The supply and demand-side impacts of uncertainty shocks. Evidence on advanced and emerging economies

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Uncertainty has broad impacts on the economy, but it is unclear whether it affects only aggregate demand or both sides of the market. Using available uncertainty measures, this paper aims to quantify the impact of uncertainty shocks on output growth and inflation through their effects on aggregate supply and demand. The empirical strategy, applied to 19 advanced and 15 emerging countries, involves two steps. First, identifying in each country the parts of GDP-growth and GDP-inflation that are explained by shifts in aggregate supply and demand curves respectively. Second, estimating the country-effects of two (financial and non-financial) uncertainty shocks on the supply/demand components for growth and inflation. Considerations on reverse causality and identification of uncertainty types are made. Results show that in advanced and emerging economies, financial uncertainty shocks affect both sides of the market. When faced with greater uncertainty, consumers demand fewer goods, but producers reduce their supply as well, cutting back production and attempting to raise prices. Since the demand-side are larger than the supply-side effects, these shocks end up reducing inflation in all countries. Alternatively, non-financial uncertainty shocks' impacts on output are rather small.

Keywords: uncertainty, aggregate demand, aggregate supply, inflation.

JEL codes: D80, E3, C18.

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1. Introduction

Uncertainty is a broad concept that affects all economic agents, impairing their ability to forecast the future or make decisions. The COVID-19 has significantly risen uncertainty. But the deep reach of pandemic has also led economists to discuss its nature. Largely, the profession seems to agree that the COVID-19 and its containment measures have dampened both aggregate demand and supply in countries in the short-term. That would mean that aggregate demand and supply curves have shifted to the left, as explained in Guerrieri, Lorenzoni, Straub, & Werning (2020). The literature on uncertainty stemming from this global event has also been large, but the discussion in terms of its aggregate supply/demand impacts has been less clear-cut.

Generally, uncertainty shocks are seen as demand shocks. Papers such as Leduc & Zheng (2016) show that nominal rigidities and labor market frictions endow uncertainty surges with aggregate demand-like features -reducing employment and inflation. Basu & Bundick (2017) also show that in a DSGE model with nominal rigidities and non-competitive markets, uncertainty shocks can depress aggregate demand components. These works imply that uncertainty shocks shift the aggregate demand curve to the left. Alternatively, works such as Bloom (2009), Baker, Bloom, & David (2016), and Ahir, Bloom, & Furceri (2019) have empirically shown the broad scope of increasing uncertainty. Surges in uncertainty contract output, postpone consumption, delay firms' investments and hires, and reduce total factor productivity. In that context, one would presume that uncertainty shocks simultaneously shift both aggregate supply and demand curves to the left.

This paper aims to contribute to the empirical literature on uncertainty, determining whether uncertainty shocks shift aggregate demand and supply curves. Should uncertainty affect both sides of the market, we estimate each of those impacts in terms output growth and inflation. We also explore whether uncertainty effects are different in advanced and emerging economies or vary with uncertainty measures. To our knowledge, these questions have not been answered in the past. The paper's more general contribution is to make the case that uncertainty shocks can prompt impacts on both sides of the market, by simultaneously altering aggregate demand and supply. Finding that uncertainty hikes reduce aggregate supply highlights a link with producers' decisions in the short-term, as it is suggested in Bloom (2009), Bloom (2014), and Choi, Furceri, Huang, & Loungani (2018). In those papers, firms' decisions lead to a reduction in total or information technology investments, ultimately decreasing firms' productivity. Such decisions are related to a "wait and see" attitude or binding liquidity constraints that arise with uncertainty, and not with demand slumps.

The empirical strategy developed is based on the notion that aggregate supply and demand interact to determine real GDP growth and inflation in countries. Therefore, orthogonal (not correlated) shifts in these aggregate curves shape output growth and inflation fluctuations. When specific shocks (monetary, fiscal, financial, uncertainty or any other) hit the economy, they move aggregate curves. So, shifts in aggregate curves summarize the impact of all the specific shocks that distress the goods market. This interpretation is similar to the one advanced in in Blanchard & Quah (1989) where aggregate structural shocks convey the occurrence of other specific shocks in the economy.

In such a context, our empirical strategy has two parts. First, we identify the two aggregate structural shocks that affect the goods markets: supply and demand. These shocks represent the orthogonal shifts in aggregate curves. We also estimate the components of GDP growth and inflation explained by these shocks. Second, we determine whether an uncertainty shock has a supply or demand-side effect, depending on its impact on supply and demand (output growth and inflation) components.

Aggregate supply and demand shock identification uses sign restrictions within a structural VAR (SVAR), with GDP-growth and GDP-inflation, similarly as in Pagliacci (2019). That econometric procedure is applied to each of the 34 countries considered. Because of the way sign-restriction identification works, the basic predictions from an aggregate textbook model can be imposed in the SVAR: supply shocks trigger output and inflation responses in opposite directions, while demand shocks bring about responses in the same direction. This identification allows us to interpret aggregate shocks as measures of the shifts in aggregate curves.

To disentangle structural shocks' impacts, we compute the historical decompositions of GDP growth and inflation and obtain two (unobserved) components for each variable, named: supply growth, demand growth, supply inflation and demand inflation, respectively. Crucially, these supply (demand) components are interpreted as the counterfactual output and price impacts of the changes in producers' (consumers') willingness to supply (demand) goods in response to specific shocks. That is the case because shifts in aggregate curves convey the occurrence of all specific shocks. An example on the use of a supply price-component to understand producers' response to a specific shock (a depreciation shock) can be found in Pagliacci (2020).

The second part of the empirical strategy determines whether uncertainty shocks have a supply or demand-side effect. In the above context, this is relatively straightforward. It entails testing if adequately identified uncertainty shocks have significant impacts on supply and demand components. When applied to output components, this strategy allows us to determine if an increase in uncertainty reduces output because consumers demanded fewer goods (a shift to the left in aggregate demand) or producers were willing to provide fewer goods to the market (a shift to the left in aggregate supply). This part of the strategy is implemented through four country-panel Local Projections estimations (LPs) and four country-panel-SVAR models (P-SVARs): one model for each component. These estimations consider the discussion about endogeneity and the financial/non-financial nature of uncertainty.

Identification of uncertainty shocks requires considering its endogeneity with respect to output and, in our case, with respect to supply/demand output components. As Bloom (2014) states, all empirical measures of uncertainty are countercyclical -with respect to the business cycle-, indicating that uncertainty always increases during recessions. However, uncertainty cyclicality could be interpreted in two "causal" ways. It could mean that by negatively affecting consumers and producers' decisions, uncertainty sets off recessions -a mechanism of direct causality. On the other hand, by causing a blur in agents' economic forecasts, recessions could instead lead to increasing uncertainty -a mechanism of reverse causality for uncertainty.

Most empirical measures of uncertainty, such as the implied volatility index of the S&P500 (VIX) used in Bloom (2009), the Economic Policy Index constructed in Baker, Bloom, & David (2016), and the World Uncertainty Index presented in Ahir, Bloom, & Furceri (2019), register significant surges when non-economic events (political events, wars, and pandemics) take place. That hints to the existence of an important exogenous component in these measures that can disrupt agents' decision-making and bring about recessions. Such a description supports the notion of a direct causality for uncertainty.

Estimations in this paper simultaneously use two distinct measures of uncertainty in countries: the World Uncertainty Index (WUI), from Ahir, Bloom, & Furceri (2019), and the VIX. Including these two measures simultaneously aims to distinguish the potential dual nature of uncertainty -financial versus non-financial-, as similarly discussed in other papers. For instance, Ludvigson, Ma, & Ng (2018), using event-identification techniques in SVARs, distinguish financial from macroeconomic uncertainty. According to those authors, contractionary financial uncertainty shocks cause important output contractions, but macroeconomic uncertainty tends to endogenously arise as a result of recessions -it does not generally cause them. In Choi & Shim (2019), in emerging markets, financial uncertainty has larger economic significance than policy uncertainty (measured by the Economic Policy Index index of Baker, Bloom, & David, 2016). We further justify our choice of uncertainty measures in section 3.

Country-panel LPs for supply and demand growth (the output components) estimate the output-impacts of uncertainty shocks. More concretely, each of these LPs quantifies the time-impacts of both financial and non-financial uncertainty shocks through aggregate supply and demand adjustments. According to Plagborg-Møller & Wolf (2019), LPs and VARs estimate the same properties of a population, if lag restrictions are kept equal. We use both LPs and SVARs to understand the effects on estimation results of the causality assumptions held and, consequently, assess their robustness.

Uncertainty shocks are identified in LPs by placing the appropriate regressors in the supply or demand growth equation: current and lagged values of both uncertainty measures, and lagged values of the output component. Since uncertainty measures and the component are considered mutually endogenous, lagged variables represent control variables, as in VAR estimations. We include four lags for each variable. Current uncertainty measures are also regressors in LPs so that the contemporaneous correlation -between the output component and uncertainty- is attributed to run from uncertainty to output. That is, in LP estimations, the possibility of reversed causality -from output to uncertainty- is disregarded. Additionally, each uncertainty coefficient captures the marginal effect of that uncertainty shock over the output component, i.e., an impact that is clean of the other uncertainty type.

P-SVAR models are used to assess whether disregarding reverse causality could have affected LPs results. Estimations with P-SVARs are kept analogous to those in LPs, in terms of control variables, number of lags, and the separation of financial/non-financial uncertainty shocks. So, each P-SVAR includes one of the estimated supply/demand output components and the two measures of uncertainty.

Identification of shocks in P-SVARs is implemented through a standard Cholesky decomposition, placing first the unobserved output component, second the VIX, and third the WUI. By placing the output component first, this recursive identification scheme allows for the reverse causality assumption. For example, it allows unexpected supply or demand output contractions to explain contemporaneous (within the same period) rises in uncertainty. By placing the VIX second in the specification, the structural shock to VIX would capture the uncertainty related to global financial markets that cannot be explained by simultaneous output contractions in countries. The orthogonal shock attributed to WUI would mostly capture instead, the uncertainty related to domestic non-financial events, since any financial component of WUI is already captured by the VIX. Although disputable, this identification strategy sets the experiment so that the null hypothesis -uncertainty shocks cause changes in output components- is easier to reject. So, any evidence found in the data of such effects could be considered substantial.

Because the identification of aggregate supply and demand shocks also allows for the estimation of supply/demand price components, we repeat the above LPs and P-SVARs estimations for GDP-inflation components, i.e., supply and demand inflation. These estimations would shed light on the effects of both uncertainty shocks on prices, distinguishing between the suppliers' willingness to increase prices and the consumers' willingness to buy at lower prices. Depending on the magnitude of those effects, uncertainty shocks could lead to either higher or lower GDP-inflation. According to most narratives in the literature, uncertainty shocks are likely to cause lower inflation.

Estimations of LPs and P-SVARs for output and price components of GDP are carried out for a sample of 34 economies (19 advanced and 15 emerging), in Latin America and Europe, for the period 1998-2019. We use quarterly data.

Section 2 describes the estimation of output and price components, emphasizing the variance decomposition of shocks. Section 3 describes the LPs results for output and price components, while section 4 presents results from the P-SVARs estimations. Section 5 takes stock of the findings and concludes.

