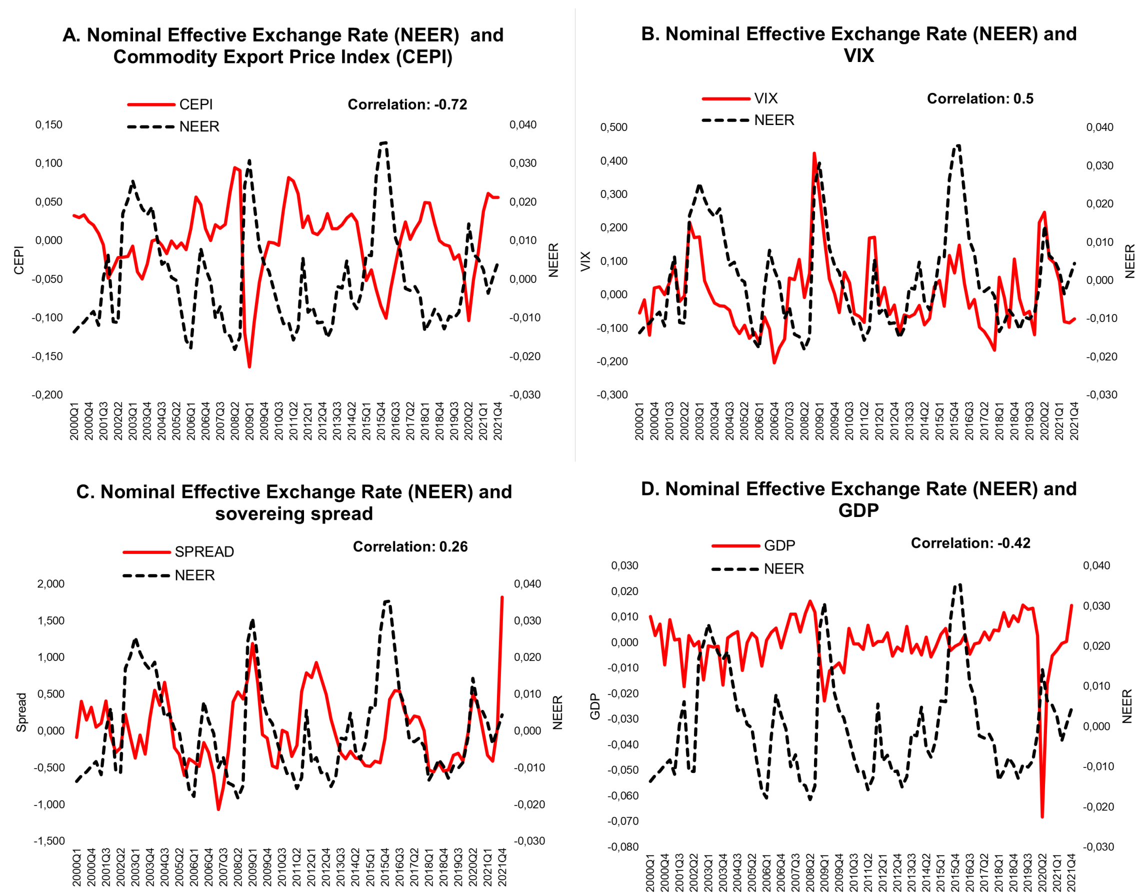
Although the booms and recessions of the GFC are determined in global financial centers, their effects could differ across economies and, particularly, between AEs and EMEs. In this regard, Obstfeld et al. (2018) find that the GFC is stronger in EMEs: the correlations of the VIX with credit creation, asset prices, capital inflows, and exchange rates are much stronger, and unlike in AEs, capital flows are countercyclical. The reason is that when the VIX decreases, global investors' appetite for risk increases, leading them to invest capital primarily in emerging economies; then, when uncertainty rises, investors shelter their capital in developed economies (Obstfeld, 2018; Carrera et al., 2021). Furthermore, capital flows are more relevant in EMEs, as they represent a more significant percentage of their total output. In fact, they are so relevant that Akinci (2013) estimated that 18% of the business cycles in EMEs are solely due to fluctuations in the GFC.

Although studies on the effects of the GFC on the CPI are scarce, there is a greater body of work on its effect on the exchange rate, which appears to be highly relevant in determining prices in EMEs. Carrera et al. (2021) document the positive correlation between the VIX and currency depreciation in EMEs, meaning that during a downturn in the cycle, currencies depreciate in these economies. Furthermore, they find that when the VIX increases, financial spreads and commodity prices also rise (the opposite occurs during a boom).

Figures 4 and 5 complement the findings of Carrera et al. (2021). They demonstrate that the positive correlation between global uncertainty, measured by the VIX, and depreciations of the NEER, is stronger in EMEs than in AEs. In other words, currencies of emerging economies depreciate more when global uncertainty increases. Furthermore, the figures show that in EMEs, when sovereign spreads and prices of exported commodities, measured by CEPI, increase, there are also depreciations of the NEER. Both results are expected since EMEs tend to export a limited

Figure 4: Correlation of the Cyclical Component of NEER with VIX, CEPI, Spreads and GDP in EMEs.

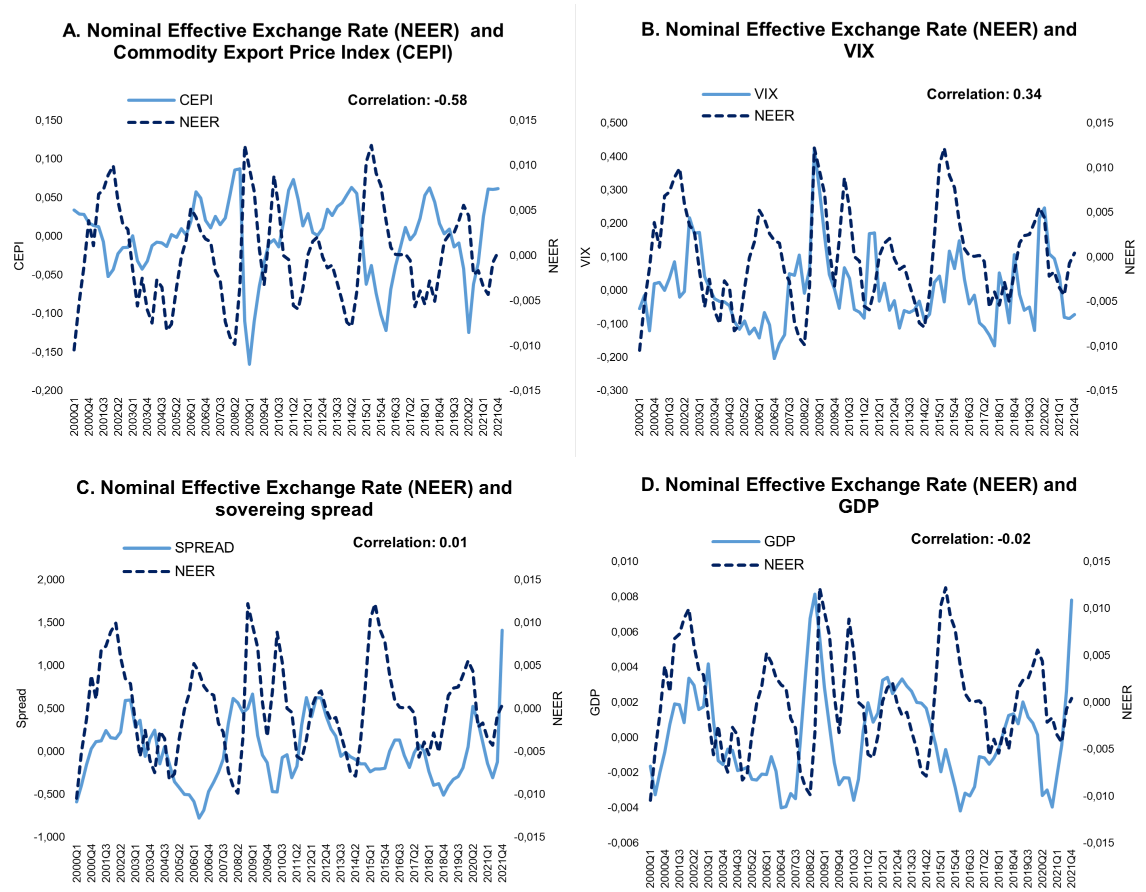
The figure illustrates the evolution of the simple average of the cyclical component of the Nominal Effective Exchange Rate (NEER) in Emerging Economies (EMEs) from 2000Q1 to 2021Q4. Graphs A, C, and D additionally consider, along with the NEER of these economies, the simple average of the cyclical component of: Commodities Price Export Index (CEPI), Sovereign Spread (calculated as the difference between the interest rate of local government bonds at 10 years and the rate of the United States), and GDP. Graph B also shows the evolution of the cyclical component of the VIX.



Notes: The data for the CEPI is sourced from (Gruss and Kebhaj, 2019); the VIX data is extracted from the Federal Reserve Bank of St. Louis (FRED); the sovereign bond yields and GDP data are obtained from the International Monetary Fund (IMF). The analysis encompasses a total of 12 EMEs, as detailed in Table 2 (Appendix).

Figure 5: Correlation of the Cyclical Component of NEER with VIX, CEPI, Spreads and GDP in AEs.

The figure illustrates the evolution of the simple average of the cyclical component of the Nominal Effective Exchange Rate (NEER) in advanced economies (AEss) from 2000Q1 to 2021Q4. Graphs A, C, and D additionally consider, along with the NEER of these economies, the simple average of the cyclical component of: Commodities Price Export Index (CEPI), Sovereign Spread (calculated as the difference between the interest rate of local government bonds at 10 years and the rate of the United States), and GDP. Graph B also shows the evolution of the cyclical component of the VIX.



Notes: The data for the CEPI is sourced from (Gruss and Kebhaj, 2019); the VIX data is extracted from the Federal Reserve Bank of St. Louis (FRED); the sovereign bond yields and GDP data are obtained from the International Monetary Fund (IMF). The analysis encompasses a total of 24 AEs, as detailed in Table 2 (Appendix).

number of products, mainly commodities, and because increases in country risk may lead to capital outflows, resulting in depreciation. In other words, during a GFC downturn, everything happens simultaneously: increases in global uncertainty, rises in spreads, declines in prices of exported commodities, and depreciations of the exchange rate. This phenomenon does not occur in AEs and could amplify the GFC in EMEs, which will be further studied in Section 5.

In Figures 4 and 5, it is also evident that there is a positive correlation between NEER appreciations and output in EMEs, whereas this correlation is zero in AEs. This implies that, in EMEs, periods of growth above trend often coincide with appreciations of the exchange rate, meaning that appreciations are procyclical. Conversely, appreciations are acyclical in AEs. One possible reason is that the GFC is highly relevant in EMEs, and a boom (recession) leads to appreciations (depreciations) simultaneously with increases (decreases) in output. Additionally, it could be the case that the exchange rate is highly sensitive to local shocks that also affect output. For example, a political change could increase the country's risk perception and depreciate the exchange rate while simultaneously decreasing output. This possibility will also be explored in Section 5.

4 Dynamic Factor Model

In this section, the level of co-movement between inflation in emerging and developed economies with global inflation is studied. To accomplish this, a Dynamic Factor Model (DFM), highly similar to that of Neely and Rapach (2011)[10] and Ha et al. (2019), is estimated. This model facilitates the decomposition of inflation for each country into three factors: common, group-specific, and idiosyncratic. Subsequently, differences between AEs and EMEs are analyzed.

This methodology has been implemented by several studies, typically concluding that the common factor of inflation is greater in AEs than in EMEs. For instance, Ha et al. (2019) find that from 2001 to 2017, the common factor explained 18% and 27% of the variation in inflation in emerging and developed economies, respectively. Similarly, Neely and Rapach (2011) demonstrate that the common factor is higher in developed economies with solid institutions, developed financial markets, low average inflation, and independent central banks.

In contrast to the aforementioned studies, my focus is solely on economies with a central bank that passes the filter. This is pertinent because inflation co-movements could be explained by the presence of common shocks, similar responses in monetary policy, and/or membership in monetary unions (Neely and Rapach, 2011). Therefore, given that it is expected for an economy with a central bank adhering to seigniorage objectives to have a high idiosyncratic factor in inflation, controlling for central bank characteristics is essential for comparing AEs and EMEs.

4.1 Econometric Methodology

The Dynamic Factor Model is described by[11]:

$$y_{i,t} = \beta_i^c f_t^c + \beta_i^g f_{j,t}^g + \varepsilon_{i,t}, \tag{3}$$

[10] For the estimation of the Dynamic Factor Model (DFM), I make slight modifications to the codes used by Neely and Rapach in their work "*International Comovements in Inflation Rates and Country Characteristics*" These codes are available on David Rapach's website (link).

[11] Essentially, my econometric model is the Dynamic Factor Model by Neely and Rapach (2011). Therefore, while in this section I describe the most important points of the model, for a more detailed description, I recommend reviewing the work of Neely and Rapach (2011).

Where $y_{i,t}$ is the demeaned inflation of country $i \in (1, 2, ..., N)$ in year $t \in (1, 2, ..., T)$; f_t^c is the common inflation factor[12], which is common to all countries in the sample; $f_{j,t}^g$ is the group inflation factor, common to all countries within group $j \in (1, 2, ..., J)$; and $\epsilon_{i,t}$ is the idiosyncratic factor. The loadings, β_i^c and β_i^g, are parameters - distinct for each country - that measure how inflation responds to the common and group-specific factors. For instance, a positive β_i^c implies that, on average, the inflation of country i rises when the common factor increases. In the extreme case where $\beta_i^c = \beta_i^g = 0$, local inflation is purely idiosyncratic, meaning it does not respond to either common or group-specific factors.

Similarly to Ha et al. (2019), I group economies into three categories: AEs, the 12 EMEs that pass the central bank filter, and the remaining EMEs. Thus, annual data from 2000 to 2021 are considered for 91 countries (29 developed, 12 EMEs passing the filter, and the remaining 50 EMEs). It is pertinent to emphasize that this alteration in sample compared to Section 3 is solely for grouping purposes and estimating the DFM. However, for making comparisons, the same small and large AEs and EMEs described in Table 2 are considered. The rationale for incorporating more economies in the estimation is to study the co-movements of local inflations with global inflation. To obtain a robust proxy of global inflation, it is necessary to consider a larger number of countries.

Note that if the loadings, β_i^c and β_i^g, and the factors, f_t^c and $f_{j,t}^g$, were known, it would be possible to measure what percentage of the variance in inflation of each country is explained by the common, group-specific, and idiosyncratic factors. This is achieved by applying variance to both sides of Equation 3 to obtain:

$$\operatorname{var}(y_{i,t}) = (\beta_i^c)^2 \operatorname{var}(f_t^c) + (\beta_i^g)^2 \operatorname{var}\left(f_{j,t}^g\right) + \operatorname{var}(\varepsilon_{i,t})\,(i = 1, \ldots, N), \tag{4}$$

Where the cross-products are equal to zero because the factors are perpendicular to each other. In this way, it is possible to determine what percentage of the variance in inflation can be attributed to the common factor as follows:

$$\theta_i^c = (\beta_i^c)^2 \operatorname{var}(f_t^c) / \operatorname{var}(y_{i,t}) \quad (i = 1, \ldots, N), \tag{5}$$

Similarly, we can obtain the percentage of the variance in inflation attributable to the group-specific factor and the idiosyncratic factor. However, it is not possible to observe the loadings or the factors. Therefore, they must be estimated. To do so, the following structure, used by Neely and Rapach (2011) and standard in the literature, needs to be imposed. Thus, I will assume that f_t^c, $f_{j,t}^g$, and $\epsilon_{i,t}$ follow $AR(2)$ processes[13]:

$$\varepsilon_{i,t} = \rho_{i,1}\varepsilon_{i,t-1} + \rho_{i,2}\varepsilon_{i,t-p} + u_{i,t} \quad (i = 1, 2, \cdots, N) \tag{6}$$

$$f_t^c = \rho_1^c f_{t-1}^c + \rho_2^c f_{t-2}^c + u_t^c \tag{7}$$

$$f_{j,t}^g = \rho_{j,1}^g f_{j,t-1}^g + \rho_{j,s}^g f_{j,t-2}^g + u_{j,t}^g \quad (j = 1, 2, 3) \tag{8}$$

[12]Both Neely and Rapach (2011) and Ha et al. (2019) refer to the common factor as "global." The rationale behind this is that since it is common to all countries, it is considered global. However, I opt to rename it to clarify that this methodology simply studies co-movements and not how local inflation reacts to global variables. Indeed, an economy might react minimally to the common factor—referred to as "global" by Neely and Rapach (2011) and Ha et al. (2019)—while its inflation is largely explained by global causes.

[13]In Neely and Rapach (2011), as well as in Ha et al. (2019), an $AR(p)$ with $p = 2$ is also employed. This choice is theoretically reasonable as they use annual frequency data. Furthermore, they estimate the model with different values of p and do not find significant changes in their results.