2. GDP decomposition: supply/demand output and price components

In this section, we estimate the historical impacts of aggregate supply and demand structural shocks (shifts) on GDP-growth and GDP-inflation for each country individually. The decompositions obtained are respectively named: the output components (supply and demand growth) and the price components (supply and demand inflation). While the output components convey the impacts on output growth of present and past supply and demand shifts respectively, the price components summarize the impacts on GDP-inflation of such shifts.

To estimate output and price components, we follow the procedure described in Pagliacci (2019), which uses bi-variate SVARs and sign restrictions to identify supply and demand shocks. Data is quarterly and runs from 1998 to 2019. Variables used for each country VAR are the year-on-year growth rates of real GDP and GDP deflators. GDPs and GDP deflators are obtained from: Central Banks or Statistic Institutes in Latin America, the United States, and Canada; the Monetary Central American Council (Consejo Monetario Centroamericano) for Central American countries; and the Eurostat database for European countries. Details of the econometric procedure are described in appendix A.

We use Schwarz and Hannan-Quinn information criteria to determine the minimal VAR lag-length required for each country. We also consider results from residuals serial correlation (LM) tests. Estimated VARs have between two and three lags, depending on the country. The dynamic stability properties of VARs are also checked. The identification of structural aggregate supply and demand shocks is performed using the short-run sign restrictions specified in table 1 for expansionary and contractionary shocks. Restrictions are applied for two consecutive quarters. In calculating historical decompositions, the window for accumulating shocks' impacts varies between 8 and 12 quarters. Countries with more persistent impulse-responses use longer windows.

Table1. Conditions imposed on impulse-responses for structural shocks

	Expansionary Supply Shock	Expansionary Demand Shock
Real GDP-growth	+	+
GDP-inflation	-	+

Output and price components estimated for each country are presented in appendix B (figures B1 and B2, respectively). The joint analysis of the output components shows the shocks that explained the growth in countries during periods. Intuitively, when both output components have the same sign, growth is explained by the occurrence of supply and demand shocks of an identical sign. In this case, both sides of the market are contributing to describe the aggregate output performance. On the contrary, when output components have opposite signs, it means that the aggregate performance will depend on the dominant component (the largest one in absolute value). Thus, a positive (negative) sum of the components reflects a stronger (a diminished) growth (with respect to its sample mean). The wedge between output components indicates a lack of balance between the supply and the demand sides. Excessive output demand leads to higher inflation, while an excessive output supply drives lower inflation. The interpretation of price components is analogous to that of output components, considering that supply shocks negatively impact inflation. That is, a contractionary (an expansionary) supply shock causes a higher (lower) supply inflation.

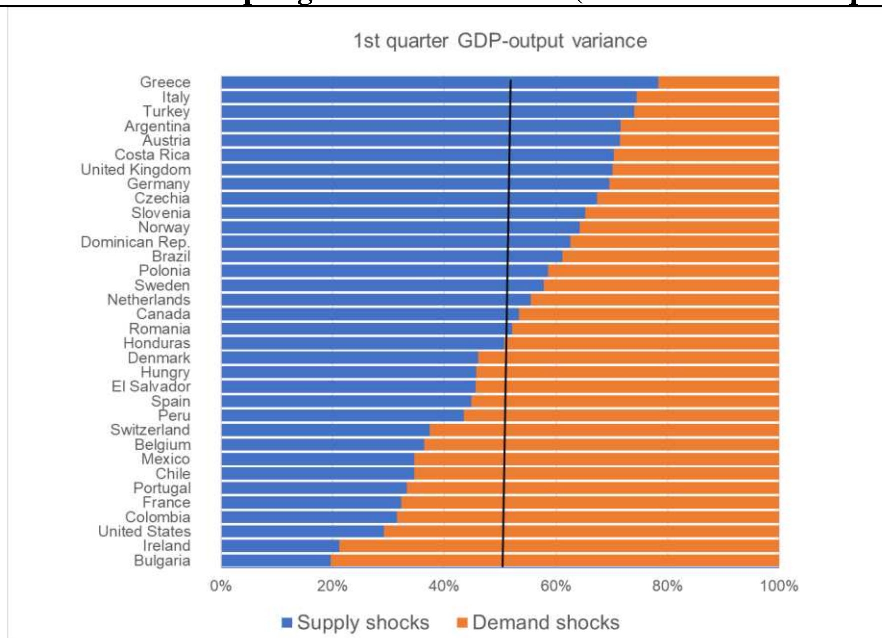
Variance decompositions summarize the average impacts of supply and demand shocks on output growth and inflation. So, they reflect the relative importance of each shock on each variable. Figure 1 and 2 show the variance decompositions for GDP-growth and GDP-inflation, calculated from accumulated impulse-responses, in all countries. Since variance decompositions change in time, each figure displays the weight of supply and demand shocks for the 1st and 12th quarters. Straight black lines represent the sample-median weight of supply shocks.

Figure 1 shows that the for the first quarter, the median weight of supply shocks is 53%, indicating that for half of the countries (the top half), supply shocks explain more than 53% of the GDP fluctuations. After three years, the median weight of supply shocks is 60%. That is, with time, on average, the importance of supply shocks for explaining output growth increases, as some of the effects of demand shocks tend to wane. Nonetheless, for some countries at the bottom of the 12th quarter figure, such as Mexico, Portugal, Ireland, and Bulgaria, demand shocks explain more than 75% of output fluctuations. In other words, a demand shock can set off an accumulated growth that is three times larger than the growth triggered by a similar-sized supply shock. For those countries, while supply shocks have either very small or short-lived impacts, demand shocks have significant and persistent effects on output.

In figure 2, we observe that, for the top half of the countries, in the first quarter supply shocks can explain more than 53% of the inflation fluctuations. Symmetrically, demand shocks can account for less than 47% of those fluctuations. After three years, the median weight of demand shocks increases to 59%, indicating that, on average, these shocks become more important for explaining inflation. However, for many countries, the impact of supply shocks remains considerable after three years. For example, for those countries at the top of the 12th quarter figure, such as Colombia, Argentina, and the Dominican Republic, supply shocks can describe more than 70% of the accumulated price change.

Overall, figures 1 and 2 suggest that growth and inflation across countries can have considerably different explanations, in terms of the aggregate shocks that originate them. That variety of results precludes to conclude whether supply or demand shocks have long-run impacts on neither variable.

Figure 1. Variance decomposition of GDP-growth for all countries: weights of supply and demand shocks on output growth fluctuations (for 1st and the 12th quarter)



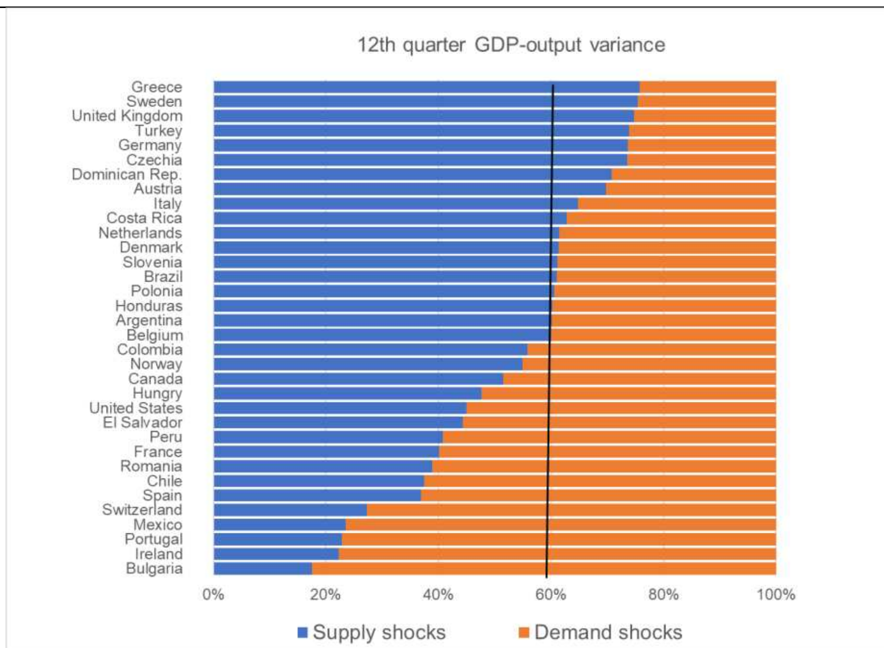
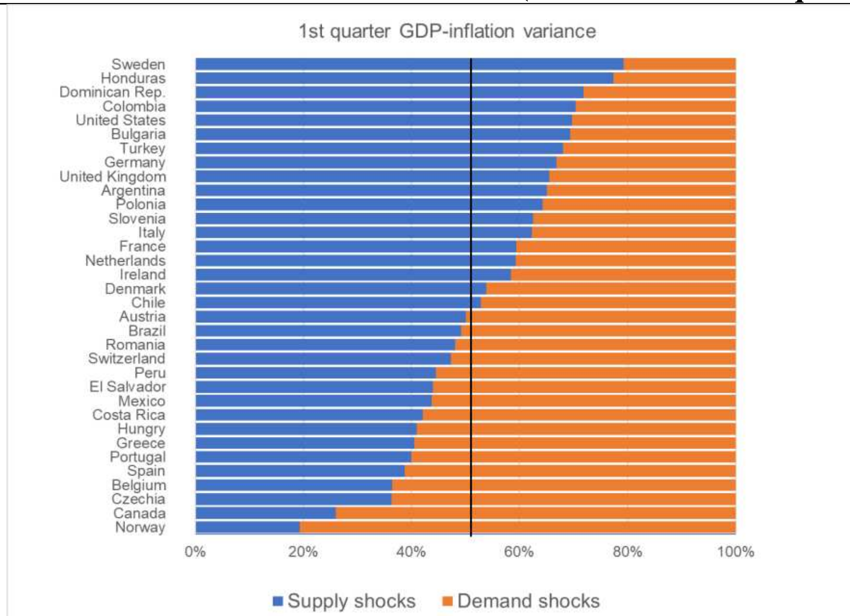
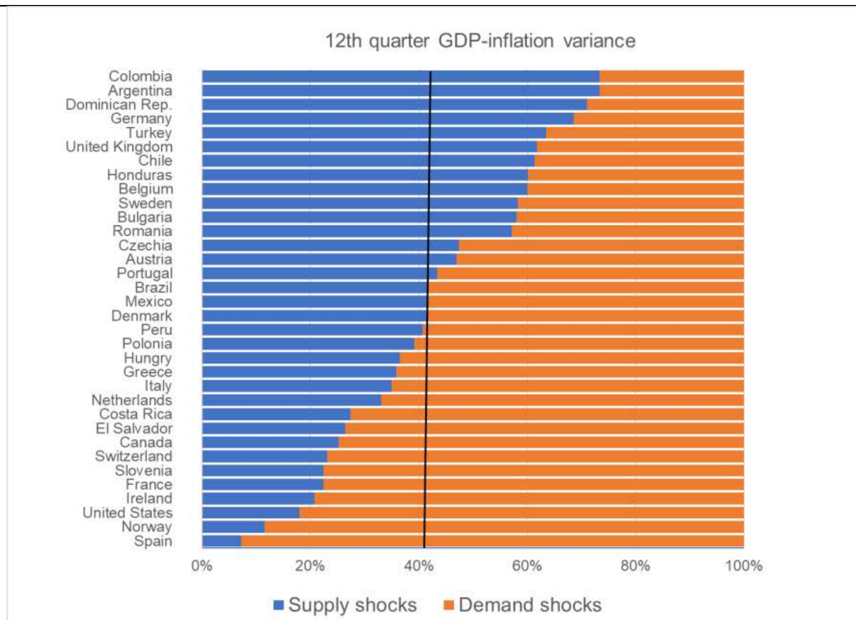


Figure 2. Variance decomposition of GDP-inflation for all countries: weights of supply and demand shocks on inflation fluctuations (for 1st and the 12th quarter)





3. The impacts of uncertainty shocks: LPs estimations

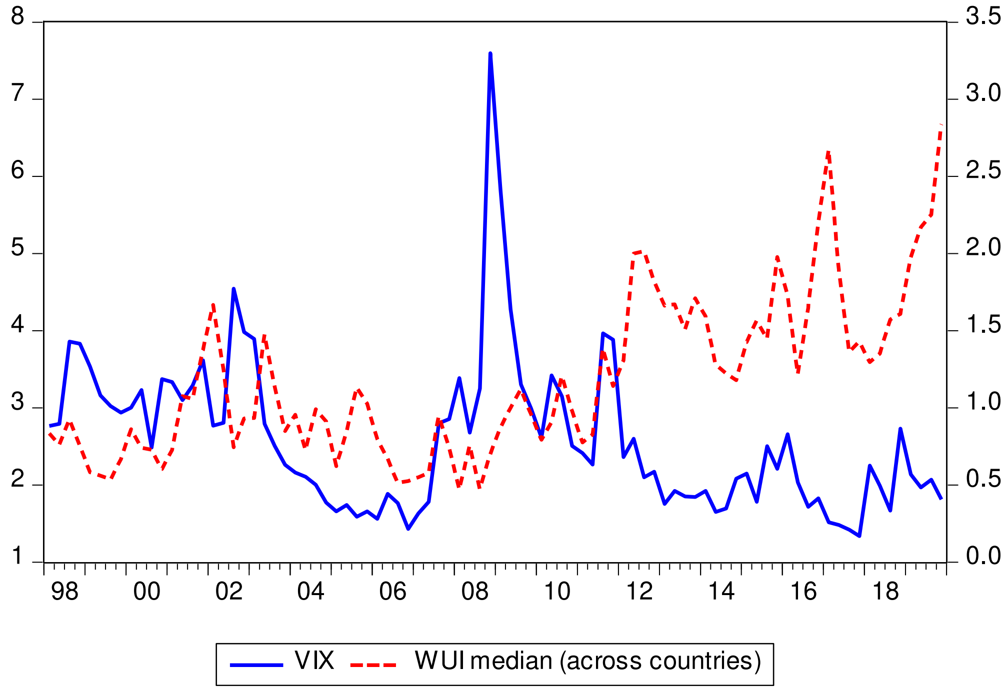
This section aims to determine whether uncertainty shocks have effects on both sides of the markets (supply and demand components). Using LP equations for output and price components, we estimate the impact of two types of uncertainty shocks several periods ahead. As in Jordá (2005), based on those estimations, then we build each component's accumulated impulse-response to uncertainty shocks. After evaluating the direction and magnitude of impulse-responses, we infer the observed net effect on growth and inflation. Our estimations run from the first quarter of 2001 through the last quarter of 2019.

Our data comprises the output and price components previously estimated in section 2. It also includes two uncertainty measures: the VIX and the WUI. The VIX refers to the quarterly average of the index obtained from the database of the Federal Reserve of St. Louis. WUI information is provided on the web by the paper of Ahir, Bloom, & Furceri (2019). As explained by these authors, the index reflects the frequencies of the word "uncertainty" (and its variants) in the Economist Intelligence Unit country reports, scaled by the total number of words in each report.

Our simultaneous inclusion of two measures of uncertainty in estimations is justified analytically and statistically. Analytically, each measure is constructed from two very different sets of information, possibly describing two distinct sources of uncertainty. Movements in the VIX have been empirically connected with important adjustments in international markets. VIX reductions (increases) have been associated with low (high) risk aversion of investors, large (contracted) cross-border flows, and increasing (diminishing) indebtedness by the sovereign and corporate sectors in countries (Miranda-Agrippino & Rey, 2015). Therefore, VIX innovations can be considered as weakly exogenous for most countries. Alternatively, based on countries' reports from the Economist Intelligence Unit, the WUI focuses on the political and economic developments in countries described by analysts. Upward fluctuations in the WUI are mainly related to uncertainty surges in countries' political and economic conditions and public policies.

Statistically, the two measures of uncertainty have a low correlation (-0.34 between the medians across countries and -0.16 for stacked country-data), suggesting that they potentially describe two different phenomena as well. This low correlation also allows for their simultaneous inclusion in regressions, without bringing up concerns on multicollinearity. Figure 3 compares the VIX and the median of the WUI across countries, both in standard units. Qualitatively, before the global financial crisis, the indexes had relatively similar behaviors. Afterward, the median of WUI has been increasing and has markedly differed from the VIX. So, while financial uncertainty seemed under control in global financial markets, other factors in countries tended to increase non-financial uncertainty. That has been the case, especially since 2012.

Figure 3. Comparison of uncertainty measures



Both vertical axes correspond to standard units of the indexes

The LP baseline equation to estimate the impacts of uncertainty shocks on output and price components is the following:

$$Y_{i,t+k} = \beta_k VIX_t + \gamma_k WUI_{i,t} + \sum_{l=1}^{4} \delta_{k,i} X_{t-l} + \alpha_{k,i} + \varepsilon_{i,t} \quad (1)$$

for $k = 0, \ldots, 12$. *Y* represents the supply/demand output or price component, whose response we want to evaluate. *X* is the set of control (lagged) variables, i.e., the potentially endogenous variables: *VIX*, *WUI*, and *Y*. To allow for a better adjustment in the estimations, the coefficients of *X* are country-specific. α are the country-fixed effects. $\varepsilon_{i,t}$ are the country-specific residuals at time *t*, which are assumed to be correlated across countries, but uncorrelated across time. β_k and γ_k are the pooled-coefficients that capture the impacts of uncertainty shocks on the output or price component *k* quarters ahead. Since *VIX* and *WUI* have been previously divided by their standard deviation in countries, their coefficients deliver the impact for one-standard deviation increase in uncertainty. To compute accumulated impulse-responses, we sum beta and gamma coefficients from period 0 to *k*, for each *k*. Bands of impulse response are obtained by adding and subtracting to β_k and γ_k their respective clustered standard errors. These statistics correspond to panel-corrected-standard deviations that allow for different variances and contemporaneous correlations of residuals across countries. Estimations of equation (1) are carried out with FGLS.

Appendix C (figures C1, C2, C3 and C4) shows the accumulated impulse-responses of all the components (supply and demand growth, and supply and demand inflation) to financial and non-financial uncertainty shocks, for all countries, and for advanced and emerging economies separately. A summary of those results is provided in tables 2 and 3, which respectively report only the maximum accumulated impacts of the financial uncertainty shock (the VIX) and the non-financial uncertainty shock (the WUI), on the different components. We also show the approximate possible net effects on output growth and inflation by adding the maximum impacts on both sides of the market.

Table 2. Summary of output and price components' accumulated responses to financial uncertainty

Financial uncertainty shock (one-standard deviation increase in VIX)				
	All countries (34)			
	y^s	y^d	π^s	π^d
max response quarter	-1.7% 7	-2.0% 7	1.2% 6	-2.5% 11
net output effect net price effect	-3.7%		-1.3%	
	Advanced countries (19)			
	y^s	y^d	π^s	π^d
max response quarter	-1.7% 8	-2.0% 6	0.5% 6	-1.2% 8
net output effect net price effect	-3.7%		-0.7%	
	Emerging countries (15)			
	y^s	y^d	π^s	π^d
max response quarter	-1.7% 12	-1.4% 6	2.1% 12	-2.5% 7
net output effect net price effect	-3.1%		-0.4%	

y^s: supply growth; y^d: demand growth; π^s: supply inflation; π^d: demand inflation

Table 3. Summary of output and price components' accumulated responses to non-financial uncertainty

Non-financial uncertainty shock (one-standard deviation increase in WUI)				
	All countries (34)			
	y^s	y^d	π^s	π^d
max response quarter	-0.3% 3	-0.3% 8	0.4% 10	-0.2% 8
net output effect net price effect	-0.5%		0.2%	
	Advanced countries (19)			
	y^s	y^d	π^s	π^d
max response quarter	-0.2% 3	-0.2% 7	0.1% 3	-0.2% 7
net output effect net price effect	-0.4%		-0.1%	
	Emerging countries (15)			
	y^s	y^d	π^s	π^d
max response quarter	-0.5% 3	-0.9% 12	0.9% 10	-0.5% 12
net output effect net price effect	-1.4%		0.4%	

y^s: supply growth; y^d: demand growth; π^s: supply inflation; π^d: demand inflation

Overall, figures C1-C4 and results from table 2 and 3 show that the two uncertainty shocks tend to shift both aggregate supply and aggregate demand to the left. The aggregate supply shift explains the reductions in supply growth (y^s) and the increases in supply inflation (π^s), for all countries. The aggregate demand shift accounts for the drops in both demand growth (y^d) and demand inflation (π^d). In other words, uncertainty shocks show consistent contractionary effects on both sides of the market, for all countries.

These shifts can also be described in terms of the responses of market participants. On the one hand, an uncertainty surge drives consumers to purchase fewer goods, pushing cuts in goods' production and prices. On the other hand, higher uncertainty leads suppliers to reduce the quantities of goods produced and raise their prices. These synchronized -suppliers' and consumers'- behaviors end up reinforcing a fall in output growth, which is be clearly observed in the data. Nevertheless, these same responses can also trigger different observable effects on inflation. For instance, for the financial uncertainty shock, a lower inflation is predicted. The downward price pressure from a lower aggregate demand tends to be larger than the upward price pressure from a reduced aggregate supply. Instead, for the non-financial shock, in emerging countries, the net price-impact is slightly inflationary: suppliers' price-increases outweigh consumer-driven price-reductions.

Comparisons of results can also lead to other observations about the different nature of financial and non-financial shocks.

Overall, financial uncertainty shocks seem to produce more extensive adjustments in aggregate supply and demand curves, in both advanced and emerging economies. Estimations for all countries show that, while financial uncertainty shocks could explain net output contractions of 3.6% (table 2), non-financial uncertainty shocks could reduce net growth by only 0.5% (table 3). So, financial uncertainty shocks can have output impacts that are sevenfold larger than those of non-financial shocks, especially in advance economies. These larger output impacts of financial uncertainty shocks are consistent with the empirical evidence found in Ludvigson, Ma, & Ng (2018), which considers two types of uncertainty (financial versus macroeconomic).These authors find that a financial uncertainty shock always reduces US industrial production -in about 1%-, but a macro uncertainty shock can have mixed impacts on output, depending on the estimation model.