Where $u_{i,t} \sim N\left(0, \sigma_i^2\right), u_t^c \sim N\left(0, \sigma_c^2\right), u_{j,t}^g \sim N\left(0, \sigma_{j,t}^2\right)$, and $E\left(u_{i,t}u_{i,t-s}\right) = E\left(u_t^c u_{t-s}^c\right) = E\left(u_{j,t}^g u_{j,t-s}^g\right) = 0$ for $s \neq 0$. It is also assumed that the shocks u_t^c, $u_{j,t}^g$, and $u_{i,t}$ are uncorrelated with each other, and neither do any of their lags correlate.

The equation 3 can be estimated in various ways. Neely and Rapach (2011) build on previous work by Otrok and Whiteman (1998) and Kose et al. (2003, 2008), who propose Bayesian estimation with augmented data. The first step is to assume the distribution of prior distributions. For this purpose, I simply use the ones assumed by Neely and Rapach (2011) and Kose et al. (2003)[14]:

$$\left(\beta_i^c, \beta_i^g\right)' \sim N\left(0, I_2\right) \quad (i = 1, \ldots, N), \tag{9}$$

$$\left(\rho_{i,1}, \rho_{i,2}\right)' \sim N\left[0, \operatorname{diag}\left(1, 0.5\right)\right] (i = 1, \ldots, N), \tag{10}$$

$$\left(\rho_1^c, \rho_2^c\right)' \sim N\left[0, \operatorname{diag}\left(1, 0.5\right)\right], \tag{11}$$

$$\left(\rho_{j,1}^g, \rho_{j,2}^g\right)' \sim N\left[0, \operatorname{diag}\left(1, 0.5\right)\right] (j = 1, 2, 3), \tag{12}$$

$$\sigma_i^2 \sim IG(6, 0.001)(i = 1, \ldots, N), \tag{13}$$

The algorithm used to estimate the DFM can be summarized as follows. The goal is to obtain the joint posterior distribution $p(\mathbf{f}, \mathbf{b}|y)$, where $\mathbf{f}$ represents all factors (common and group-specific factors for each group at each time t), $\mathbf{b}$ includes all loadings (for all countries i), and y denotes the inflation for each country at each time t. Generally, the posterior distribution is approximated using some sampling method; however, in this case, it is not possible. Despite this, thanks to the imposed structure, the conditional posterior distributions $p(\mathbf{b}|\mathbf{f}, y)$ and $p(\mathbf{f}|\mathbf{b}, y)$ are known. With this, we can generate a sample from $p(\mathbf{f}, \mathbf{b}|y)$ using a Markov Chain Monte Carlo (MCMC) procedure with Gibbs sampling. The estimation algorithm starts with values $\mathbf{f_0}$ and $\mathbf{b_0}$. Then, a sample $\mathbf{b_1}$ is drawn from $p(\mathbf{b}|\mathbf{f_0}, y)$. After that, a sample $\mathbf{f_1}$ is drawn from $p(\mathbf{f}|\mathbf{b_1}, y)$. Subsequently, a $\mathbf{b_2}$ is drawn from $p(\mathbf{b}|\mathbf{f_1}, y)$, and so on. This process is repeated 10,000 times after 1,000 burn-in replications. The result is a sample of $p(\mathbf{f}, \mathbf{b}, y)$, from which we can derive means and other statistics of the factors and parameters.

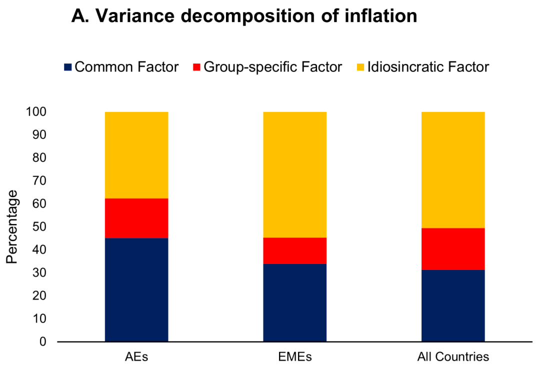
It should be noted that neither the magnitude of the factors nor the loadings are separately identified in equation 3. For example, if f_t^c is multiplied by -2 and $\beta_{i,t}$ is multiplied by $-\frac{1}{2}$ for all i and t, the result will not change. To address this issue, a similar approach to Neely and Rapach (2011) is adopted, where the common loading for Australia and the group loadings for Australia, Botswana, and Argentina are restricted. In other words, the common loading is restricted for an arbitrary representative of the world and one for each group, chosen simply by alphabetical order. To normalize the scales, it is assumed that each of the factor shock variances, σ_c^2 and $\sigma_{g,j}^2$ (j = 1,2,3), is equal to one.

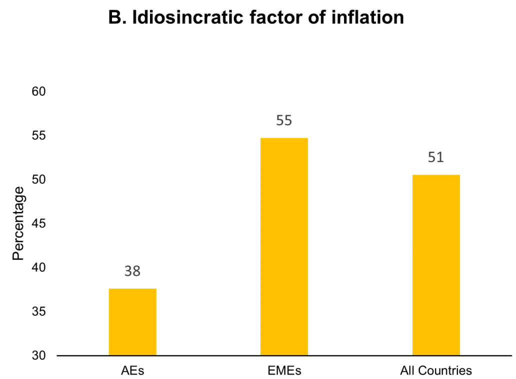
Once distributions for the factors and loadings are obtained, it is possible to conduct a variance decomposition of inflation. Specifically, it is feasible to determine the percentage of its variance explained by common, group-specific, and idiosyncratic factors and then compute simple averages for groups of countries. It is important to clarify that this is a purely empirical exercise, which examines inflation co-movements but remains silent on their causes. For instance, if a country exhibits a high idiosyncratic factor, it is not possible to ascertain the causes through this estimation. Nor does it necessarily imply that its inflation is not explained by global variables; rather, its co-movement with global inflation may simply be low.

[14] Neely and Rapach (2011) describe the priors as relatively agnostic, and they find that their results are not highly sensitive to this arbitrary choice.

Figure 6: Variance Decompositions of Inflation.

The figure displays the results of the estimation of the Dynamic Factor Model (DFM). This model allows for the decomposition of the inflation variance in each country into three components: global, group-specific, and idiosyncratic. Subsequently, economies are grouped into two categories: Advanced Economies (AEs), Emerging Market Economies (EMEs). For each of these groups, the simple average of the global, group-specific, and idiosyncratic components is calculated, and this is presented in both graphs.





Notes: Inflation data is considered at an annual frequency from 2000 to 2021. The data corresponds to the Consumer Price Index (CPI) from Ha et al. (2019). The analysis includes a total of 12 small and medium-size EMEs and 24 AEs, the composition of which is detailed in Table 2 (Appendix).

4.2 Results

In Figure 6 and Table 3 (Appendix), the results are presented. Firstly, the significance of common and regional factors in AEs, which I have found to account for 62%, surpasses findings in the literature, where values range from 20% to 51% (Ha et al., 2019), and exceeds those reported by Neely and Rapach (2011), Forbes (2019), and Ha et al. (2019). Similarly, these factors explained a larger fraction of inflation in EMEs (45%) compared to similar studies. However, this disparity is likely attributed to the inclusion of data from 2000Q1 to 2021Q4, whereas other studies often incorporate earlier information. This is noteworthy, as various studies document that the global factor of inflation has gained greater prominence in recent years (Forbes, 2019; Ha et al., 2019; Ha et al., 2023).

The second finding is that the idiosyncratic component of inflation is more significant in EMEs than in AEs. Indeed, the idiosyncratic component accounted for 55% of the variance in inflation in EMEs, compared to only 38% in AEs. This result suggests that co-movements of local inflation with global inflation are lower in emerging economies.

This difference may be attributed to various factors, one of which is the correlation between the common factor of inflation and NEER depreciations in EMEs. As depicted in Figure 19 (Appendix), when global inflation increases, the NEER tends to appreciate in these economies, which, due to their higher ERPT to domestic prices, generates deflationary pressures. Conversely, in AEs, this correlation also exists but is weaker, and the ERPT is also lower. This phenomenon implies that the behavior of inflation in EMEs exhibits a more idiosyncratic pattern, meaning lower co-movement with global inflation, precisely as observed.

The higher idiosyncratic component could also stem from differences in central bank scores between AEs and EMEs; however, this does not seem to be the case. As previously mentioned, it is expected that an economy with a central bank pursuing seigniorage objectives would exhibit a higher idiosyncratic factor, meaning poorer central bank scores could increase idiosyncratic behavior. Furthermore, AEs have a lower idiosyncratic component and higher scores. However, Figure 19 (Appendix) illustrates that within both AEs and EMEs, there is no clear relationship between central bank scores and the idiosyncratic factor. In fact, in both AEs and EMEs, the relationship seems to be positive—if it exists at all. This, once again, suggests that economies with central banks financing the fiscal authorities are not considered in this analysis.

5 Structural Vector Autoregressive (SVAR) Model

In this section, an SVAR model is estimated, followed by the computation of Impulse Response Functions (IRFs) and variance decompositions of the prediction error for AEs and EMEs. This methodology is also common in the literature that examines economic cycles in EMEs as it enables the investigation of the sign, timing, and relevance of various shocks (see Uribe & Yue, 2006; Akinci, 2013; Fernández et al., 2017; Schmitt-Grohé & Uribe, 2017). Once again, the primary departure from prior studies lies in the focus on the effects of these shocks on output, while the current focus is on prices.

From Sections 3 and 4, five key findings emerge. First, quarters with high prices in EMEs are typically not preceded by periods of high output, consumption, investment, or government spending. This suggests that prices may not depend as heavily on domestic variables, or at least to a lesser extent than in AEs. Second, in EMEs, these high price quarters are preceded by depreciations of the NEER. While this phenomenon also occurs in AEs, it is milder, emphasizing the importance of the exchange rate in EMEs. Third, in EMEs, increases in the VIX, NEER depreciations, declines in the CEPI, and rises in sovereign spreads often occur simultaneously. This phenomenon does not occur in AEs and could amplify the GFC in EMEs. Fourth, output correlates negatively with the NEER in EMEs, meaning that periods of high growth often coincide with currency appreciations. In contrast, exchange rates in AEs are acyclical. The final finding is that inflation in EMEs exhibits a greater idiosyncratic factor, indicating that its co-movements with global inflation are lower than in AEs.

One possible explanation for these findings is that the GFC may be more relevant in explaining variations in output and inflation in EMEs compared to AEs. Specifically, during a boom in the GFC, capital inflows into EMEs could precipitate a substantial appreciation of the exchange rate while simultaneously bolstering output. As previously mentioned, several studies posit the importance of this explanation, noting that the GFC accounts for a significant portion of the business cycle in EMEs and triggers more countercyclical capital flows, which are proportionally larger relative to GDP and exert greater effects on the exchange rate (Akinci, 2013; Obstfeld, 2018; Carrera et al., 2021). This proposition will be denoted as *Hypothesis 1*.

Another possibility is that negative shocks to output and/or country risk may lead to a more pronounced depreciation of the exchange rate in EMEs compared to AEs. A negative output shock could be interpreted by investors as an increase in country risk, prompting capital outflows and a depreciation of the exchange rate, which in turn may have inflationary effects. A similar scenario could occur in the event of an escalation in political conflict, leading to an increase in perceived risk. This proposition is also supported by prior research. For instance, Neumeyer and Perri (2002) argue that country risk is induced by domestic fundamentals and, in turn, amplifies the business cycle in EMEs; meanwhile, Della Corte et al. (2015) document that exchange rates depreciate when sovereign risk increases. This proposition will be denoted as Hypothesis 2.

The simultaneous fulfillment of *Hypotheses 1* and *2* could indeed collectively account for the five results outlined. In such a scenario, a GFC boom would lead to stronger appreciations and output increases in EMEs compared to AEs. Additionally, positive local shocks to output or country risk could also lead to exchange rate appreciations. Consequently, appreciations would exhibit cyclical patterns in EMEs and acyclical patterns in AEs, as observed. Moreover, given the higher ERPT to domestic prices in EMEs, these appreciations would generate deflationary pressures. Thus, it is expected that periods of high growth are not followed by periods of equally high inflation, as observed, since exchange rate appreciation would exert a deflationary effect counteracting the inflationary effect of buoyant aggregate demand. Lastly, the hypotheses also elucidate why EMEs exhibit more idiosyncratic inflation: because their exchange rate appreciates when global inflation increases, as observed, but also due to their response to local shocks.

To test *Hypotheses 1* and *2*, IRFs and variance decompositions of the prediction error are estimated, distinguishing economies as either AEs or EMEs. Through the IRFs, it is possible to determine the sign and magnitude of shocks from variables such as output or the NEER on inflation. With the variance decompositions, it is possible to ascertain the relevance of each shock.

5.1 Econometric Methodology

The specification I will use is based on Uribe and Yue (2006) and Akinci (2013). The model is described by:

$$Ay_{i,t} = \sum_{k=1}^{p} B_k y_{i,t-k} + \eta_i + \varepsilon_{i,t} \tag{14}$$

Where:

$$y_{i,t} = [\hat{vix}_t, \hat{p}^*_t, \hat{cepi}_{i,t}, \hat{spread}_{i,t}, \hat{gdp}_{i,t}, \hat{g}_{i,t}, \hat{money}_{i,t}, \hat{mp}_{i,t}, \hat{neer}_{i,t}, \hat{p}_{i,t}]' \tag{15}$$

$$\varepsilon_{i,t} = [\varepsilon^{vix}_t, \varepsilon^{p^*}_t, \varepsilon^{cepi}_{i,t}, \varepsilon^{spread}_{i,t}, \varepsilon^{gdp}_{i,t}, \varepsilon^{g}_{i,t}, \varepsilon^{money}_{i,t}, \varepsilon^{mp}_{i,t}, \varepsilon^{neer}_{i,t}, \varepsilon^{p}_{i,t}]' \tag{16}$$

Where $i \in (1, 2, \ldots, N)$ denotes the country in quarter $t \in (1, 2, \ldots, T)$. η_i represents a fixed country effect. The variables $p_{i,t}$, $gdp_{i,t}$, $g_{i,t}$, $neer_{i,t}$, $money_{i,t}$, $vix_{i,t}$, $cepi_{i,t}$ $spread_{i,t}$ denote the CPI, GDP per capita, government spending per capita, NEER, broad money per capita, VIX, CEPI and sovereing spread; $mp_{i,t}$ is the monetary policy rate, and $p^*_{i,t}$ is the U.S. CPI. A hat signifies the cyclical component of the variable, obtained following the methodology explained in Section 3. Furthermore, all variables have been seasonally adjusted. The model is estimated separately for the 12 EMEs and 24 AEs. Additionally, quarterly frequency data are considered.

The objective of this model is to explain price dynamics. Therefore, GDP per capita has been incorporated, as it has traditionally been used to study inflation. Additionally, the monetary policy rate is considered because it is the primary tool that these economies have to control inflation. Furthermore, given Figure 4 and the literature already mentioned, it is necessary to incorporate the NEER (Ho & McCauley, 2003; Aizenman et al., 2008; Ha et al., 2019). Additionally, I incorporate broad money per capita and government spending. The rationale behind this inclusion is twofold: firstly, there are authors who suggest that inflation remains predominantly a monetary phenomenon in EMEs (Asfuroglu, 2021); and secondly, it is common for EMEs to issue money to finance government expenditure.

As previously mentioned, the GFC could have effects on prices, thus the VIX is incorporated as a proxy for global risk perception. Considering the relationship between the VIX, CEPI, and sovereign spreads with the NEER suggested by both similar studies (Carrera et al., 2021) and Figure 4, the CEPI and sovereign spreads are added. Additionally, US prices are taken into account as a proxy for global prices, which could impact inflation in both AEs and EMEs primarily through international trade.

It is worth noting that I have used broad money from the Eurozone and the European Central Bank's interest rate as proxies for broad money and monetary policy in Eurozone economies. Otherwise, it would be necessary to eliminate a significant portion of the AEs. Additionally, to maintain a larger sample size, I have not excluded countries without sovereign spreads data; instead, I have set their cycle as zero for all years. This decision has minimal effects on the results.

Structural shocks are identified by imposing that the matrix A is lower triangular with unit diagonal elements, meaning zero short-run restrictions are imposed. This is a common identification strategy in the literature (see Uribe and Yue, 2006; Akinci, 2013; Fernández et al., 2017; Schmitt-Grohé and Uribe, 2018). However, it implies that the ordering of $y_{i,t}$ is relevant. In effect, the first variable – in this case, $\hat{vix}_t$ – is only affected by ε_t^{vix}, i.e., no other shock affects it contemporaneously. The shock to the second variable – in this case, $\hat{p}^*_{i,t}$ – is only affected in the same period by ε_t^{vix} and ε_t^{p*}. In turn, $\hat{cepi}_{i,t}$ is affected only by the two preceding shocks plus its own, and so forth.