A financial uncertainty shock, although shifts both supply and demand to the left, is likely to push aggregate demand further to the left (table 2). More massive falls in aggregate demand could explain the observable (net) reductions in both output growth and inflation. Aggregate curves' shifts are probably similar in advanced and emerging economies, but their observed net effects are slightly different. In emerging economies, net year-on-year output contractions could be around 3% (versus 3.7% in advanced), and net GDP-inflation falls by 0.4% (versus 0.8% in advanced). The observed drop in the inflation rate is smaller in emerging economies because supply inflation is larger.

Regarding non-financial uncertainty shocks, WUI innovations have some significant impacts only in emerging economies (figures C3-C4). In advanced economies, surges in non-financial uncertainty have negligible effects (table 3). In emerging economies, both a reduced supply and demand growth can explain a net year-on-year output contraction of 1.4%. However, the observed (net) GDP-inflation is positive (0.4%). That is the case because supply inflation is larger than demand deflation, ultimately pushing GDP-prices upward. Also, in this case, supply inflation is larger in emerging than in advanced economies.

Dynamically speaking, some interesting narratives also arise from results. Table 2 shows that demand output components reach their maximum responses earlier than supply components, in advanced and emerging economies. While demand growth contractions build up during the first year and a half after the financial uncertainty shock, supply growth reductions can continue piling up for the next half year. So, potentially, when a financial uncertainty surge initiates, consumers start reducing their demand for goods, leading to drops in production. Simultaneously, suppliers undertake further exogenous production cuts that can go on after the fall in demand has stopped. In terms of the shock's price-effects, the downward demand pressure is most of the time larger than the upward supply pressure, leading to a continuous reduction in prices. However, larger reductions in GDP-inflation are possibly seen after the first year, when supply inflation stops building up. Three years after a financial uncertainty shock, inflation remains below its historical average.

Table 3 displays an opposite narrative to table 2, especially for emerging economies. When non-financial uncertainty takes off, producers start adjusting the quantities and prices of their production. Suppliers' production cuts seem to occur within the first three quarters after the surge in uncertainty. However, consumers will continue to reduce their demand for those goods, causing additional exogenous shifts in aggregate demand. Regarding prices, inflation would start rising above its average after the shock, until consumers' reactions will reverse such trajectory. Three years after the shock, non-financial uncertainty shocks' inflationary effects are probably no longer noticeable in emerging economies.

4. Checking robustness of results under reversed causality: VARs estimations

This section aims to check the robustness of prior results, by estimating P-SVARs that can consider a reverse causality assumption for uncertainty.

Data is identical to the one employed in LPs estimations. Each VAR contains three variables (one component and two uncertainty measures). There are four VARs estimations, one for each component. All VARs also have four lags and account for country fixed-effects. Estimations are carried out through OLS.

The reverse causality assumption is imposed by identifying VARs according to the following recursive structure: the output or price component is ordered first; the VIX is placed second; and the WUI third. Ordering a component first assumes that its innovations are responsible for the contemporaneous correlation that arises between uncertainty and the component. For example, given a negative contemporaneous correlation, this ordering presumes that, within a given quarter, unexpected contractions in demand growth lead to rising uncertainty. The above ordering also implies that uncertainty shocks can affect supply and demand (growth and inflation) components only in the future, and not when shocks occur.

Ordering the VIX before the WUI presumes that VIX innovations are relatively more exogenous and, therefore, can explain any co-movement between VIX and WUI innovations. Consequently, structural WUI innovations have been cleaned up of possible exogenous global financial effects, and likely describe domestic non-financial sources of uncertainty.

A summary of the relevant impulse-responses is presented in figures 4 and 5. Figure 4 shows the accumulated components' responses to a financial uncertainty shock for all countries, while figure 5 illustrates responses to a non-financial uncertainty shock in emerging economies. Recall from previous results that emerging economies were more sensitive to non-financial shocks than advanced ones.

In figure 4, despite assuming a reversed causality, financial uncertainty shocks can induce very significant responses in all components. Moreover, responses are consistent with the ones found in prior LPs estimations. The contraction (shift to the left) in aggregate demand is probably larger than the retrenchment (shift to the left) in aggregate supply. Both supply and demand growth fall after a surge in financial uncertainty. But the demand growth drop is larger than the supply growth decline (see two upper graphs of figure 3). Likewise, demand deflation is larger than supply inflation. That implies that, a financial uncertainty shock induces lower inflation than the average.

In figure 5 instead, all impulse-responses turn out to be mostly statistically non-significant. Components do not respond to non-financial uncertainty shocks, except for demand growth, which marginally falls about 1%. Compared to LPs findings, assuming a reverse causality has wiped out the effects of the shock on the supply side of the economy. According to these impulse responses, a non-financial uncertainty surge induces only an output contraction with non-visible effects on inflation.

To make sure that figure 5 results were not driven by the change in estimation technique, we also estimated impulse-responses under the direct causality assumption. Although not shown, these responses were consistent, in direction and magnitude, with previous LPs. That confirms that causality assumptions are crucial for interpreting the effects of non-financial uncertainty shocks.

Figure 4. Output and price components' accumulated responses to a financial uncertainty shock (one-standard deviation increase in VIX) for all countries (reverse causality assumption)

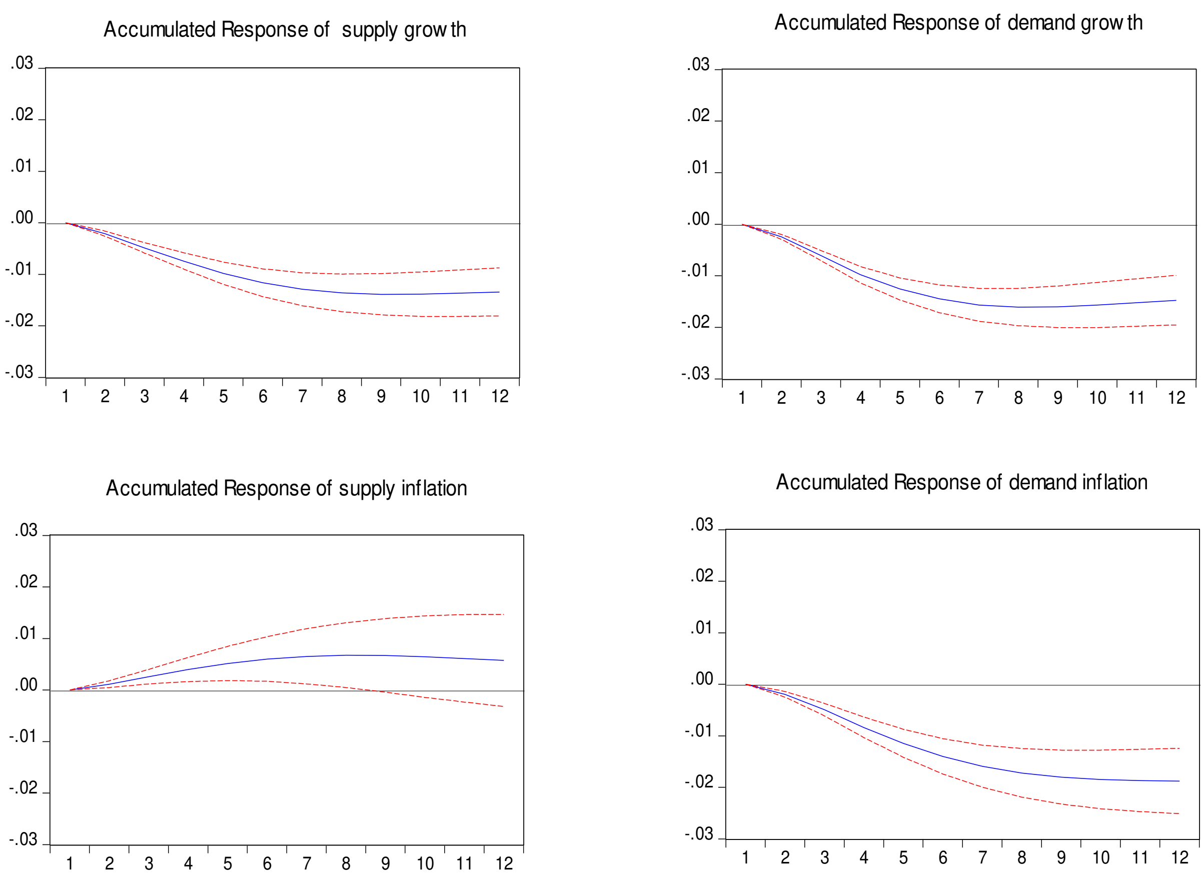
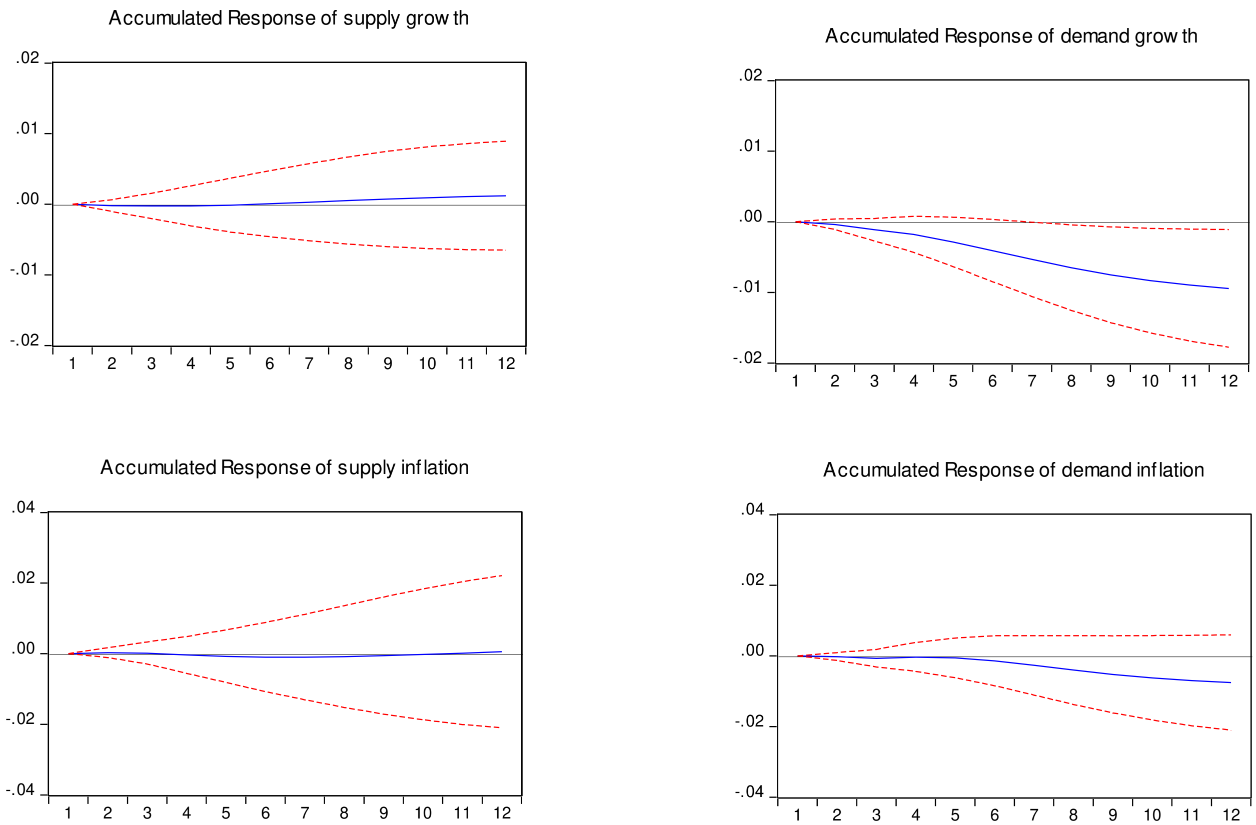


Figure 5. Output and price components' accumulated responses to a non-financial uncertainty shock (one-standard deviation increase in WUI) for emerging economies (reverse causality assumption)



Our understanding of these robustness exercises is the following. Estimations cannot disentangle the true causality among variables but can help assess our assumptions' importance. Financial uncertainty innovations have very strong impacts that are not affected by the causality assumption imposed. Alternatively, non-financial uncertainty shocks have very small effects, which are not robust to changes in causality. Consequently, we know that non-financial uncertainty innovations reduce aggregate demand, but we are unsure whether they decrease aggregate supply as well. Foreseen output contraction could range between 1% and 1.4% for emerging economies, depending on the causality assumption held. Despite methodological differences, these GDP contractions are in line with the findings presented in Ahir, Bloom, & Furceri (2019), which estimates that one-standard deviation in the WUI reduces growth by 1.4% - 1.5% after 8 - 10 quarters. Our estimated price-effects of non-financial uncertainty shocks are somewhat unclear: these innovations could have no impact at all or display a slightly inflationary effect (around 0.4% increase in GDP-inflation).

Regarding other innovations in SVAR impulse-responses, demand growth and inflation shocks have robust effects only on non-financial uncertainty. A stronger aggregate demand will always reduce non-financial uncertainty (the WUI). For all countries, one-standard deviation increase in demand growth could reduce the WUI between 0.7 and 0.9 standard deviations. Likewise, one-standard deviation increase in demand inflation could diminish the WUI between 0.6 and 0.7 standard deviations. These results are all statistically significant and suggest that non-financial uncertainty reacts endogenously to aggregate demand. Regarding financial uncertainty, its endogenous response to positive demand growth and inflation shocks tends to be positive, but not always statistically significant, i.e. significance depends on the causality assumption.

To understand the relative importance of shocks on variables' performances, table 4 shows some of the variance decompositions implicit in P-SVARs, for all and emerging countries, considering both causality exercises. We only present the results that relate uncertainty measures with aggregate demand components (four estimation models in total).

Table 4. Accumulated variance decomposition for aggregate demand and uncertainty (after 12 quarters)

	Demand growth (y^d)	**Demand inflation (π^d)**	**Financial uncertainty (VIX)**	**Non-financial uncertainty (WUI)**
All countries				
VIX shock	11.4% - 19.0%	6.7% - 11.7%	92.4% - 93.2%	0.1%
WUI shock	0.7% - 0.9%	0.4% - 0.5%	4.2% - 4.4%	97.1% – 97.8%
y^d shock	80.1% - 87.9%	--	2.6% - 3.2%	2.2% - 2.8%
π^d shock	--	87.8% - 92.9%	--	--
Emerging economies				
VIX shock	10.0% - 17.0%	7.7% - 12.9%	93.9% - 94.7%	0.1% - 0.4%
WUI shock	1.9% - 2.3%	0.7%	2.7% - 2.9%	94.3% - 95.6%
y^d shock	80.7% - 88.1%	--	2.6% -3.2%	4.3% - 5.3%
π^d shock	--	86.4% - 91.6%	--	--

Table 4 puts on perspective some of the earlier results. On the one hand, non-financial uncertainty (WUI) shocks contribute little to explaining aggregate demand components under any causality assumption. These shocks can explain at most 2.3% of demand growth and 0.7% of demand inflation in emerging economies, where their effects are relatively more important. Instead, financial uncertainty (VIX) shocks can explain sizable fluctuations in both demand components (up to 19% of demand growth and 13% of demand inflation). These results confirm the greater strength of financial uncertainty shocks to affect aggregate demand.

Unexpected aggregate demand expansions (positive shocks in y^d) always reduce non-financial uncertainty. These shocks, however, can account for up to 5.3% of non-financial uncertainty, in emerging economies, and up to 2.8% in all countries. Cross-uncertainty effects are also small under any causality assumption. Overall, the bulk of fluctuations of both types of uncertainty is mostly accounted for by their own innovations -or variables outside the model. That implies that uncertainty measures have their own dynamics: they depend little on aggregate demand's present or past performance.

5. Summary of results and conclusions

Disentangling supply and demand components from output growth and inflation provides a valuable summary of which type of aggregate shock -supply or demand- can better explain countries' fluctuations. Such information can be valuable for analyzing the sources of business cycle fluctuations and for stabilizing economies.

Estimation results confirm that uncertainty surges tend to generate orthogonal contractionary adjustments in both sides of the market. As consumers are willing to demand fewer goods, production cuts take place, and prices adjust downward. Nevertheless, besides the perceived slumps in demand, producers also respond on their own to uncertainty surges by reducing their willingness to offer their products. Such a reaction entails further decreases in output and attempting to push prices upward. As uncertainty unravels, production of goods plunges, while the price-effect of demand reductions overcomes suppliers' intended price-response. The observable results are a reduction in production -driven by consumers' and producers' behavior- and lower inflation.

Regarding the dual nature of uncertainty, our findings seem to confirm some prior interpretations. Financial uncertainty shocks lead to more potent output impacts than non-financial uncertainty shocks for all countries. Non-financial uncertainty shocks could explain modest output contractions mostly in emerging economies. Nonetheless, it is possible that non-financial uncertainty results rely importantly on the selected measure (in this paper, the WUI). So, results could vary with alternative measures of non-financial uncertainty.

In terms of inflation, results depend on the type of uncertainty considered. Financial uncertainty shocks will always reduce inflation in countries because aggregate demand shifts are potentially larger than supply shifts. Non-financial uncertainty surges may -or may not- lead to some inflation. However, for both uncertainty shocks, inflationary pressures from the aggregate supply are always greater in emerging than in advanced economies. This result hints at the possibility that the link between rising uncertainty and firms' lower productivity is stronger in emerging markets, leading producers to push for larger price increases.

Regarding our two uncertainty measures, the bulk of their fluctuations does not seem to depend on present or past aggregate market developments: unexpected aggregate demand contractions can slightly increase non-financial uncertainty or reduce financial uncertainty to some extent. Alternatively, uncertainty seems to capture both agents' economic expectations and perceptions about other factors, which could range from political events to public policies' regulation and implementation.

Our inference related to the COVID-19 pandemic is that the financial uncertainty swells observed at the beginning of 2020 could have an enormous toll. For a two-standard deviations shock in the VIX, output growth in countries could contract 7.4%, and inflation could fall 2.6% within an approximate 6-quarters window. Moreover, those adjustments would affect both sides of the market, i.e., consumers' and producers' decisions. Therefore, observed growth contractions and inflation reductions since the beginning of the pandemic would likely reflect the intertwined effects of the COVID-19 containment measures and of the uncertainty hike that came along.

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Appendix A. Procedure to compute supply and demand inflation

Consider Z a vector of endogenous variables $Z = [y, \pi]'$ that represents the annual growth rates of GDP and GDP deflator respectively. The reduced VAR is given by:

$$Z_t = AZ_{t-1} + e_t \quad \text{(A1)}$$

where A is the companion matrix of auto-regressive coefficients, and $e = [e^y,\ e^\pi]'$ is the vector of the reduced-form residuals with covariance matrix Σ. The system (A1) can be associated with the structural model:

$$\Psi^{-1} Z_t = \Gamma Z_{t-1} + \varepsilon_t \quad \text{(A2)}$$

where ε is the vector of structural supply and demand shocks $\varepsilon = [\varepsilon^S, \varepsilon^D]'$, $A = \Psi\Gamma$ and $e_t = \Psi\varepsilon_t$. Structural impulse-responses are computed from the expression:

$$IR_t = A^{t-1} PQ \quad \text{(A3)}$$

where P is a decomposition of the covariance matrix of reduced residuals that satisfies $\Sigma = P\ P\ '$, and Q is a rotation matrix that satisfies $Q\ Q\ ' = Q\ '\ Q = I$.[2] Operationally, identifying structural shocks using sign restrictions entails finding enough rotations matrices *Qs* that satisfy the restrictions imposed on *IRs* (the responses of activity growth and inflation to supply and demand shocks). Because there are always several rotation matrices that satisfy the restrictions imposed, the model is over-identified. *Qs* matrices convey the uncertainty on structural parameters that stems from this identification technique.

Since $e_t = PQ\ \varepsilon_t$, structural shocks can be recovered. The median trajectory of structural shocks is considered the most robust representation of historical shocks. See Pagliacci (2019) for a more detailed discussion on this matter.

Historical decompositions (*HDZ*) are function of the median trajectory of structural shocks and the time horizon τ, for which shocks' impacts are evaluated. For each structural shock we compute HDZ as follows:

$$HDZ_t^S(\varepsilon^S, \tau) \equiv [y_t^S, \pi_t^S]' = Z_t(\varepsilon^S) - A^\tau Z_{t-\tau-1} = \sum_{j=0}^{\tau-1} A^j P\ q^S\ \varepsilon_{t-j}^S$$

$$HDZ_t^D(\varepsilon^D, \tau) \equiv [y_t^D, \pi_t^D]' = Z_t(\varepsilon^D) - A^\tau Z_{t-\tau-1} = \textstyle\sum_{j=0}^{\tau-1} A^j P\ q^D\ \varepsilon_{t-j}^D \quad \text{(A4)}$$

where $Z_t(\varepsilon)$ denotes the forecast of Z at time *t*, using information on τ shocks $(\varepsilon_t,\ \varepsilon_{t-1}, \ldots,\ \varepsilon_{t-\tau+1})$. q^S and q^D denote the first and second column of a matrix Q respectively. For these calculations, a particular Q must be selected in order to ensure the orthogonality between its column vectors. We follow Fry & Pagan (2011) and choose Q^*, that is, the rotation matrix that delivers structural residuals closer to their median value. y_t^S, π_t^S represent the supply output and price components, while y_t^D, π_t^D are the demand output and price components respectively.

[2] P can be obtained either from a Cholesky or a spectral decomposition. We use Cholesky. Rotation matrices are obtained by applying the QR decomposition to a unitary random matrix following Rubio-Ramirez, Waggoner, & Zha, (2010).