Undoubtedly, this assumption is somewhat implausible. However, there are compelling reasons to adopt this identification. Firstly, the primary interest lies in computing IRFs and variance decompositions of prices. For this reason, the variables have been ordered such that all shocks contemporaneously affect prices, i.e., no zero short-run restrictions are imposed on prices. Although this may still have unintended consequences, they are undoubtedly less pronounced than attempting to study IRFs for a larger set of variables. Additionally, unlike other studies, quarterly frequency data is employed. This is also desirable since the identification assumption does not imply that certain shocks do not have contemporaneous effects on some variables within a year or semester but "only" within a quarter.

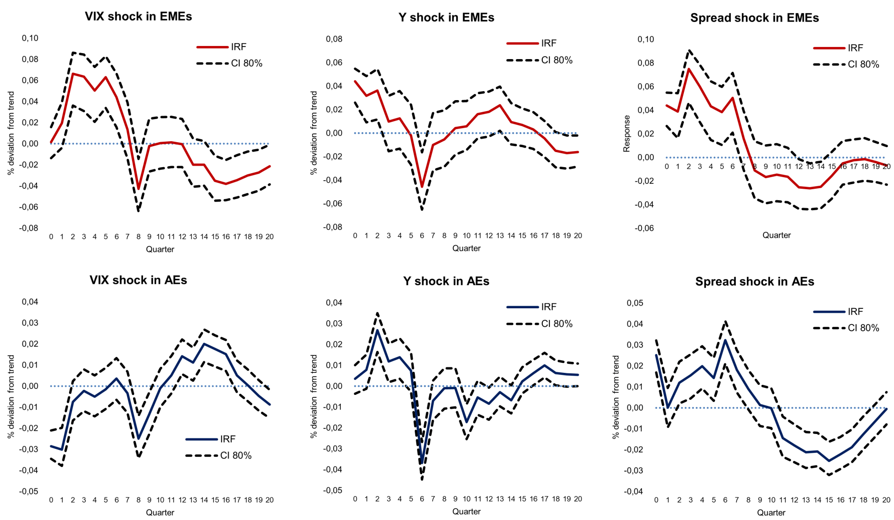
On the other hand, similar to Uribe and Yue (2006) and Akinci (2013), I assume that global variables (VIX, U.S. prices, and CEPI) are exogenous for each economy. In other words, it is assumed that small economies cannot determine global prices or risk. This assumption is summarized by imposing $B_{k,1j} = B_{k,2j} = B_{k,3j} = 0$ for all $k \in (1, 2, \dots, P)$ and all $j \in (4, 5, \dots, 10)$. Finally, I have set $P = 8$ following an Akaike selection criterion (AIC). It is worth noting that the results are not very sensitive to this choice. Additionally, this is the same P value set by Uribe and Yue (2006) and Akinci (2013).

5.2 Impulse Response Functions: Price Responses

When computing IRFs and analyzing price responses to all shocks, a fundamental difference becomes apparent. Specifically, the GFC does not affect prices in developed and emerging economies in the same manner. Indeed, it has opposite effects: in EMEs, increases in global uncertainty lead to price hikes, while in AEs, they result in price declines. This phenomenon can be observed in Figure 7, which depicts the IRF of prices in response to a positive shock in the VIX. In EMEs, VIX spikes lead to price increases after 3 quarters, with these pressures persisting until semester 7. In contrast, the deflationary effects of the same shock in AEs are immediate and endure until the third quarter. This difference reinforces *Hypothesis 1*, and its underlying reasons will be elaborated upon in the subsequent subsections.

Figure 7: Impulse Response Function: Price Responses

The figure displays the Impulse Response Functions (IRFs) of prices to different shocks in advanced economies (AEs) and emerging market economies (EMEs), along with an 80% confidence interval calculated through Bootstrap with 1000 repetitions. The estimated SVAR model and the identification assumption are detailed in the Section 5. The data on quarter frequency, so the numbers on the horizontal axis represent quarters. Only small and medium-size AEs and EMEs with a central bank rated at 5 or higher in all years from 2000 to 2021 in the Dincer and Eichengreen (2014) index are considered.



Notes: Local price data and United States prices is sourced from the Consumer Price Index (CPI) by Ha et al. (2019); the VIX data is extracted from the Federal Reserve Bank of St. Louis (FRED); GDP, consumption, broad money, Nominal Effective Exchange Rate (NEER) and monetary policy data are obtained from the International Monetary Fund (IMF).The analysis encompasses a total of 24 small and medium-size developed economies, as detailed in Table 2 (Appendix).
Y = GDP; P = local CPI; P* = US CPI; Money = Broad Money; G = Government Spending.

Another difference between economies can also be observed, although it is smaller than the first one. Specifically, while increases in sovereign spreads exert upward pressure on prices in both AEs and EMEs, the price increases are more significant in EMEs. Indeed, in these economies, this particular shock leads to immediate price hikes that persist for up to a year and a half. This outcome is expected, as suggested in *Hypothesis 2*, given that increases in sovereign spreads should depreciate the exchange rate. This possibility will be thoroughly analyzed in the subsequent sections.

On the other hand, a positive shock to output leads to short-term increases in prices in both AEs and EMEs. This finding appears to contradict the results presented in Section 3, where I demonstrated that in EMEs, periods of high inflation are not preceded by periods of high growth. However, this graph suggests that output is relevant for explaining inflation, and its effect aligns with expectations if we consider a Phillips curve framework. Therefore, it is likely that the correlations observed in Figure 12 are not due to the insignificance of output but rather to the presence of other variables that negatively correlate with output and positively correlate with inflation (such as the exchange rate).

Figures 21 and 22 (Appendix) are analogous to Figure 7. They illustrate the response of local prices in EMEs and AEs to shocks from the other variables. The IRFs are orthogonalized, depicting the response to a one-standard deviation shock in each variable, and are accompanied by an 80%

confidence interval estimated using 1000 bootstrap repetitions.

Beyond these differences, the response of prices to other shocks is similar and generally follows the expected sign and timing. For instance, in both AEs and EMEs, increases in global prices lead to inflationary pressures. Similarly, both emerging and developed economies exhibit comparable responses of prices to a shock in the CEPI, as prices increase in both cases. Likewise, a positive shock to the NEER, indicating depreciation, has inflationary effects in both groups of economies.

In both AEs and EMEs, a positive shock to government spending does not appear to have significant effects on the price level. This is an interesting result because, even though I am only considering countries with independent central banks, government spending still increases aggregate demand. Additionally, as expected, increases in the money supply lead to higher price levels. Lastly, a shock to the policy rate would increase the price level. This is contradictory, however, similar to findings in similar studies, which have been termed the ”Price Puzzle’[15].

5.3 Variance Decompositions of the Prediction Error of Prices

The IRFs are useful for studying the sign and timing of the effects of each shock; however, they do not allow us to determine how relevant each one is in explaining the price cycle. For this reason, I also estimate forecast error variance decompositions for AEs and EMEs. Following Akinci (2013), I will associate the economic cycle with prediction errors over a 5-year horizon (20 quarters). Figure 8 contain the variance decompositions of price prediction errors for EMEs and AEs at different horizons: from 1 quarter ahead to 5 years[16].

The main difference lies in the relevance of the NEER: its shocks accounted for 30% of the price cycle in EMEs, but only 13% in AEs. This again suggests the significant importance of the exchange rate in EMEs. In fact, NEER shocks explained nearly half of the variance unexplained by price shocks. The difference is even more significant when considering that prices are twice times more volatile in EMEs, meaning that the NEER not only explains a higher proportion of the cycle but also a greater variation. As previously mentioned, this result is expected, given the higher ERPT to domestic prices and greater exchange rate volatility observed in EMEs.

Another difference is that in EMEs, shocks from the VIX, CEPI, and sovereign spreads explained 7%, 5%, and 6%, respectively, while in AEs, they explained 3%, 5%, and 5%. This, in turn, suggests that the GFC has not only a different effect on prices, but also a greater impact in EMEs, suporting *Hypothesis 1.* Finally, U.S. prices explained a relatively important fraction of the variance in the local price cycle (9% in EMEs and 12% in AEs), indicating the relevance of international trade.

A similarity is the low relevance of local variables, commonly used to study inflation. Shocks to output, government spending, and money supply explained only 2%, 1%, and 2% of the price cycle in both EMEs and AEs (i.e., only 6% combined). On the other hand, the policy rate explained 3% and 8% in EMEs and AEs, respectively.

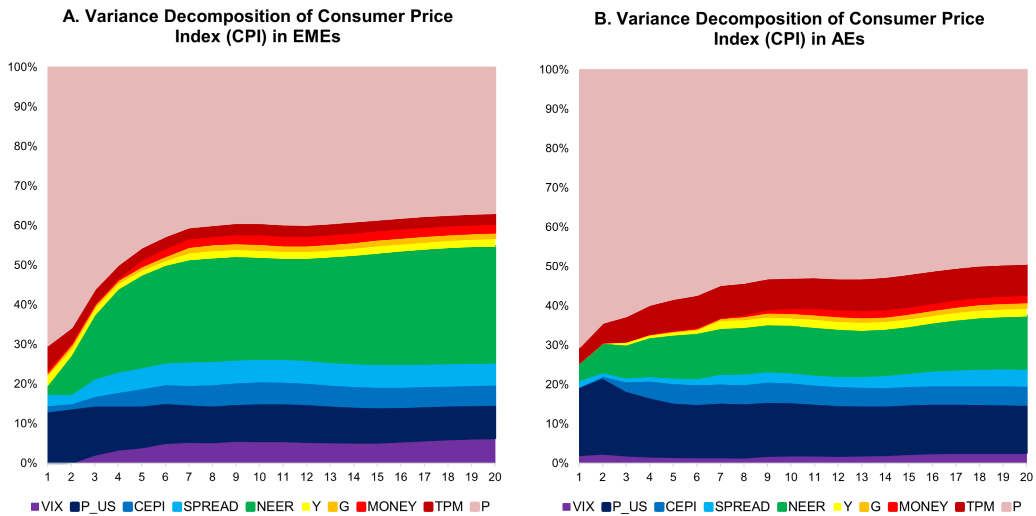
These findings seem to contradict economic intuition; however, they do not necessarily imply that the price cycle is not explained by domestic variables for two reasons. First, only economies with independent central banks are considered, whose objective includes reducing output volatility. Therefore, output shocks could be less persistent than, for example, NEER shocks. Thus, their

[15] The ”Price Puzzle’ refers to the positive response in prices following a contractionary innovation to monetary policy in the estimation of a SVAR. This goes against intuition and economic theory and was first documented by Sims (1992), who studied the effects of the U.S. monetary policy rate. Subsequently, this phenomenon has been documented for more economies, and various authors have attempted to explain this puzzle (Eichenbaum, 1992; Christiano et al., 1999; Hanson, 2004).

[16] For a more detailed breakdown of the variance decompositions, refer to Figures 23 and 24 (in the Appendix).

Figure 8: Variance Decompositions of the Prediction Error of Prices in AEs and EMEs

The figure depicts the variance decomposition of the prediction error for prices over a maximum horizon of 5 years (20 quarters) for advanced economies (AEs) and emerging market economies (EMEs). The estimated SVAR model and the identification assumption are elaborated in the Section 5. The numbers on the horizontal axis denote quarters. Only economies with a central bank rated at 5 or higher in all years from 2000 to 2021 in the Dincer and Eichengreen (2014) index are considered.



Notes: Local price data and United States prices is sourced from the Consumer Price Index (CPI) by Ha et al. (2019); the VIX data is extracted from the Federal Reserve Bank of St. Louis (FRED); GDP, consumption, broad money, Nominal Effective Exchange Rate (NEER) and monetary policy data are obtained from the International Monetary Fund (IMF).The analysis encompasses a total of 12 EMEs and 24 small and medium-size AEs, as detailed in Table 2 (Appendix).
Y = GDP; P = local CPI; P* = US CPI; Money = Broad Money; G = Government Spending; MPR = Monetary Policy Rate.

final effect on prices would be smaller, not because domestic variables are irrelevant but due to institutional reasons (i.e., we could be simply observing effective product stabilization policies). The second reason is related to the Lucas critique. It is highly likely that in these economies with central banks having a certain degree of credibility, increases in broad money may not have such large effects on prices. However, this does not imply that money issuance does not explain the price cycle. Rather, it suggests that since the 2000s, in EMEs with reliable central banks, these shocks have not been as relevant. Certainly, if the institutional framework of these economies were to change, the results would be different.

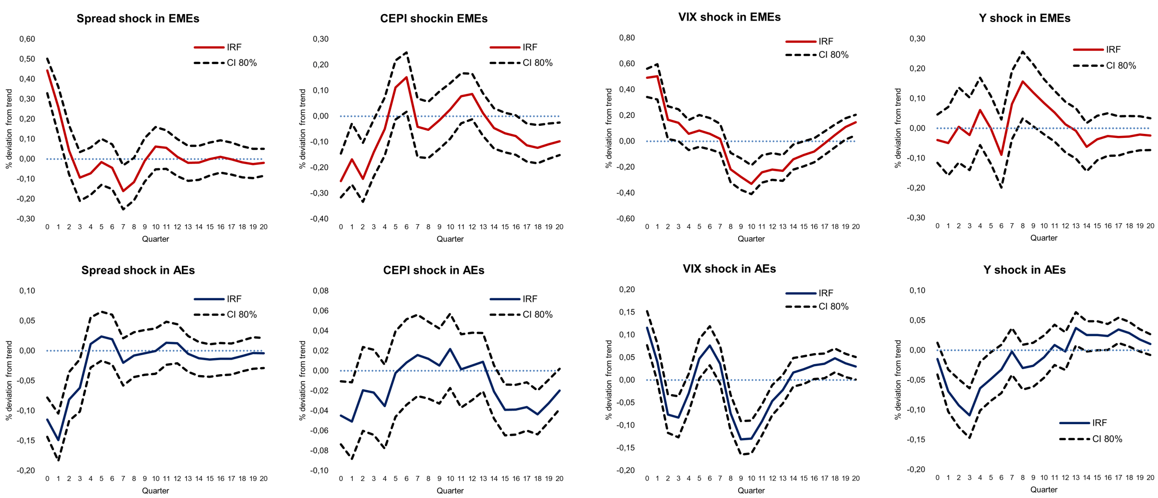
5.4 NEER Responses: What Explains the Exchange Rate Cycle?

It is clear that the NEER is fundamental in explaining the price cycle in EMEs. But what explains the NEER cycle? Figure 9 displays IRFs of the NEER to various shocks in both EMEs and AEs.

There are four significant differences between AEs and EMEs. The first one is the reaction of the NEER to increases in sovereign spreads: in EMEs, the exchange rate depreciates, whereas in AEs, it appreciates. Indeed, in both economies, this effect, although opposite, occurs in the

Figure 9: Impulse Response Functions for NEER

The figure displays the Impulse Response Functions (IRFs) of the Nominal Effective Exchange Rate (NEER) to various shocks, , along with an 80% confidence interval calculated using Bootstrap with 1000 repetitions. The estimated SVAR model and the identification assumption are detailed in Section 5. The numbers on the horizontal axis represent quarters. Only Emerging Market Economies (EMEs) and Advanced Economies (AEs) with a central bank consistently classified as 5 or higher in all years from 2000 to 2021 according to the Dincer and Eichengreen (2014) index are considered.



Notes: Local price data and United States prices is sourced from the Consumer Price Index (CPI) by Ha et al. (2019); the VIX data is extracted from the Federal Reserve Bank of St. Louis (FRED); GDP, consumption, broad money, Nominal Effective Exchange Rate (NEER) and monetary policy data are obtained from the International Monetary Fund (IMF).The analysis encompasses a total of 12 Emerging Market Economies (EMEs) and 24 small and medium-size developed economies, as detailed in Table 2 (Appendix).

Y = GDP; P = local CPI; P* = US CPI; Money = Broad Money; G = Government Spending.

same quarter as the shock and persists for up to a year. As previously mentioned, depreciation of the exchange rate in response to increases in spreads is expected in EMEs, particularly because local and international investors might withdraw their capital from these economies in the face of increased risk to seek refuge in safer assets. This capital outflow would lead to depreciation. However, it should be noted that the increase in spreads could have both local and global causes. For example, it could be elevated due to rises in country risk stemming from political changes, but also due to changes in US sovereign bond yields or shifts in global risk perception.

The second difference is that in EMEs, the NEER appreciates in response to positive shocks in the prices of exported commodities, namely, shocks to the CEPI. These effects are also instantaneous and persist for up to a year following the shock. On the other hand, the same shock only modestly appreciates the NEER in AEs, and its effects last only up to one quarter after the shock. This result, once again, is expected, given that EMEs are characterized by concentrating a significant portion of their exports in a few commodities. Consequently, their output and investment depend on the price of these commodities. Both differences provide evidence in favor of *Hypothesis 2*, as both decreases in spreads and increases in the CEPI appreciate the exchange rate in EMEs while increasing output. However, this phenomenon is not observed in AEs.