Appendix B. Historical decompositions for output growth and GDP-inflation

Figure B1. Output components (supply growth and demand growth)

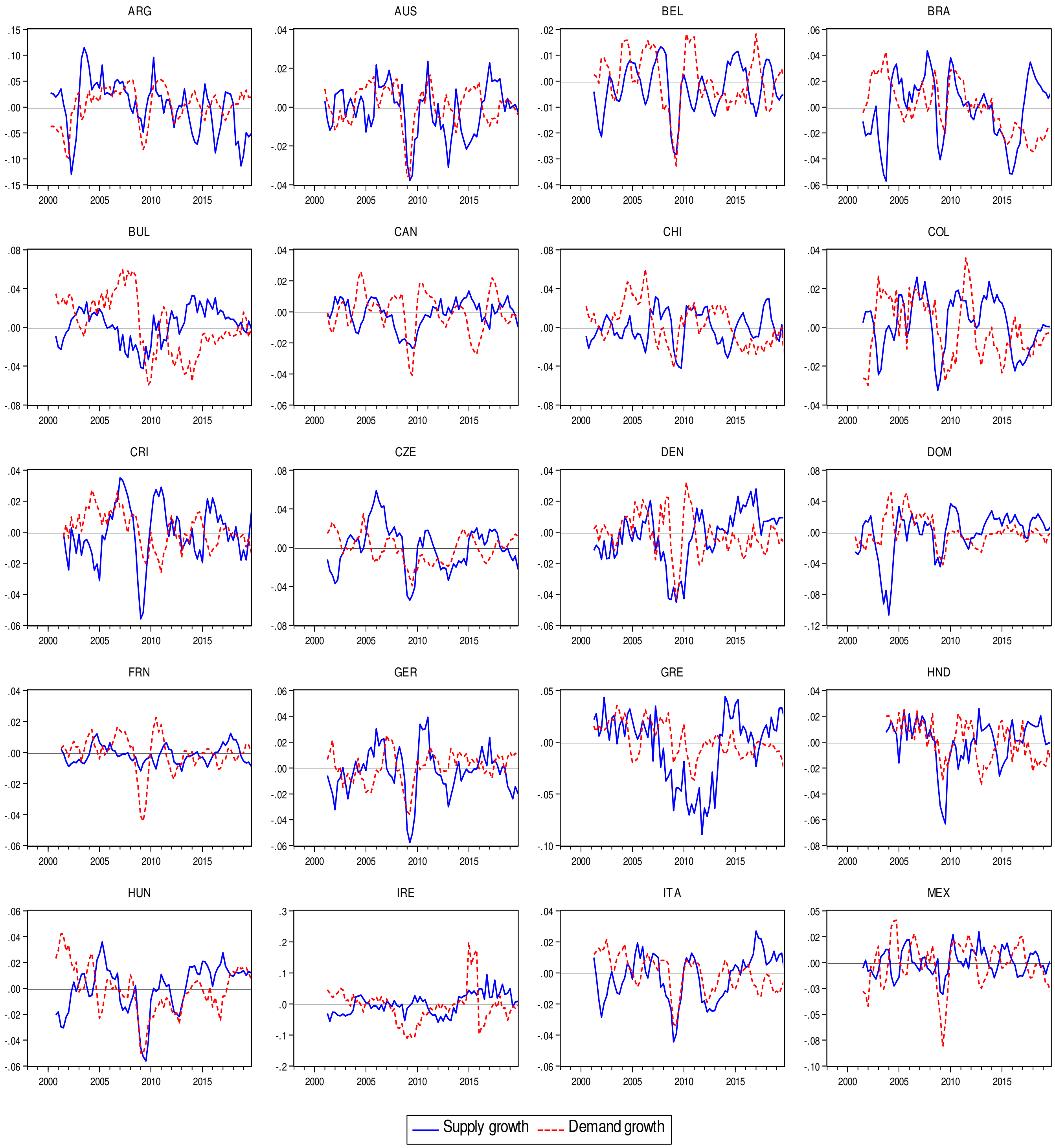


Figure B1. Output components (supply growth and demand growth) (cont.)

ARG: Argentina, AUS: Austria, BEL: Belgium, BRA: Brazil, BUL: Bulgaria, CAN: Canada, CHI: Chile, COL: Colombia, CRI: Costa Rica, CZE: Czechia, DEN: Denmark, DOM: Dominican Republic, FRN: France, GER: Germany, GRE: Greece, HND: Honduras, HUN: Hungary, IRE: Ireland, ITA: Italy, MEX: Mexico, NED: Netherlands, NOR: Norway, PER: Peru, POL: Polonia, POR: Portugal, ROM: Romania, SLV: El Salvador, SPA: Spain, SVN: Slovenia, SWE: Sweden, SWT: Switzerland, TUR: Turkey, UK: United Kingdom, USA: United States.

Figure B2. Price components (supply and demand inflation)

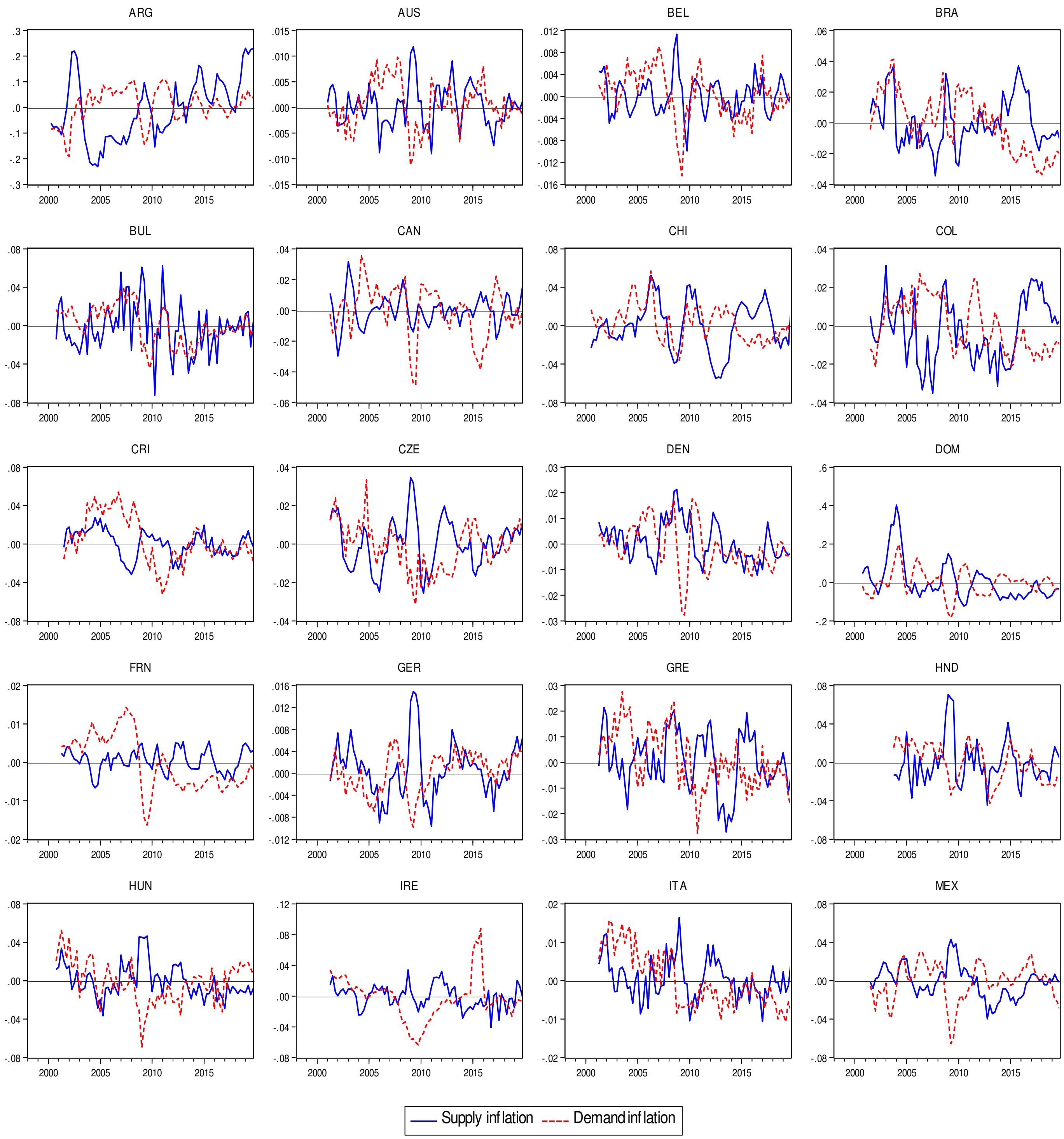
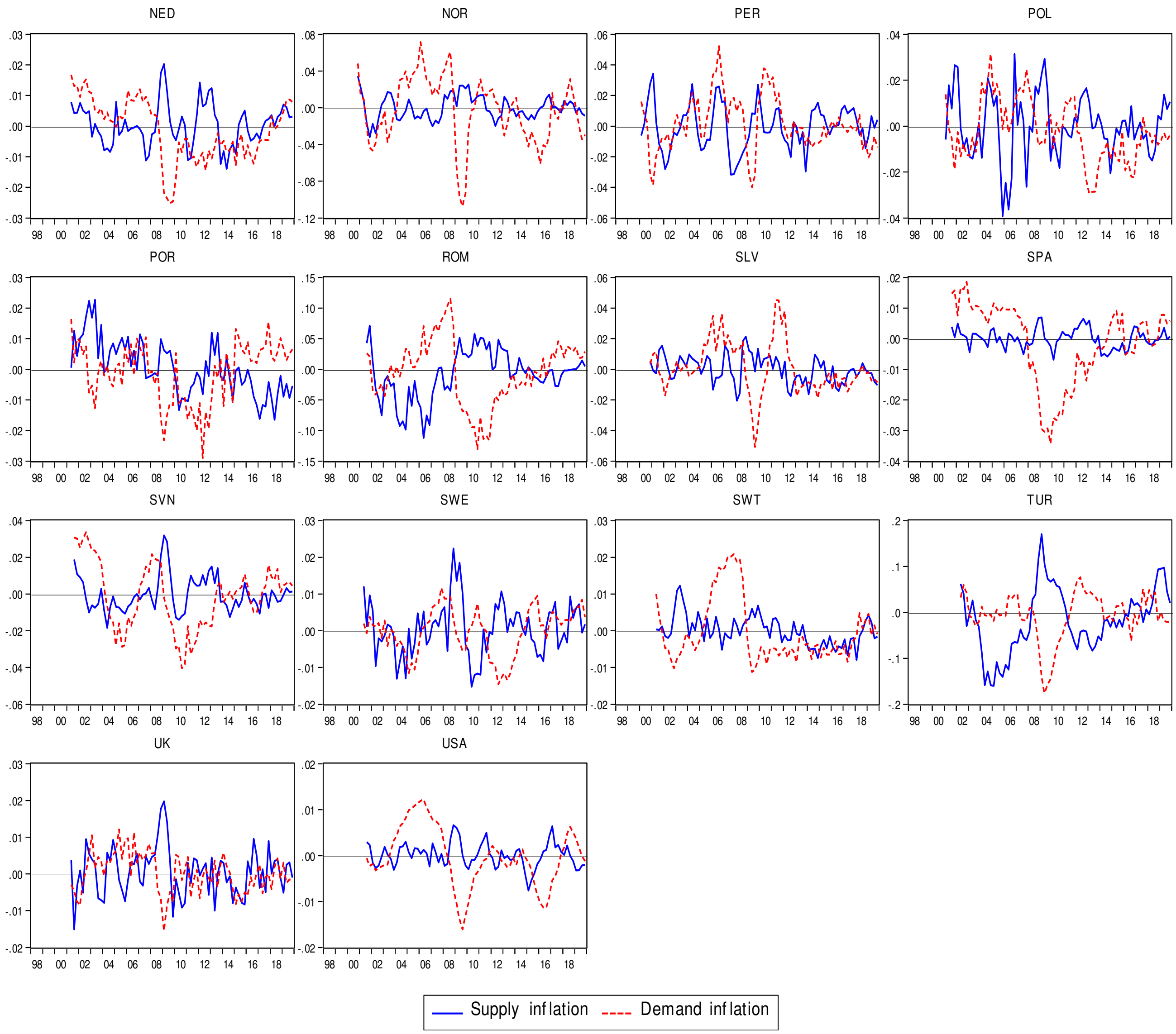


Figure B2. Price components (supply and demand inflation) (cont.)