A third difference can be observed in the reaction to output shocks: in EMEs, although it appears to generate a modest appreciation, the effects are not statistically different from zero; conversely, in AEs, a clear appreciation occurs. This implies that, in response to idiosyncratic output shocks, the NEER appreciates more in AEs than in EMEs, which is contrary to what is expected by *Hypothesis 2*. This could be explained if capital flows are not as sensitive to output shocks in EMEs as they would be to changes in country risk.

The fourth difference lies in how the NEER reacts to the GFC. In EMEs, increases in the VIX lead to depreciations of the NEER. This depreciation is immediate and then gradually weakens. On the other hand, the reaction of the NEER in AEs is not as clear, as it appears to depreciate in the first two quarters but then appreciates. These results are expected for two reasons. Firstly, global investors tend to withdraw their invested capital from EMEs in the face of increased global uncertainty (Obstfeld, 2018; Carrera et al., 2021), depreciating the currency in these economies. Secondly, in EMEs, there exists an amplifying mechanism of the GFC, which is explained in the following subsection

There are no significant differences in the NEER's reaction to the other variables, and they are of the expected sign: decreases in the policy rate and increases in monetary mass depreciate the exchange rate (see Figures 25 and 26 in Appendix).

Finally, Figures 27 and 28 (Appendix), through a variance decomposition, show what fraction of the NEER cycle is attributable to each variable in EMEs and AEs. It can be noted that in EMEs, global variables were more relevant than local ones, and the opposite occurred in AEs. In the former economies, the VIX alone explained 12% of the NEER cycle, while US prices and the CEPI explained 2% and 3%, respectively. That is to say, global variables accounted for 18%, whereas the fraction in AEs was only 8%. On the other hand, shocks to output (1%), government spending (0.2%), monetary mass (3%), and policy rate (2%) together explained 6% of the NEER in EMEs, while in AEs, this fraction was 21%.

5.5 VIX Shocks: How Does the Global Financial Cycle Affect Prices?

Why does a recession in the GFC lead to price increases in EMEs but decreases in AEs? In short, this is because EMEs have an amplifying mechanism, as illustrated in Figure 10.

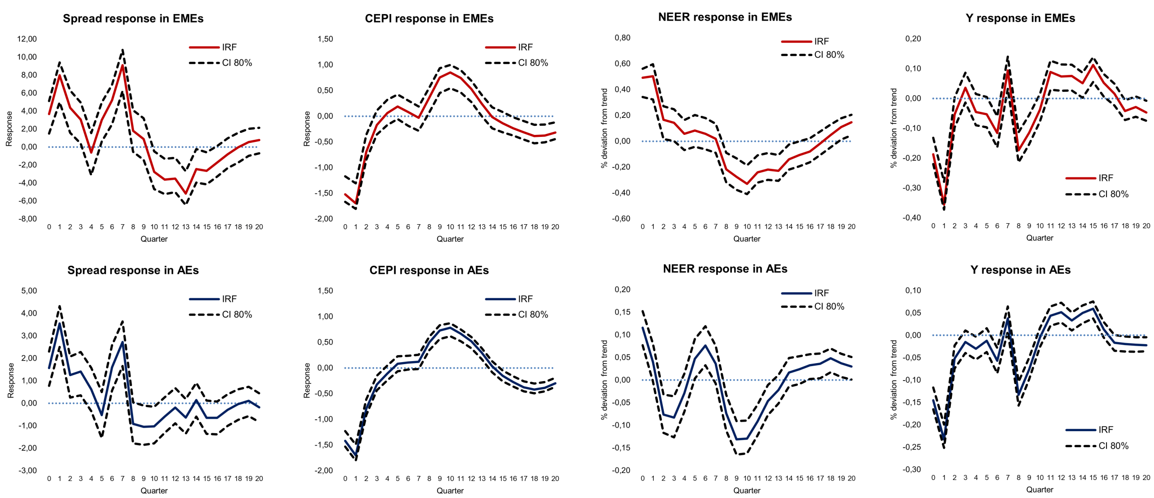
The amplifier occurs because increases in global uncertainty decrease commodity prices, particularly the CEPI, while simultaneously increasing sovereign spreads. It should be noted that this happens in both EMEs and AEs; however, the amplifying effect only occurs in EMEs because decreases in the CEPI and increases in sovereign spreads depreciate the exchange rate in these economies. As a result, a recession in the GFC affects the NEER in EMEs not only through direct effects (i.e., capital inflows and outflows) but also through indirect effects (i.e., CEPI and sovereign spreads). This phenomenon amplifies the effects of the GFC on the exchange rate and helps to understand why increases in the VIX are deflationary in AEs while they are inflationary in EMEs.

On the other hand, increases in the VIX lead to decreases in output in EMEs, a phenomenon already documented by Akinci (2013). Consequently, recessions in the GFC cause depreciations of the NEER as well as declines in output, while the opposite effects occur in a boom. Moreover, since the NEER explains a larger fraction of the price cycle in EMEs, these depreciations generate significant inflationary pressures. Therefore, it is reasonable to expect that a recession in the GFC generates periods of low growth and high inflation simultaneously. In other words, this provides evidence in favor of *Hypothesis 1*.

It should be noted that the exchange rate is not the only channel through which the GFC can determine local prices in both AEs and EMEs. Figures 29 and 30 (Appendix) show that US prices, unlike those in EMEs, decrease in response to increases in the VIX. This could be due to

Figure 10: Impulse Response Functions to a VIX Shock

The figure displays the Impulse Response Functions (IRFs) of various variables to VIX shocks, along with an 80% confidence interval calculated using Bootstrap with 1000 repetitions. The estimated SVAR model and the identification assumption are detailed in Section 5. The numbers on the horizontal axis represent quarters. Only Emerging Market Economies (EMEs) and Advanced Economies (AEs) with a central bank consistently classified as 5 or higher in all years from 2000 to 2021 according to the Dincer and Eichengreen (2014) index are considered.



Notes: Local price data and United States prices is sourced from the Consumer Price Index (CPI) by Ha et al. (2019); the VIX data is extracted from the Federal Reserve Bank of St. Louis (FRED); GDP, consumption, broad money, Nominal Effective Exchange Rate (NEER) and monetary policy data are obtained from the International Monetary Fund (IMF).The analysis encompasses a total of 12 Emerging Market Economies (EMEs) and 24 small and medium-size developed economies, as detailed in Table 2 (Appendix).
Y = GDP.

various reasons. Firstly, the Federal Reserve's federal funds rate may lead the VIX (Rey, 2013; Miranda-Agrippino and Rey, 2020). It could also be the case that the VIX does not depreciate the dollar as strongly against other currencies, resulting in a lower ERPT, and therefore, the decrease in output generates downward pressure on prices greater than those caused by the exchange rate alone. Altogether, increases in the VIX decrease p^* , and through international trade, they generate downward pressures on prices in both AEs and EMEs.

Another channel is that increases in the VIX decrease broad money in both AEs and EMEs, although this phenomenon is more delayed in EMEs. This is also an expected result since higher uncertainty restricts credit (Rey, 2013; Obstfeld et al., 2018; Miranda-Agrippino and Rey, 2020), which will decrease the total money supply in these economies. In other words, by reducing credit, a recession in the GFC generates deflationary pressures.

Hence, a recession in the GFC generates deflationary pressures in economies through three channels: a decrease in output and aggregate demand, a decrease in US prices, and a decrease in credit creation. These three channels would be more significant in AEs, and therefore, increases in the VIX are deflationary. Conversely, the inflationary effect of depreciation is more relevant in EMEs, so increases in the VIX are inflationary.

6 Conclusion

In Sections 3 and 4, I demonstrated that if the analysis is conditioned on the existence of an independent and transparent central bank, the price cycle differs between emerging and developed economies. However, why does the cycle differ? Essentially, because EMEs are structurally different from AEs and, in particular, possess three characteristics that define their price cycle. These characteristics, together, imply the fulfillment of *Hypotheses 1* and *2*. In other words, shocks affecting these economies tend to decrease output while depreciating the exchange rate, thereby generating inflationary pressures through this channel. The opposite effects occur in response to a negative output shock, resulting in both an apparent disconnection of prices from domestic variables and a more idiosyncratic behavior of inflation.

The first characteristic is that in EMEs, the NEER is more relevant in the price cycle. Indeed, NEER shocks explained 30% of the price cycle in EMEs compared to only 13% in AEs. This is due to a series of structural characteristics of EMEs, which imply a somewhat higher ERPT to domestic prices as well as a more volatile exchange rate (Ha et al., 2019).

The second characteristic concerns the response of the NEER to sovereign spread shocks and commodity prices. In EMEs, a higher sovereign spread depreciates the exchange rate. This is because an increase in risk often leads foreign investors to withdraw their capital, triggering capital outflows and depreciating the exchange rate (Carrera et al., 2021). However, this phenomenon does not occur in AEs. On the other hand, a negative shock in the prices of exported commodities results in a greater depreciation of the exchange rate in EMEs compared to AEs. This is because EMEs are characterized by a high concentration of their exports in a few commodities. Thus, only in EMEs do both shocks decrease the output while depreciating the NEER.

The third characteristic is that a recession from the GFC depreciates the NEER more because there exists an amplification mechanism in EMEs. This amplifier operates in two stages. Firstly, increases in the perception of global risk, measured by rises in the VIX, depreciate the NEER more in EMEs than in AEs. The second stage occurs because VIX upticks lead to increases in sovereign spreads and decreases in commodity prices. Both effects further depreciate the exchange rate in EMEs, which does not happen in AEs. The outcome is that GFC recessions, through the exchange rate, generate inflationary pressures in EMEs but deflationary pressures in AEs (the opposite occurs in a boom).

These three characteristics, collectively, explain the main differences in the price cycle. Firstly, they imply a positive correlation between the output cycle and appreciations of the NEER in EMEs. This occurs because the NEER appreciates and output increases when the VIX decreases. Additionally, decreases in sovereign spreads and increases in the CEPI, whether caused by local or global factors, also appreciate the NEER while increasing output. Since these effects are weaker in AEs, the NEER is acyclical in these economies.

They also imply that positive price cycle periods occur simultaneously and are preceded by depreciations of the NEER. This happens because, in EMEs, the NEER is more relevant for explaining the price cycle. Additionally, the NEER depreciates when the common (global) factor of inflation is high, and these higher prices could be transferred to EMEs through international trade in goods. Since the NEER is less relevant in AEs, this phenomenon is evidenced in these economies, but to a lesser extent.

Moreover, they explain why in EMEs, unlike in AEs, quarters of high prices do not occur simultaneously, nor are they preceded, by positive cycles of output, consumption, investment, imports, or exports. The reason is not the irrelevance of domestic variables, but rather because periods of high growth often coincide with exchange rate appreciations. Thus, inflationary pressures stemming from buoyant aggregate demand are offset by the deflationary effect of appreciation.

Lastly, they also help explain the greater idiosyncratic component of inflation in EMEs. Firstly, this occurs because the NEER appreciates when global inflation increases. Thus, deflationary pressures are generated in EMEs at the same time as global inflation is high. Therefore, the price reaction in EMEs will be more idiosyncratic, as it responds differently to global factors compared to other economies. Additionally, the behavior of inflation in EMEs could also be attributed to their reaction and the relevance of local shocks affecting prices; however, this possibility will need to be subject to further studies.

6.1 Final Remarks

This study succeeds in incorporating prices, a variable traditionally excluded, into the analysis of cycles in EMEs. Although it represents a preliminary approach, it at least demonstrates that, when controlling for central bank characteristics, inflation in EMEs can be studied similarly to how the cycle of real variables is commonly examined. Moreover, it also incorporates the effect of the GFC both on prices in AEs and EMEs.

Future studies could incorporate into the analysis how exchange rate policies affect the price cycle and how the GFC propagates to EMEs. Given the significant importance of the NEER, there could be considerable heterogeneity in price cycles among emerging economies. Furthermore, this study did not develop theoretical models that underpin the stylized facts found, nor did it delve into the mechanisms of GFC propagation to EMEs' prices. Finally, the effect and relevance of specific shocks on the inflation of AEs and EMEs could also be studied in more detail. For instance, examining oil price shocks, which should move inflation and output in opposite directions, or global demand shocks, which should move them in the same direction, and their differentiated effects on AEs and EMEs.

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Appendix

Table 1: Descriptive Statistics of Inflation by Year, Economy Type, and Central Bank Independence.

The table provides descriptive statistics for anual inflation, measured by the Consumer Price Index (CPI). The upper section of the table details statistics for the entire sample period (1970Q1-2021Q4), the second panel encompasses data only from 1970Q1-1999Q4, and the third panel spans from 2000Q1-2021Q4. Each panel categorizes economies into three groups: developed, emerging markets (EMEs), and EMEs with ITCB (Independent and Transparent Central Bank). The latter comprises economies whose central banks received a score of 5 or higher for every year from 2000 to 2014 in the Central Bank Transparency and Independence Index by Dincer and Eichengreen (2014)

	Mean	Median	Quartile 1	Quartile 3	Max	Min	Variance
1970-2021							
Developed	10,15	2,81	1,53	6,45	1.281,44	-4,48	3534,34
EMEs	71,76	6,83	3,05	13,97	65.374,08	-71,33	1.457.066,00
EMEs with ITCB	54,07	6,91	3,60	13,98	7.356,82	-3,71	135.565,00
1970-1999							
Dveloped	16,63	5,44	2,46	10,10	1.281,44	-1,90	6.262,76
EMEs	72,01	10,10	4,57	20,94	15.606,50	-71,33	235.544,50
EMEs with ITCB	92,51	11,76	6,77	23,48	7.356,82	-3,71	23.7811,80
2000-2021							
Developed	2,03	1,90	0,89	2,76	15,40	-4,48	3,41
EMEs	71,47	4,61	2,39	8,24	65374,08	-9,86	2.969.672,00
EMEs with ITCB	4,27	3,66	2,26	5,94	15,84	-1,14	11,54

Notes: Consumer Price Index inflation data is sourced from Ha et al., (2019).

Table 2: Country Classification

After applying the filter for central bank independence and transparency, the groups of economies are:

Emerging Market Economies: Botswana, Brazil, Chile, Colombia, Hungary, Malaysia, Peru, Poland, South Africa, Sri Lanka, and Thailand.

Developed Economies: Australia, Austria, Belgium, Canada, Czech Republic, Denmark, Estonia, Finland, France, Germany, Iceland, Ireland, Israel, Italy, Japan, Latvia, Luxembourg, Malta, Netherlands, New Zealand, Norway, Portugal, Slovenia, South Korea, Spain, Sweden, Switzerland, United Kingdom, and United States.

The small and medium-sized that pass the filter are:

Emerging Market Economies: Botswana, Brazil, Chile, Colombia, Hungary, Malaysia, Peru, Poland, South Africa, Sri Lanka, and Thailand.

Developed Economies: Australia, Austria, Belgium, Canada, Czech Republic, Denmark, Estonia, Finland, Iceland, Ireland, Israel, Italy, Latvia, Luxembourg, Malta, Netherlands, New Zealand, Norway, Portugal, Slovenia, South Korea, Spain, Sweden and Switzerland.

Table 3: Variance Decompositions of Inflation.

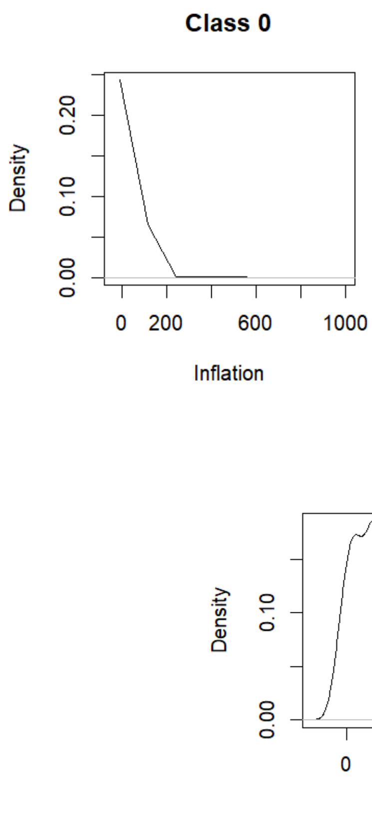
The table presents the results of the estimation of the Dynamic Factor Model (DFM). This model allows for the decomposition of the inflation variance in each country into three components: global, group-specific, and idiosyncratic. Subsequently, economies are grouped into three categories: Advanced Economies (AEs), Emerging Market Economies (EMEs) and All Countries. The simple average of the global, group-specific, and idiosyncratic components is calculated for each group. Additionally, the 0.05th and 0.095th percentiles are computed and presented in parentheses.

Factor	AEs	EMEs	All
Global	45,2 $(36,0-53,8)$	33,9 $(26,2-41,8)$	31,3 $(24,1-38,9)$
Group	17,2 $(8,3-27,7)$	11,3 $(0,2-31,2)$	18,1 $(10,3-28,2)$
Global + Group	62,4 $(55,9-69,1)$	45,3 $(30,34-65,41)$	50,0 $(41,4-58,4)$

Notes: Inflation data is considered at an annual frequency from 2000 to 2021. The data corresponds to the Consumer Price Index (CPI) from Ha et al. (2019).

Figure 11: Inflation Distribution by Score in the Central Bank Transparency and Independence Index.

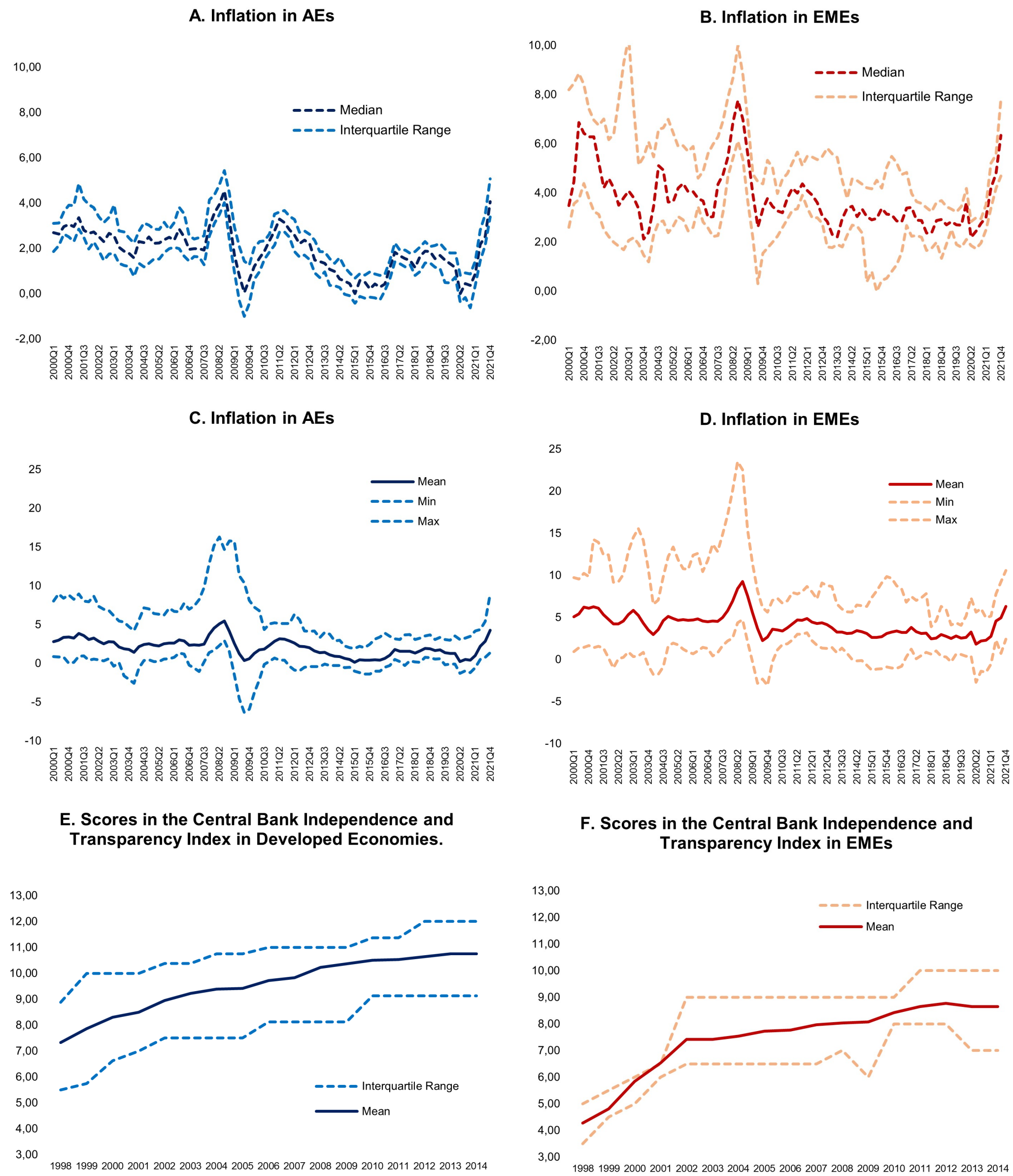
The figure displays a kernel density of inflation for four groups of economies separated based on their scores in the Central Bank Transparency and Independence Index by Dincer and Eichengreen (2014). Inflation is measured as the year-on-year change in the Consumer Price Index (CPI) and is of annual frequency. Class 4 economies are those that scored 10 or higher for all years from 2000 to 2014. Class 3 includes those with scores greater than 7 and less than 10. Class 2 comprises economies with scores 5 or higher and less than 7. Class 1 encompasses economies with scores 3 or higher and less than 5. Class 0 represents the remaining economies.



Notes: Inflation data to the Consumer Price Index is from Ha et al., (2019). The number of economies in each group is as follows: Class 0 = 46, Class 1 = 31, Class 2 = 17, Class 4 = 8, Class 5 = 6.

Figure 12: Inflation and Central Bank Scores since 2000.

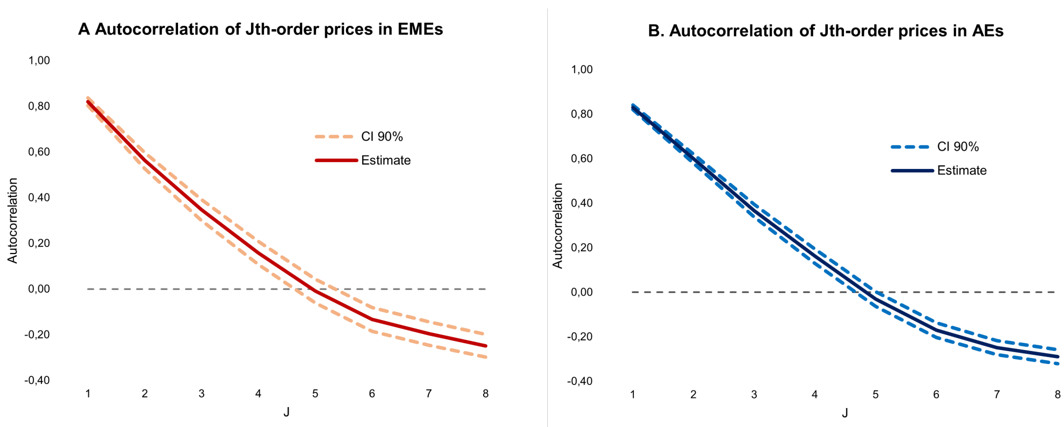
The figure depicts the quarterly annualized inflation of the Consumer Price Index for emerging market economies (EMEs) and developed economies from 2000Q1 to 2021Q4. Only economies whose central banks have received a score of 5 or higher from 2000 to 2014 in the Dincer and Eichengreen (2014) index are included. Both the simple average and the interquartile range are presented. Additionally, the evolution (simple average and interquartile range) of the Central Bank Independence and Transparency Index by Dincer and Eichengreen (2014) is also shown.



Notes: Consumer Price Index data is sourced from Ha et al., (2019). Inflation is calculated as the difference between the logarithm of the CPI for a specific quarter and the logarithm of the CPI for the same quarter of the previous year. The evolution of the Central Bank Independence and Transparency Index by Dincer and Eichengreen (2014) is presented, conditioned on countries that obtained a score of 5 or higher.

Figure 13: Autocorrelation of the Cyclical Component of Prices.

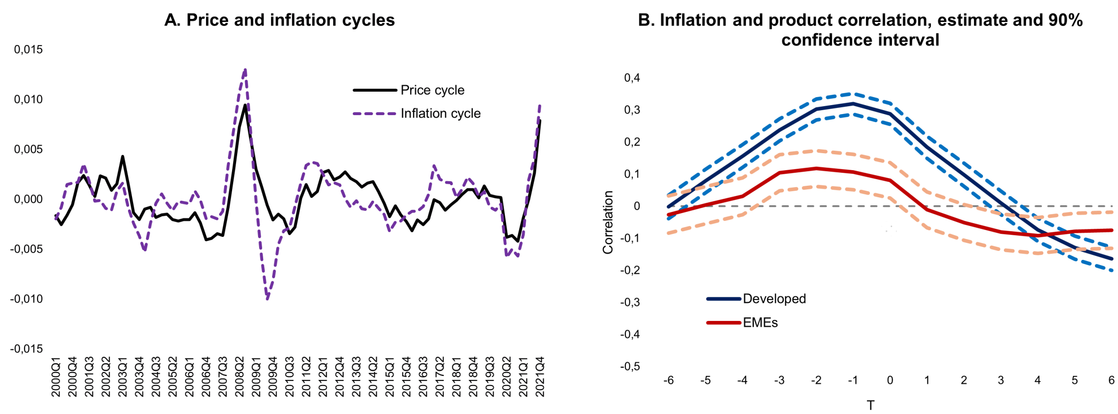
The figure depicts the autocorrelation, from orders one to eight, of the cyclical component of the price level and compares it based on the type of economies. Panel A displays the estimation and the 90% confidence interval for developed economies, while Panel B does the same for emerging market economies (EMEs). As we are working with quarterly data, the Jth-order autocorrelation represents the correlation of the current cycle of prices with that of J quarters ago.



Notes: Quarterly price data are derived from the Consumer Price Index (CPI) of Ha et al. (2019). These data undergo a seasonal adjustment using the Seasonal-Trend decomposition using LOESS (STL) method, followed by extracting the cyclical component through the Hodrick-Prescott filter. The analysis includes a total of 12 small and medium-size Emerging Market Economies (EMEs) and 24 developed economies, the composition of which is detailed in Table 2 (Appendix).

Figure 14: Price Cycle and Inflation Comparison

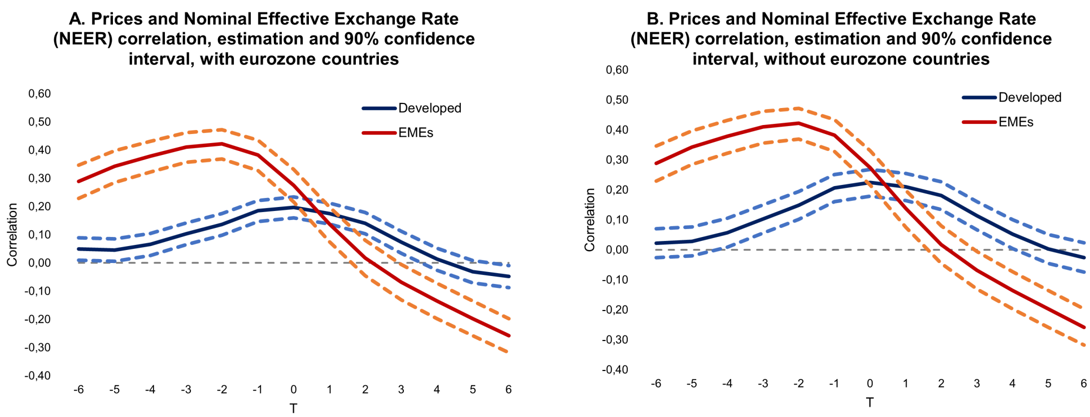
The figures present a comparison between the cyclical component of prices and the inflation cycle. Figure A displays the evolution of the simple average of the price cycle and compares it with that of the inflation cycle. To decompose each series into cycle and trend, a Hodrick-Prescott filter has been utilized. Meanwhile, Figure B illustrates the correlations of the cyclical component of prices with other relevant variables contemporaneously or T quarters forward or backward. For example, the first graph depicts the correlation between the price cycle and the output cycle. On the horizontal axis, we have T, as we calculate the value of $\text{Corr}(p_t^c, xr_{t+T}^c)$ with $T \in (-6, -5, -4, \ldots, 4, 5, 6)$.



Notes: Quarterly price data is sourced from the Consumer Price Index (CPI) by Ha et al. (2019). The temporal scope considered spans from 2000Q1 to 2021Q4. Data is seasonally adjusted using the STL method, followed by extraction of the cyclical component through the Hodrick-Prescott filter. The analysis encompasses a total of 12 Emerging Market Economies (EMEs) and 24 small and medium-size developed economies, as detailed in Table 2 (Appendix).

Figure 15: Correlation of the Cyclical Component of Prices with Nominal Effective Exchange Rate (NEER).

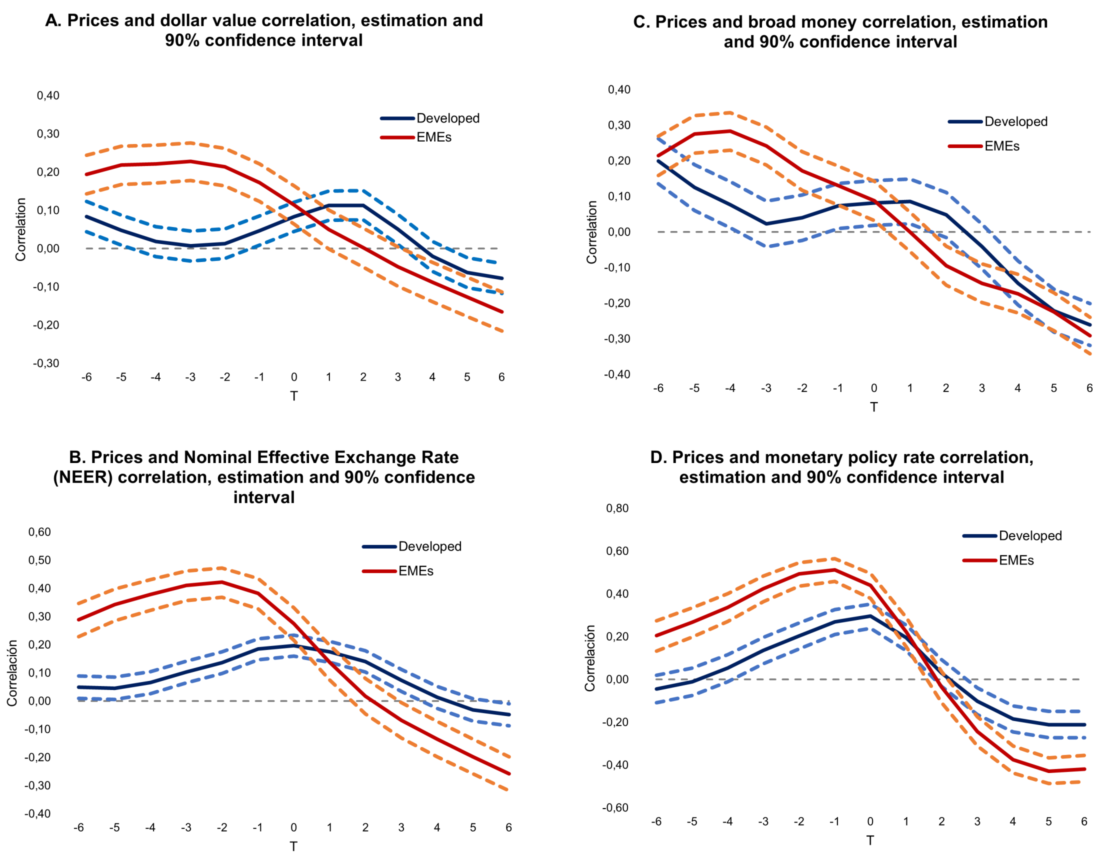
The figure depicts the correlation between the cyclical component of prices and the cyclical component of the Nominal Effective Exchange Rate (NEER). Graph A incorporates economies of the eurozone within developed economies, while Graph B excludes them. The contemporary correlation and correlations T quarters backward or forward are displayed. For example, in graph A, it shows the correlation between prices and the NEER. On the horizontal axis, we have T, as we calculate the value of $\mathrm{Corr}(p_t^c, xr_{t+T}^c)$ with $T \in (-6, -5, -4, \ldots, 4, 5, 6)$. Thus, the value on the vertical axis when T is equal to -6 represents the correlation of the cyclical component of prices with that of the NEER from 6 quarters ago.



Notes: Quarterly price data is sourced from the Consumer Price Index (CPI) by Ha et al. (2019). Nominal variables utilize quarterly frequency data from the International Monetary Fund. The temporal scope considered spans from 2000Q1 to 2021Q4. Data is seasonally adjusted using the STL method, followed by extraction of the cyclical component through the Hodrick-Prescott filter. The analysis encompasses a total of 12 Emerging Market Economies (EMEs) and 24 small and medium-size developed economies, as detailed in Table 2 (Appendix).

Figure 16: Correlation of the Cyclical Component of Prices with Nominal Variables.