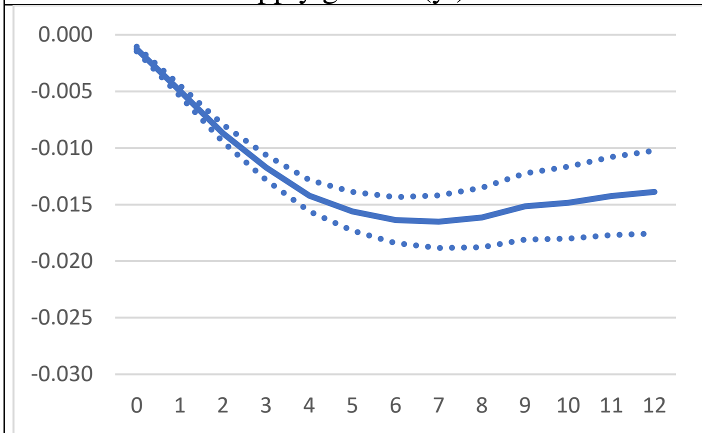
ARG: Argentina, AUS: Austria, BEL: Belgium, BRA: Brazil, BUL: Bulgaria, CAN: Canada, CHI: Chile, COL: Colombia, CRI: Costa Rica, CZE: Czechia, DEN: Denmark, DOM: Dominican Republic, FRN: France, GER: Germany, GRE: Greece, HND: Honduras, HUN: Hungary, IRE: Ireland, ITA: Italy, MEX: Mexico, NED: Netherlands, NOR: Norway, PER: Peru, POL: Polonia, POR: Portugal, ROM: Romania, SLV: El Salvador, SPA: Spain, SVN: Slovenia, SWE: Sweden, SWT: Switzerland, TUR: Turkey, UK: United Kingdom, USA: United States.

Appendix C. Local Projections' estimation results

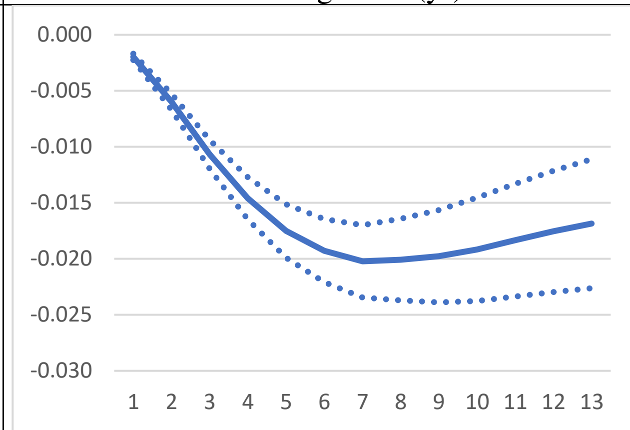
Figure C1. Responses of the output components (supply and demand growth) to one-standard deviation increase in financial uncertainty (VIX)

All countries responses

Supply growth (y^s)

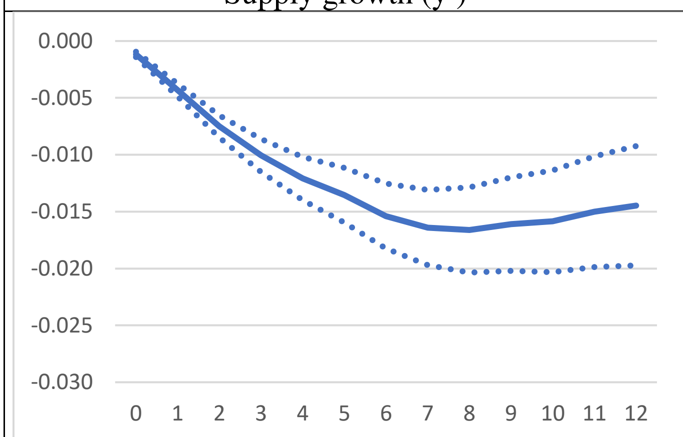


Demand growth (y^d)

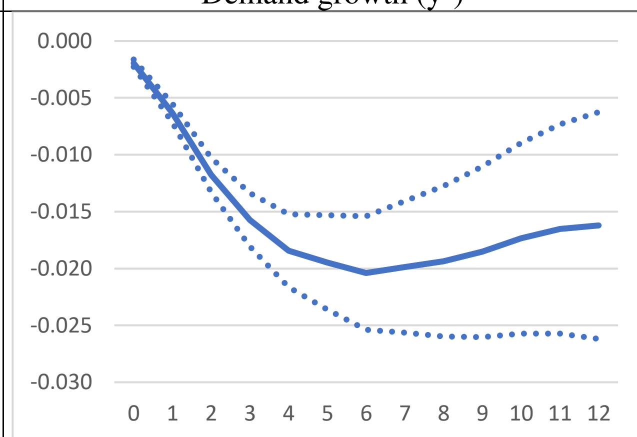


Advanced economies' responses

Supply growth (y^s)

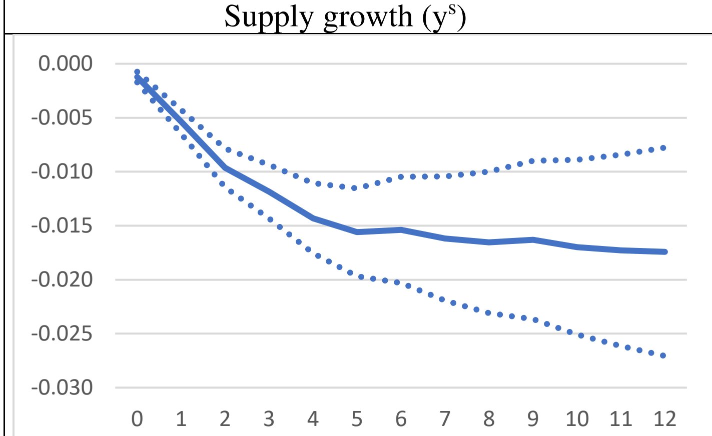


Demand growth (y^d)



Emerging economies' responses

Supply growth (y^s)



Demand growth (y^d)

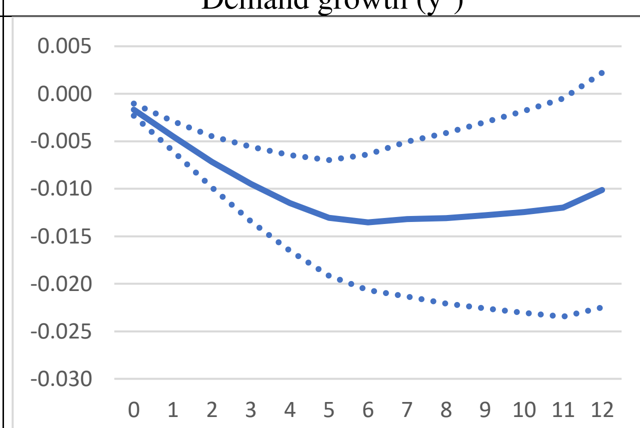
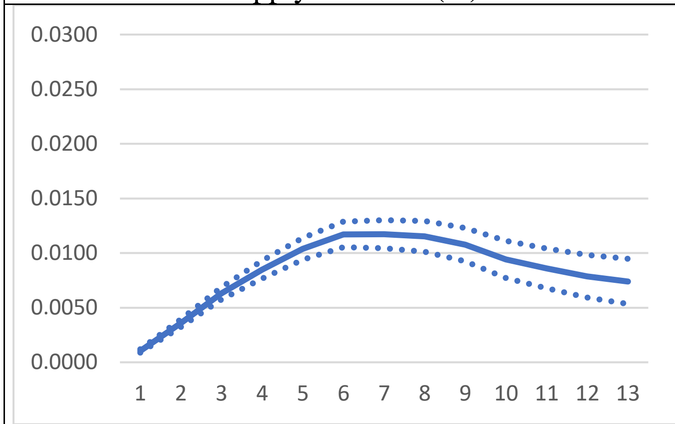


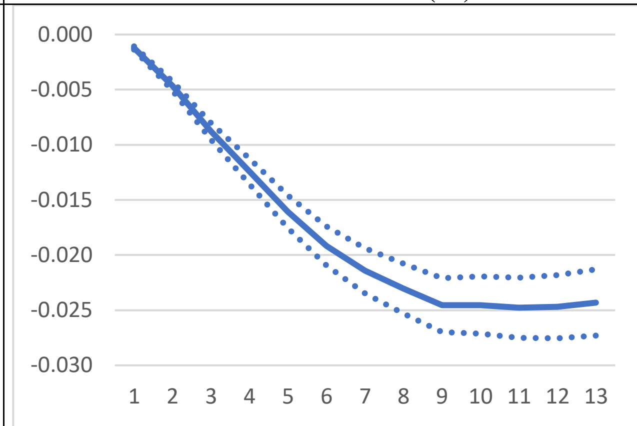
Figure C2. Responses of the price components (supply and demand inflation) to one-standard deviation increase in financial uncertainty (VIX)

All countries responses

Supply inflation (π^s)

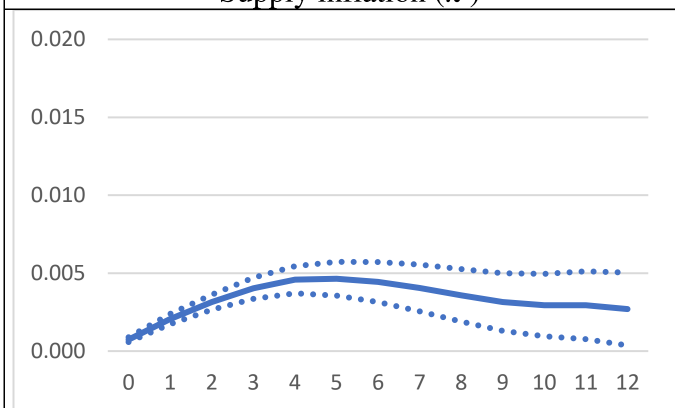


Demand inflation (π^d)