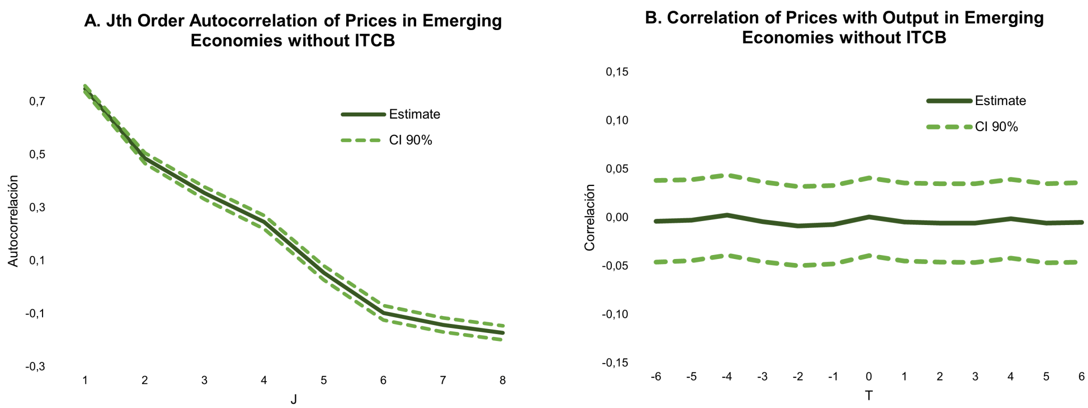
The figure contains the correlation of the cyclical component of prices with the cyclical component of the value of the dollar (A), the Nominal Effective Exchange Rate (NEER) (B), broad money (C), and the monetary policy rate (D). The contemporary correlation and correlations T quarters backward or forward are displayed. For example, in graph A, it shows the correlation between prices and the exchange rate (value of the dollar). On the horizontal axis, we have T, as we calculate the value of $\mathrm{Corr}(p_t^c, xr_{t+T}^c)$ with $T \in (-6, -5, -4, \ldots, 4, 5, 6)$. Thus, the value on the vertical axis when T is equal to -6 represents the correlation of the cyclical component of prices with that of the exchange rate from 6 quarters ago. The other graphs follow a similar pattern but consider different variables: NEER, broad money, and the monetary policy rate.



Notes: Quarterly price data is sourced from the Consumer Price Index (CPI) by Ha et al. (2019). Nominal variables utilize quarterly frequency data from the International Monetary Fund. The temporal scope considered spans from 2000Q1 to 2021Q4. Data is seasonally adjusted using the STL method, followed by extraction of the cyclical component through the Hodrick-Prescott filter. The analysis encompasses a total of 12 Emerging Market Economies (EMEs) and 24 small and medium-size developed economies, as detailed in Table 2 (Appendix).

Figure 17: Cycle Component of Prices in Emerging Market Economies without Independent and Transparent Central Banks

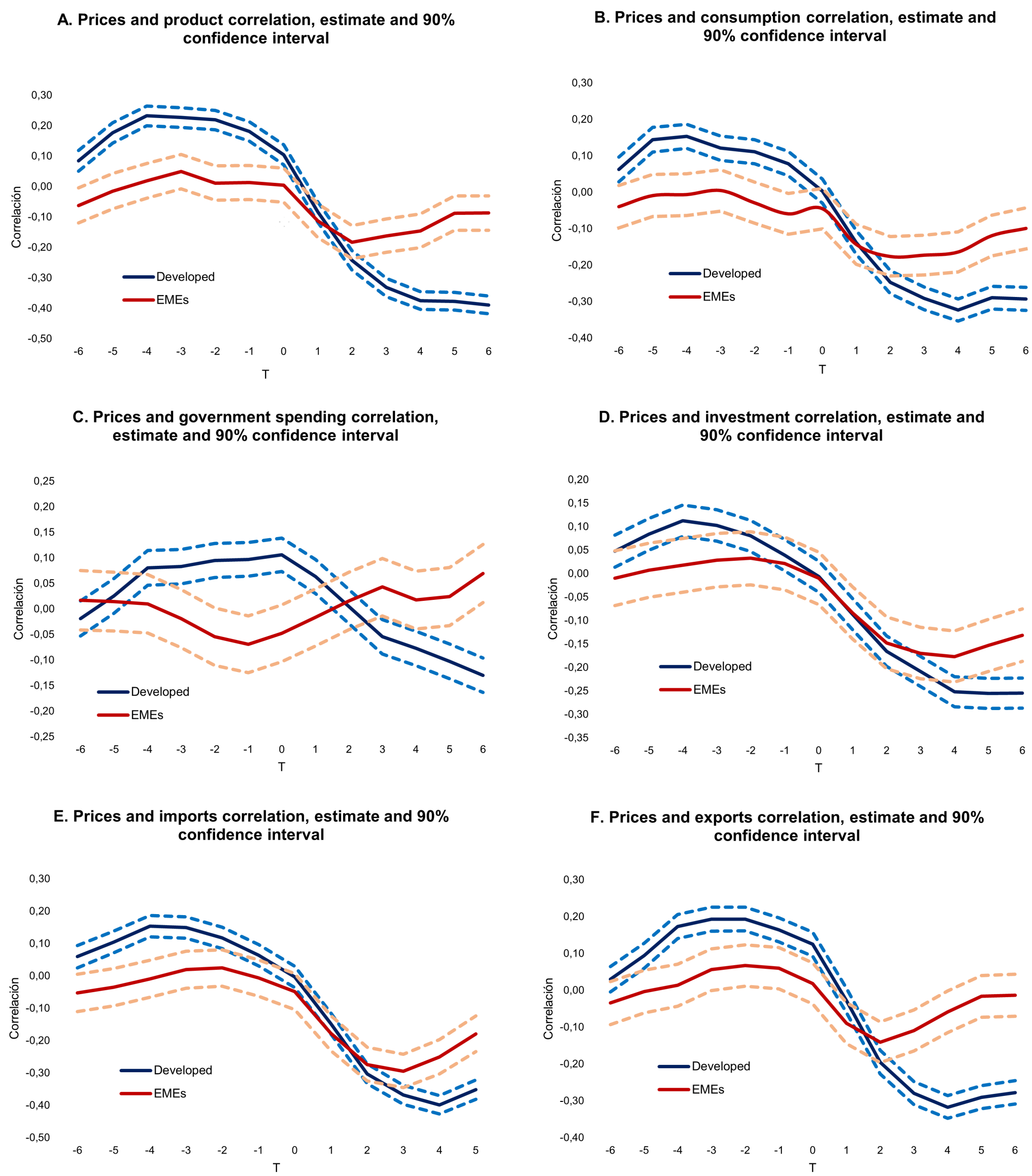
Figure A displays the autocorrelation of the cyclical component of prices, while Figure B illustrates the correlation of the cyclical component of prices with the cyclical component of the product T quarters backward or forward. Only Emerging Market Economies (EMEs) with a central bank rated below 5 in any year from 2000 to 2021 in the Dincer and Eichengreen (2014) index are considered.



Notes: Quarterly price data is sourced from the Consumer Price Index (CPI) by Ha et al. (2019). GDP data is from the International Monetary Fund. The temporal scope considered spans from 2000Q1 to 2021Q4. Data is seasonally adjusted using the STL method, followed by extraction of the cyclical component through the Hodrick-Prescott filter.

Figure 18: Correlation of the Cyclical Component of Prices with Expenditure Components, Considering Big Economies.

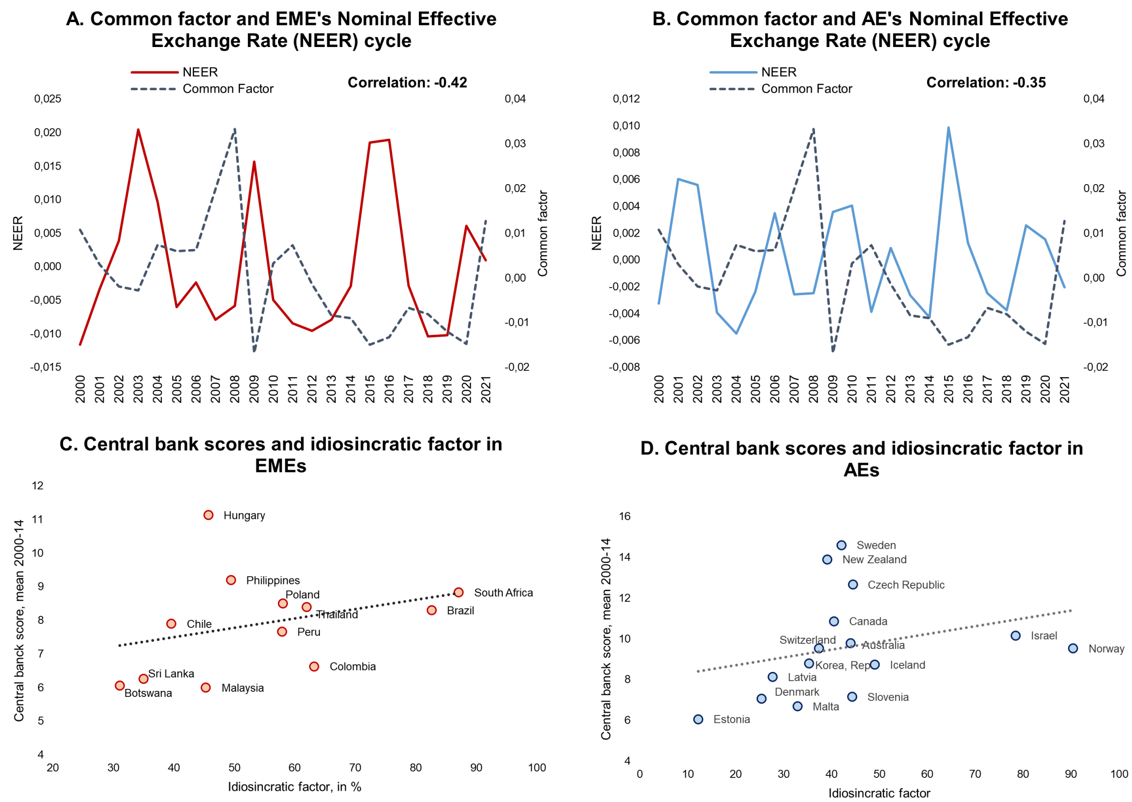
The figure contains correlations of the cyclical component of prices with that of other relevant variables contemporaneously or T quarters forward or backward. For instance, the first graph illustrates the correlation between the cycle of prices and that of output. On the horizontal axis, we have T, as we calculate the value of $Corr(p_t^c, y_{t+T}^c)$ with $T \in (-6, -5, -4, \ldots, 4, 5, 6)$. Thus, the value on the vertical axis when T is equal to -6 represents the correlation of the cyclical component of prices with that of output from 6 quarters ago. The other graphs follow a similar pattern but consider different variables: investment, consumption, government spending, imports, and exports.



Notes: Quarterly price data is sourced from the Consumer Price Index (CPI) by Ha et al. (2019). Expenditure components utilize quarterly frequency data from the International Monetary Fund. The temporal scope considered spans from 2000Q1 to 2021Q4. Data is seasonally adjusted using the STL method, followed by extraction of the cyclical component through the Hodrick-Prescott filter. The analysis encompasses a total of 12 Emerging Market Economies (EMEs) and 29 developed economies, as detailed in Table 2 (Appendix).

Figure 19: Common Inflation and Idiosincratic Factor Analysis

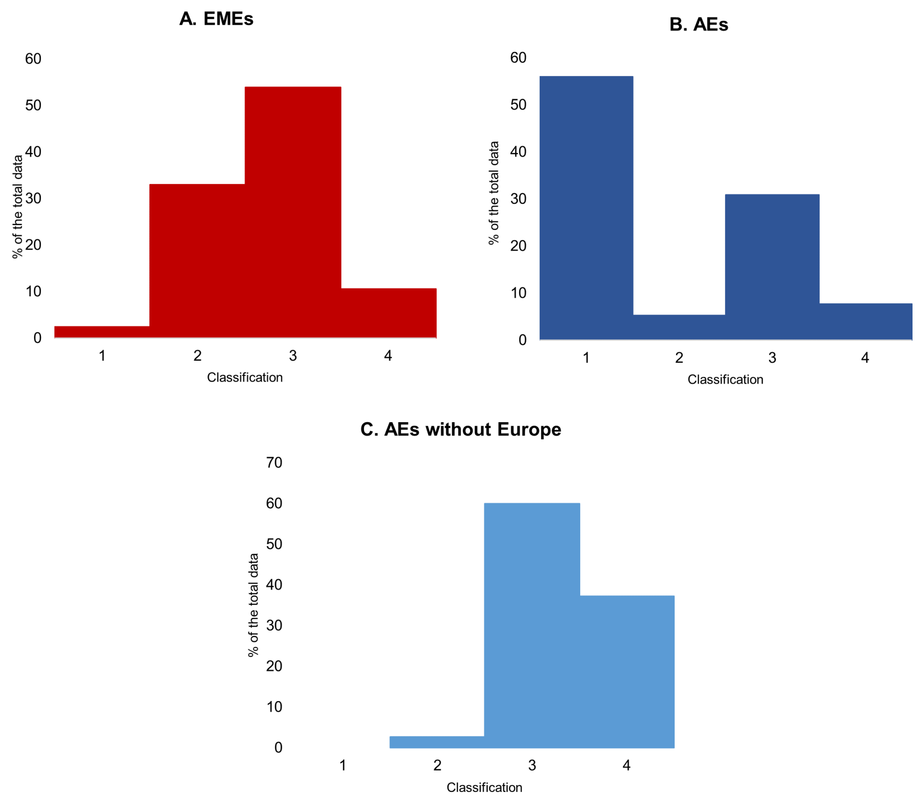
The figure presents an analysis of common (global) inflation and idiosyncratic factors in advanced economies (AEs) and Emerging Market Economies (EMEs) estimated through a Dynamic Factor Model (DFM). Panels A and B depict the correlation of the common (global) factor of inflation with the Nominal Effective Exchange Rate cycle (NEER) in EMEs and AEs, respectively. Meanwhile, panels C and D display a scatter plot between the idiosyncratic factor of economies and their central bank score in the Dincer and Eichengreen index (2014).



Notes: Inflation data is considered at an annual frequency from 2000 to 2021. The data corresponds to the Consumer Price Index (CPI) from Ha et al. (2019). The analysis includes a total of 12 small and medium-size EMEs and 24 AEs, the composition of which is detailed in Table 2 (Appendix).

Figure 20: Exchange Rate Regimes

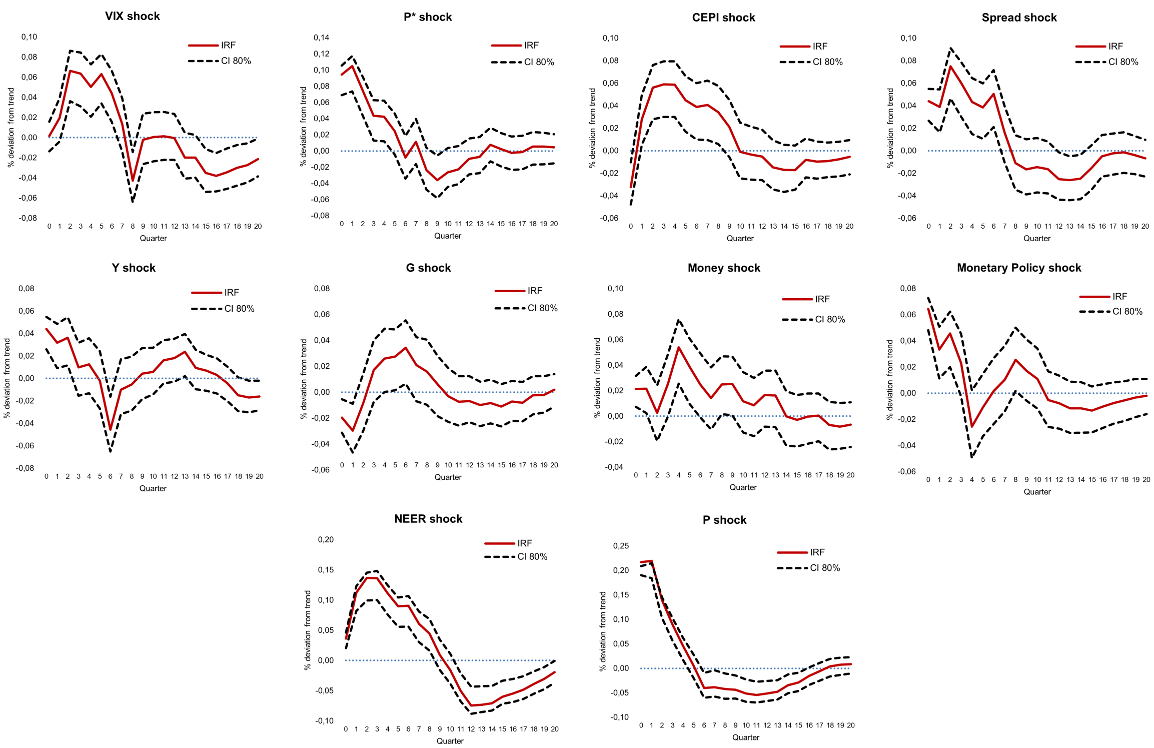
The figure illustrates the exchange rate regimes according to Ilzetzki et al. (2021). Specifically, it displays the distribution of their classifications into three groups of economies: Emerging Market Economies (EMEs), Advanced Economies (AEs), and AEs excluding European countries. The data considered spans from January 2000 to December 2021.



Notes: 1 = No separate legal tender; Pre announced peg or currency board arrangement; Pre announced horizontal band that is narrower than or equal to +/-2% De facto peg.
2 = Pre announced crawling peg; Pre announced crawling band that is narrower than or equal to +/-2%; De facto crawling peg;De facto crawling band that is narrower than or equal to +/-2%.
3 = Pre announced crawling band that is wider than or equal to +/-2%; De facto crawling band that is narrower than or equal to +/-5%; Moving band that is narrower than or equal to +/-2% (i.e., allows for both appreciation and depreciation over time); Managed floating
4 = Freely floating
5 = Freely falling

Figure 21: Impulse Response Functions for Prices in EMEs

The figure displays the Impulse Response Functions (IRFs) of prices to various shocks, along with an 80% confidence interval calculated through Bootstrap with 1000 repetitions. The estimated SVAR model and the identification assumption are detailed in the Section 5. The data is of semiannual frequency, so the numbers on the horizontal axis represent quarters. Only Emerging Market Economies (EMEs) with a central bank rated at 5 or higher in all years from 2000 to 2021 in the Dincer and Eichengreen (2014) index are considered.

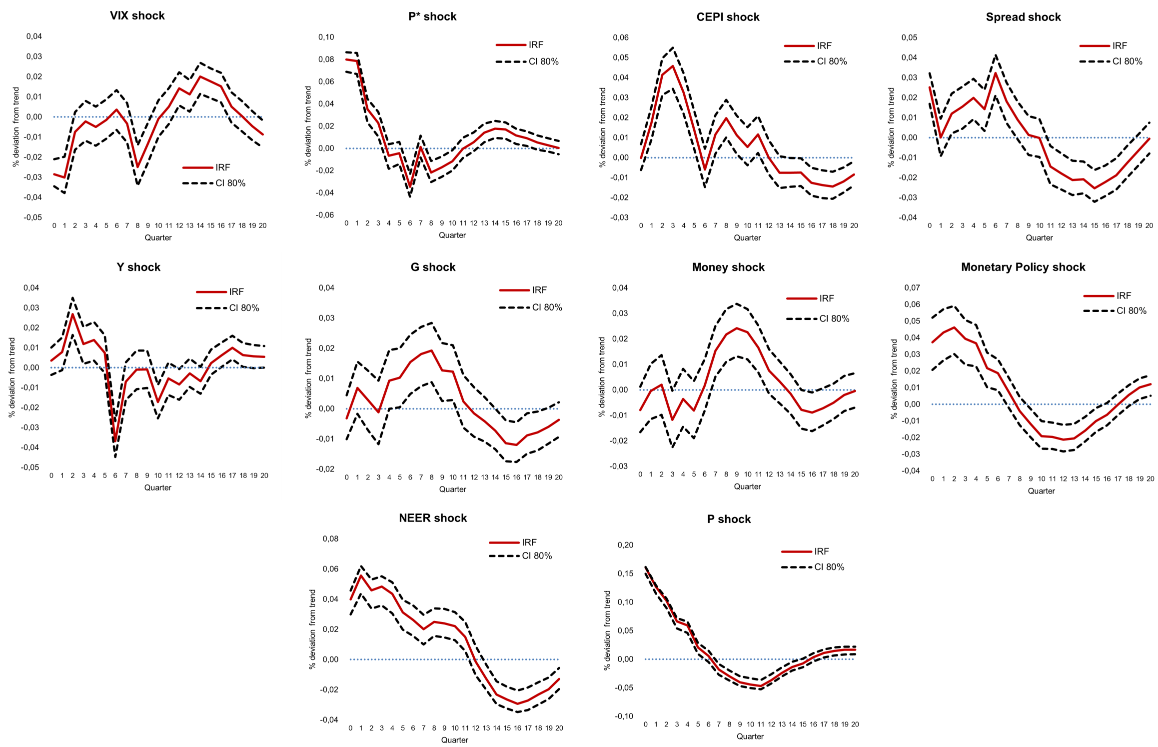


Notes: Local price data and United States prices is sourced from the Consumer Price Index (CPI) by Ha et al. (2019); the VIX data is extracted from the Federal Reserve Bank of St. Louis (FRED); GDP, consumption, broad money, Nominal Effective Exchange Rate (NEER) and monetary policy data are obtained from the International Monetary Fund (IMF).The analysis encompasses a total of 12 Emerging Market Economies (EMEs) and 24 small and medium-size developed economies, as detailed in Table 2 (Appendix).

Y = GDP; P = local CPI; P* = US CPI; Money = Broad Money; G = Government Spending.

Figure 22: Impulse Response Functions for Prices in AEs

The figure displays the Impulse Response Functions (IRFs) of prices to various shocks, along with an 80% confidence interval calculated through Bootstrap with 1000 repetitions. The estimated SVAR model and the identification assumption are detailed in the Section 5. The data is of semiannual frequency, so the numbers on the horizontal axis represent quarters. Only small and médium-size Advanced Economies (AEs) with a central bank rated at 5 or higher in all years from 2000 to 2021 in the Dincer and Eichengreen (2014) index are considered.

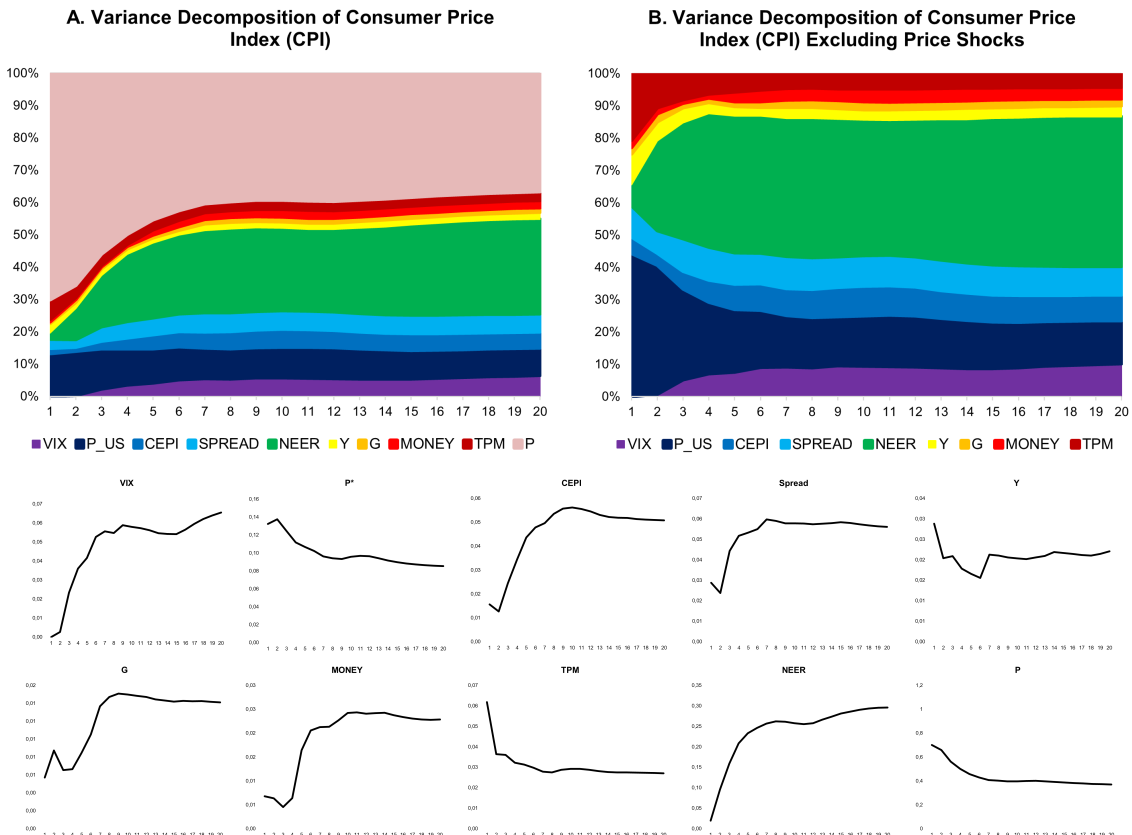


Notes: Local price data and United States prices is sourced from the Consumer Price Index (CPI) by Ha et al. (2019); the VIX data is extracted from the Federal Reserve Bank of St. Louis (FRED); GDP, consumption, broad money, Nominal Effective Exchange Rate (NEER) and monetary policy data are obtained from the International Monetary Fund (IMF).The analysis encompasses a total of 24 small and medium-size developed economies, as detailed in Table 2 (Appendix).

Y = GDP; P = local CPI; P* = US CPI; Money = Broad Money; G = Government Spending.

Figure 23: Variance Decompositions of the Prediction Error of Prices in EMEs

The figure depicts the variance decomposition of the prediction error for prices over a maximum horizon of 5 years (20 quarters). The estimated SVAR model and the identification assumption are elaborated in the Section 5. The data is of semiannual frequency, so the numbers on the horizontal axis denote quarters. Only Emerging Market Economies (EMEs) with a central bank rated at 5 or higher in all years from 2000 to 2021 in the Dincer and Eichengreen (2014) index are considered.

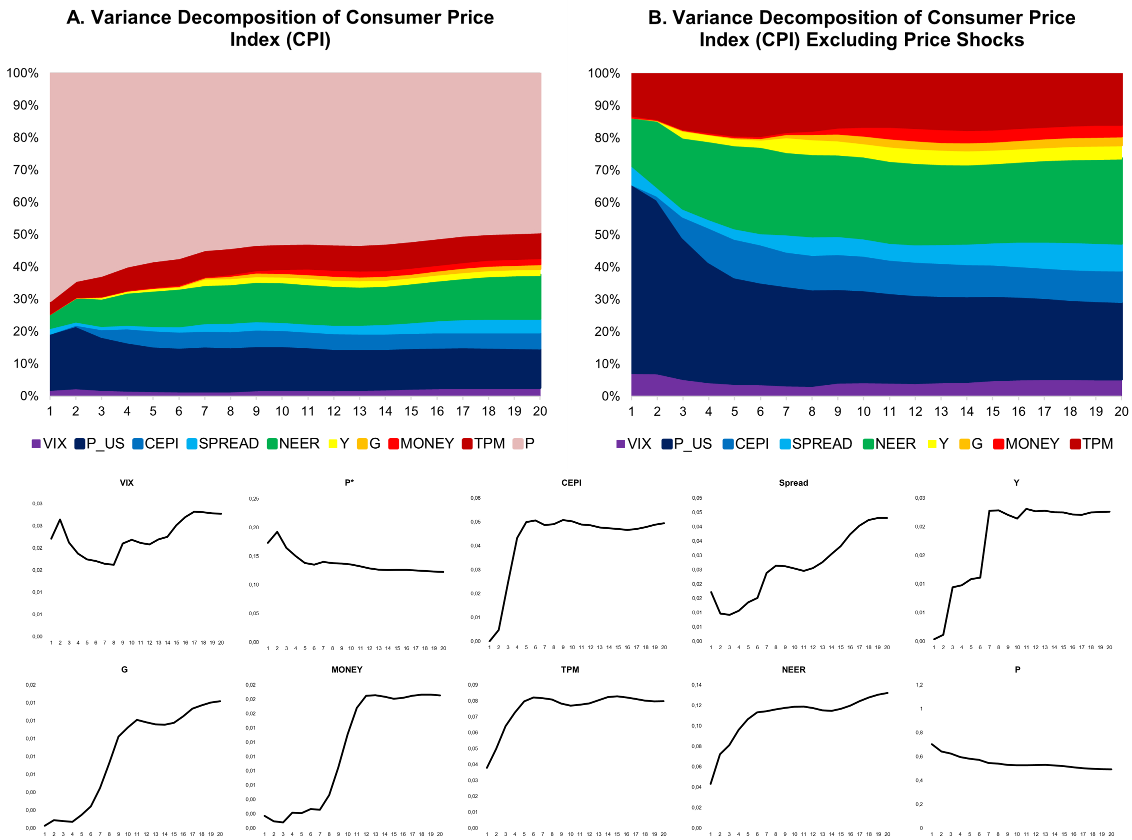


Notes: Local price data and United States prices is sourced from the Consumer Price Index (CPI) by Ha et al. (2019); the VIX data is extracted from the Federal Reserve Bank of St. Louis (FRED); GDP, consumption, broad money, Nominal Effective Exchange Rate (NEER) and monetary policy data are obtained from the International Monetary Fund (IMF).The analysis encompasses a total of 12 Emerging Market Economies (EMEs) and 24 small and medium-size developed economies, as detailed in Table 2 (Appendix).

Y = GDP; P = local CPI; P* = US CPI; Money = Broad Money; G = Government Spending; MPR = Monetary Policy Rate.

Figure 24: Variance Decompositions of the Prediction Error of Prices in AEs

The figure depicts the variance decomposition of the prediction error for prices over a maximum horizon of 5 years (20 quarters). The estimated SVAR model and the identification assumption are elaborated in the Section 5. The data is of semiannual frequency, so the numbers on the horizontal axis denote quarters. Only small and medium-size Advanced Economies (AEs) with a central bank rated at 5 or higher in all years from 2000 to 2021 in the Dincer and Eichengreen (2014) index are considered.

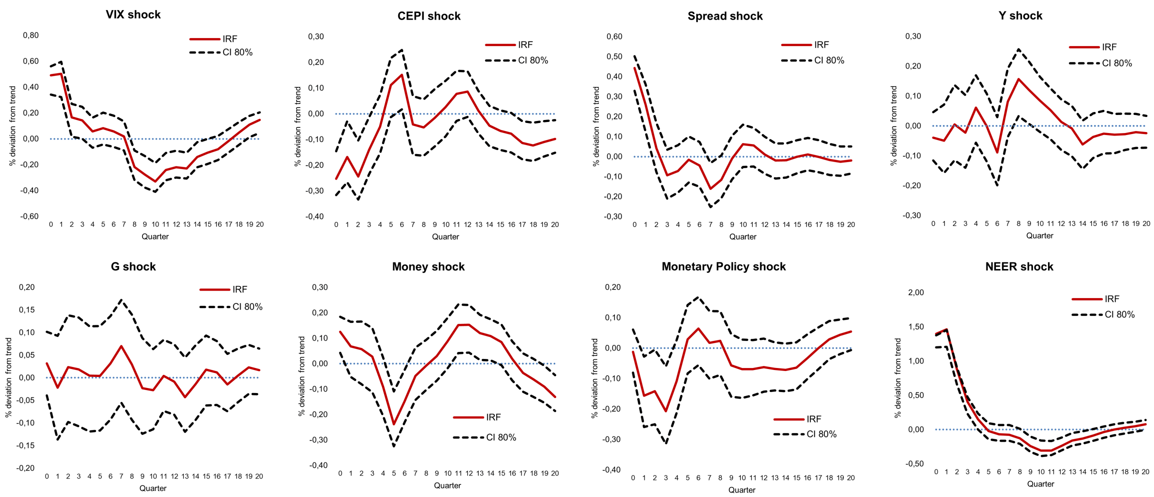


Notes: Local price data and United States prices is sourced from the Consumer Price Index (CPI) by Ha et al. (2019); the VIX data is extracted from the Federal Reserve Bank of St. Louis (FRED); GDP, consumption, broad money, Nominal Effective Exchange Rate (NEER) and monetary policy data are obtained from the International Monetary Fund (IMF).TThe analysis encompasses a total of 12 Emerging Market Economies (EMEs) and 24 small and medium-size developed economies, as detailed in Table 2 (Appendix)..

Y = GDP; P = local CPI; P* = US CPI; Money = Broad Money; G = Government Spending; MPR = Monetary Policy Rate.

Figure 25: Impulse Response Functions for NEER in EMEs

The figure displays the Impulse Response Functions (IRFs) of the Nominal Effective Exchange Rate (NEER) to various shocks, along with an 80% confidence interval calculated using Bootstrap with 1000 repetitions. The estimated SVAR model and the identification assumption are detailed in Section 5. The data has a semiannual frequency, so the numbers on the horizontal axis represent quarters. Only Emerging Market Economies (EMEs) with a central bank consistently classified as 5 or higher in all years from 2000 to 2021 according to the Dincer and Eichengreen (2014) index are considered.

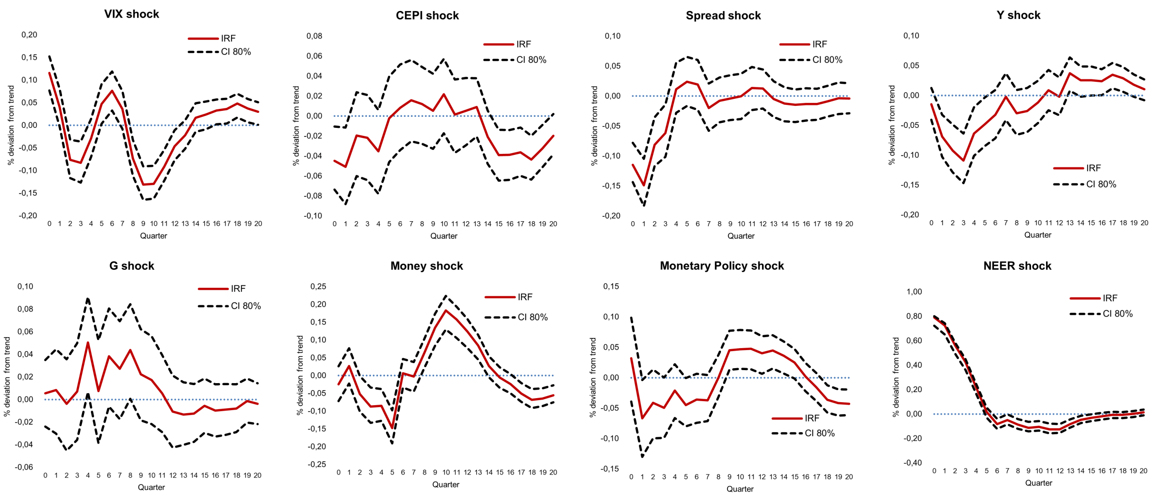


Notes: Local price data and United States prices is sourced from the Consumer Price Index (CPI) by Ha et al. (2019); the VIX data is extracted from the Federal Reserve Bank of St. Louis (FRED); GDP, consumption, broad money, Nominal Effective Exchange Rate (NEER) and monetary policy data are obtained from the International Monetary Fund (IMF).The analysis encompasses a total of 12 Emerging Market Economies (EMEs) and 24 small and medium-size developed economies, as detailed in Table 2 (Appendix).

Y = GDP; P = local CPI; P* = US CPI; Money = Broad Money; G = Government Spending.

Figure 26: Impulse Response Functions for NEER in AEs

The figure depicts the Impulse Response Functions (IRFs) of the Nominal Effective Exchange Rate (NEER) to various shocks, along with an 80% confidence interval calculated through Bootstrap with 1000 repetitions. The estimated SVAR model and the identification assumption are detailed in Section 5. The data has a semiannual frequency, with the numbers on the horizontal axis representing quarters. Only Advanced Economies (AEs) with a central bank consistently classified as 5 or higher in all years from 2000 to 2021 according to the Dincer and Eichengreen (2014) index are considered.

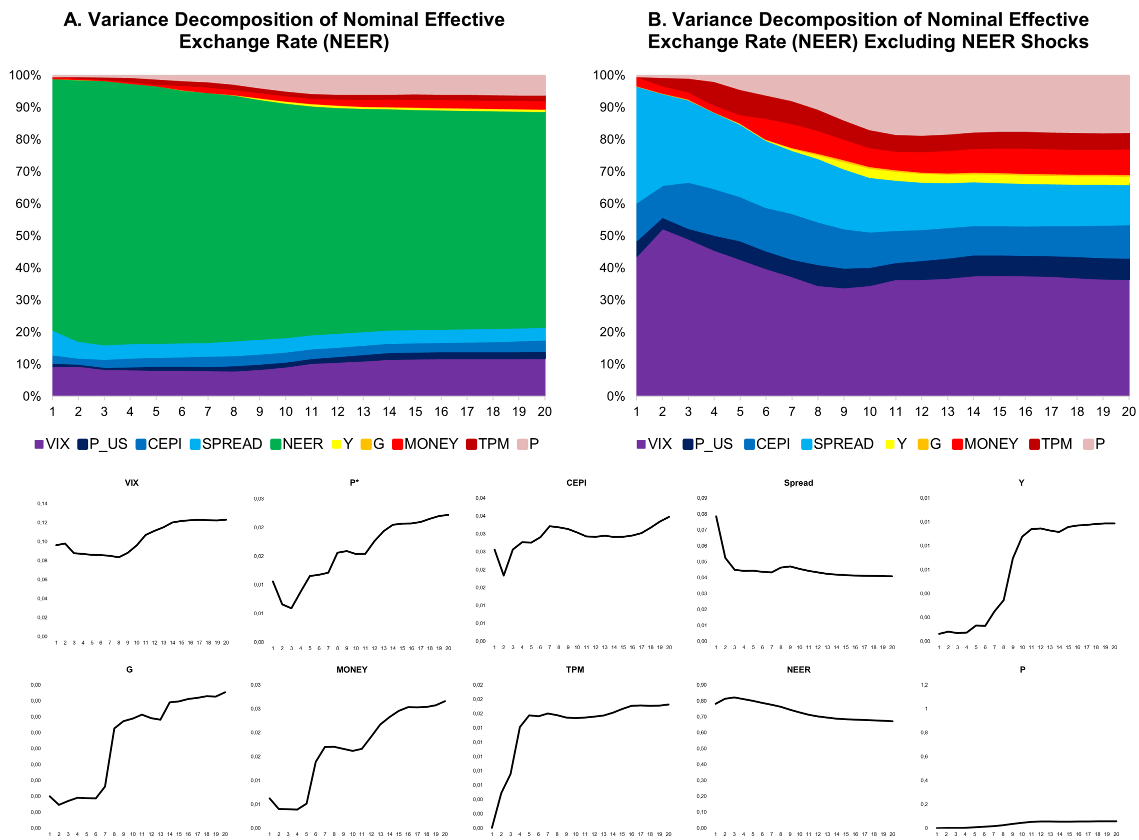


Notes: Local price data and United States prices is sourced from the Consumer Price Index (CPI) by Ha et al. (2019); the VIX data is extracted from the Federal Reserve Bank of St. Louis (FRED); GDP, consumption, broad money, Nominal Effective Exchange Rate (NEER) and monetary policy data are obtained from the International Monetary Fund (IMF).The analysis encompasses a total of 12 Emerging Market Economies (EMEs) and 24 small and medium-size developed economies, as detailed in Table 2 (Appendix).

Y = GDP; P = local CPI; P* = US CPI; Money = Broad Money; G = Government Spending.

Figure 27: Variance Decompositions of the Prediction Error of NEER in EMEs

The figure depicts the variance decomposition of the prediction error for NEER over a maximum horizon of 5 years (20 quarters). The estimated SVAR model and the identification assumption are elaborated in the Section 5. The data is of semiannual frequency, so the numbers on the horizontal axis denote quarters. Only Emerging Market Economies (EMEs) with a central bank rated at 5 or higher in all years from 2000 to 2021 in the Dincer and Eichengreen (2014) index are considered.

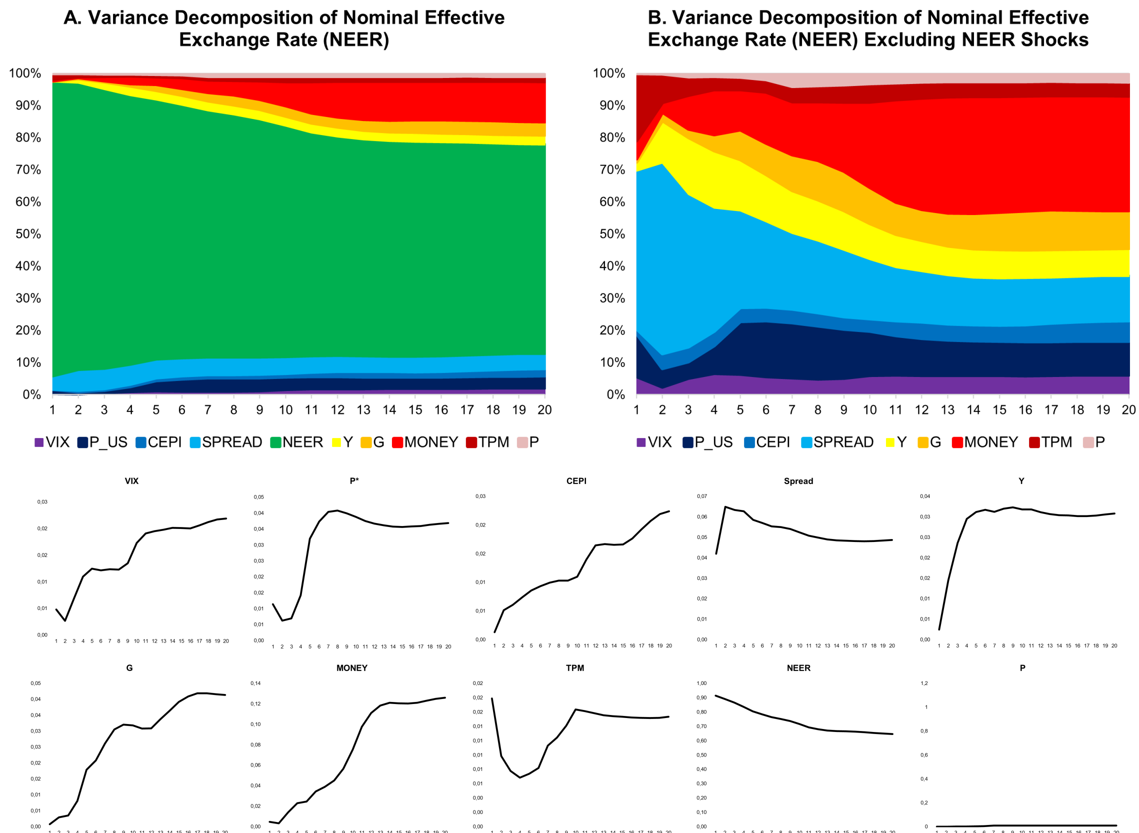


Notes: Local price data and United States prices is sourced from the Consumer Price Index (CPI) by Ha et al. (2019); the VIX data is extracted from the Federal Reserve Bank of St. Louis (FRED); GDP, consumption, broad money, Nominal Effective Exchange Rate (NEER) and monetary policy data are obtained from the International Monetary Fund (IMF).The analysis encompasses a total of 12 Emerging Market Economies (EMEs), as detailed in Table 2 (Appendix).

Y = GDP; P = local CPI; P* = US CPI; Money = Broad Money; G = Government Spending; MPR = Monetary Policy Rate.

Figure 28: Variance Decompositions of the Prediction Error of NEER in AEs

The figure depicts the variance decomposition of the prediction error for NEER over a maximum horizon of 5 years (20 quarters). The estimated SVAR model and the identification assumption are elaborated in the Section 5. The data is of semiannual frequency, so the numbers on the horizontal axis denote quarters. Only small and medium-size Advanced Economies (AEs) with a central bank rated at 5 or higher in all years from 2000 to 2021 in the Dincer and Eichengreen (2014) index are considered.

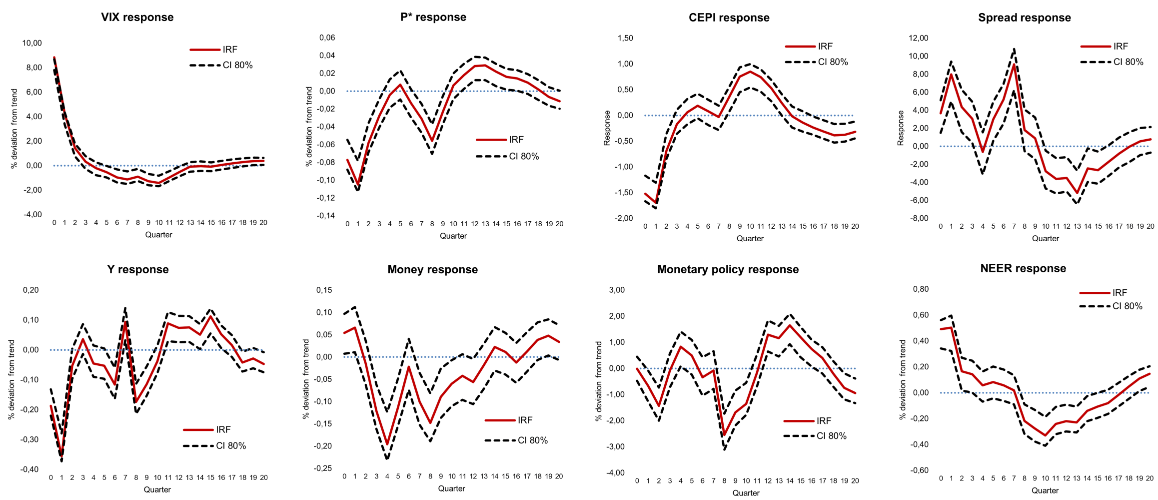


Notes: Local price data and United States prices is sourced from the Consumer Price Index (CPI) by Ha et al. (2019); the VIX data is extracted from the Federal Reserve Bank of St. Louis (FRED); GDP, consumption, broad money, Nominal Effective Exchange Rate (NEER) and monetary policy data are obtained from the International Monetary Fund (IMF).The analysis encompasses a total of 24 small and medium-size AEs, as detailed in Table 2 (Appendix).

Y = GDP; P = local CPI; P* = US CPI; Money = Broad Money; G = Government Spending; MPR = Monetary Policy Rate.

Figure 29: Impulse Response Functions to a VIX Shock in EMEs

The figure displays the Impulse Response Functions (IRFs) of various variables to VIX shocks, along with an 80% confidence interval calculated using Bootstrap with 1000 repetitions. The estimated SVAR model and the identification assumption are detailed in Section 5. The data has a semiannual frequency, so the numbers on the horizontal axis represent quarters. Only Emerging Market Economies (EMEs) with a central bank consistently classified as 5 or higher in all years from 2000 to 2021 according to the Dincer and Eichengreen (2014) index are considered.

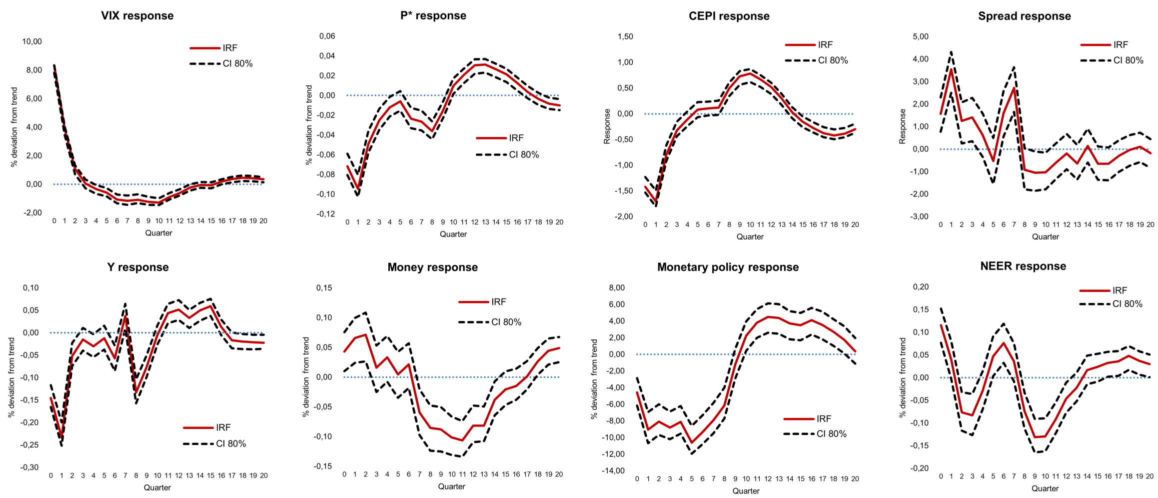


Notes: Local price data and United States prices is sourced from the Consumer Price Index (CPI) by Ha et al. (2019); the VIX data is extracted from the Federal Reserve Bank of St. Louis (FRED); GDP, consumption, broad money, Nominal Effective Exchange Rate (NEER) and monetary policy data are obtained from the International Monetary Fund (IMF).The analysis encompasses a total of 12 Emerging Market Economies (EMEs) and 24 small and medium-size developed economies, as detailed in Table 2 (Appendix).

Y = GDP; P = local CPI; P* = US CPI; Money = Broad Money; G = Government Spending.

Figure 30: Impulse Response Functions to a VIX Shock in AEs

The figure displays the Impulse Response Functions (IRFs) of various variables to VIX shocks, along with an 80% confidence interval calculated using Bootstrap with 1000 repetitions. The estimated SVAR model and the identification assumption are detailed in Section 5. The data has a semiannual frequency, so the numbers on the horizontal axis represent quarters. Only small and médium-size Advanced Economies (AEs) with a central bank rated at 5 or higher in all years from 2000 to 2021 in the Dincer and Eichengreen (2014) index are considered.



Notes: Local price data and United States prices is sourced from the Consumer Price Index (CPI) by Ha et al. (2019); the VIX data is extracted from the Federal Reserve Bank of St. Louis (FRED); GDP, consumption, broad money, Nominal Effective Exchange Rate (NEER) and monetary policy data are obtained from the International Monetary Fund (IMF).The analysis encompasses a total 24 small and medium size developed economies, as detailed in Table 2 (Appendix).

Y = GDP; P = local CPI; P* = US CPI; Money = Broad Money; G = Government Spending.