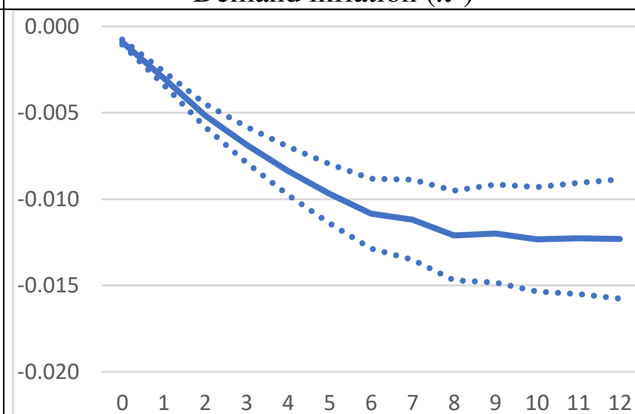


Advanced economies' responses

Supply inflation (π^s)

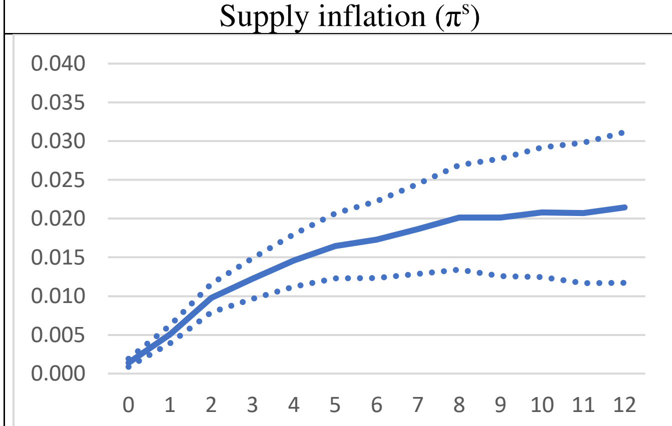


Demand inflation (π^d)



Emerging economies' responses

Supply inflation (π^s)



Demand inflation (π^d)

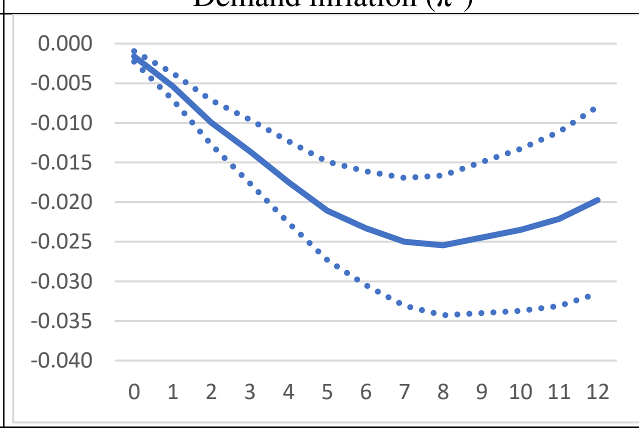
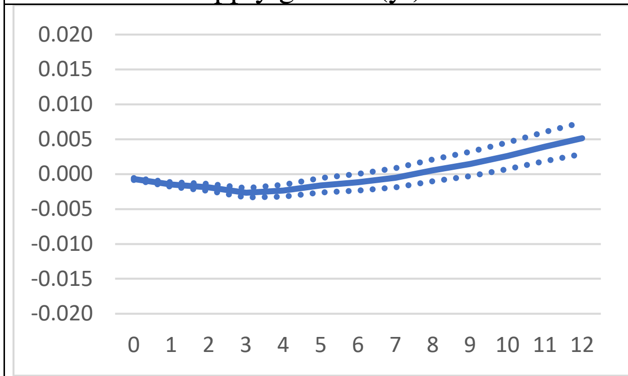


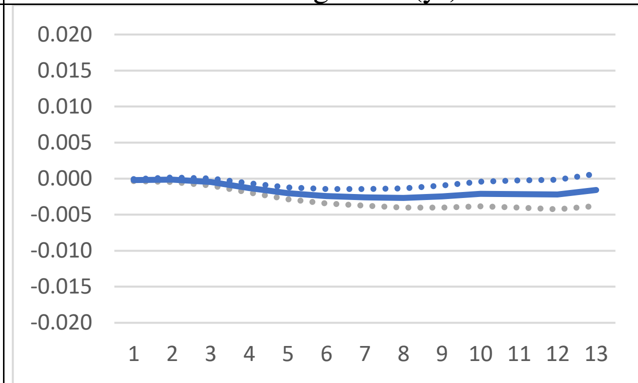
Figure C3. Responses of the output components (supply and demand growth) to one-standard deviation increase in non-financial uncertainty (WUI)

All countries responses

Supply growth (y^s)

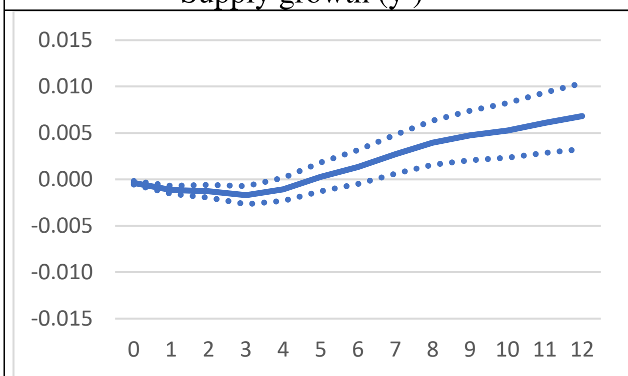


Demand growth (y^d)

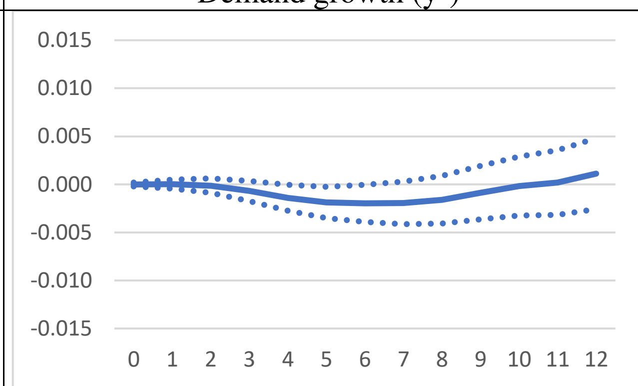


Advanced economies' responses

Supply growth (y^s)

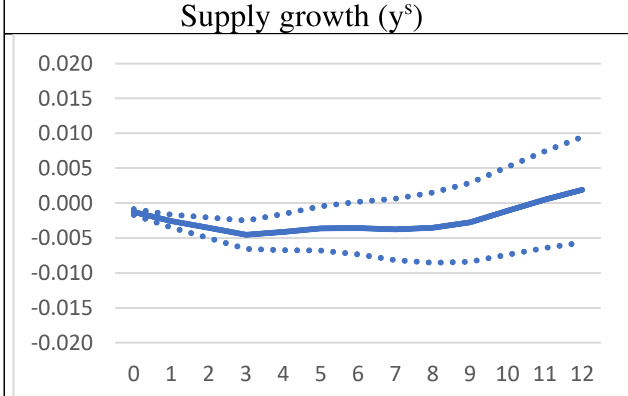


Demand growth (y^d)



Emerging economies' responses

Supply growth (y^s)



Demand growth (y^d)

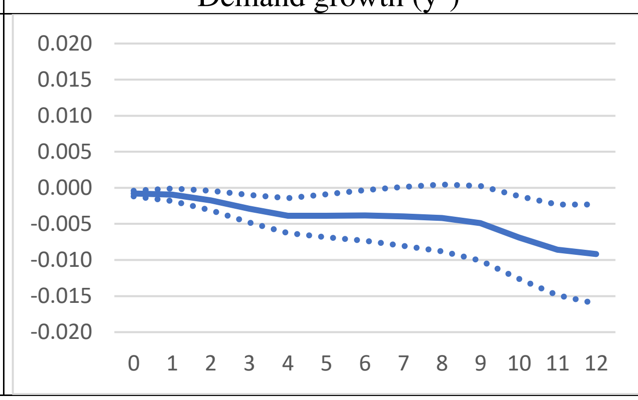
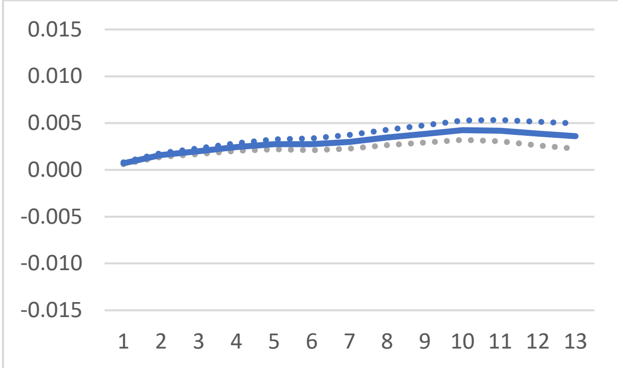


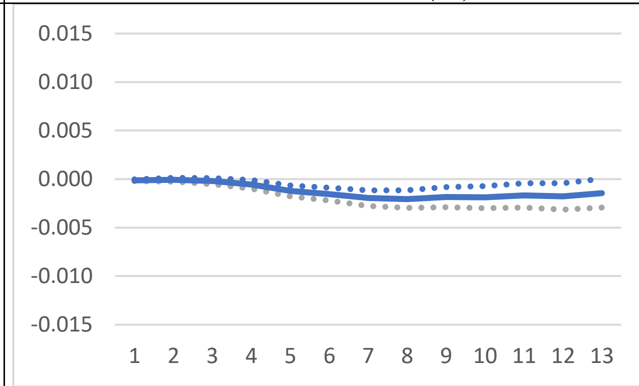
Figure C4. Responses of the price components (supply and demand inflation) to one-standard deviation increase in non-financial uncertainty (WUI)

All countries responses

Supply inflation (π^s)

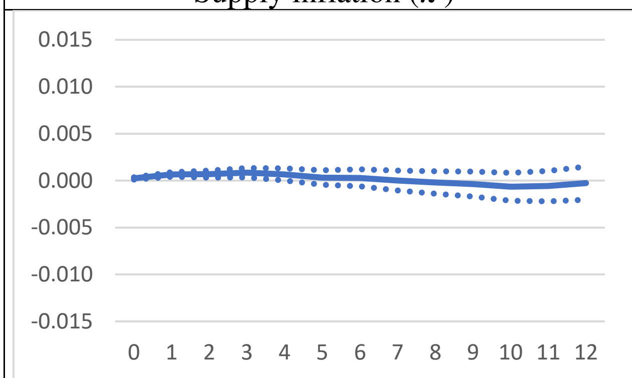


Demand inflation (π^d)

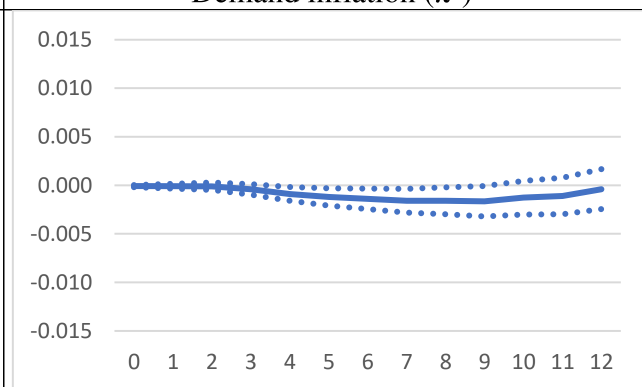


Advanced economies' responses

Supply inflation (π^s)

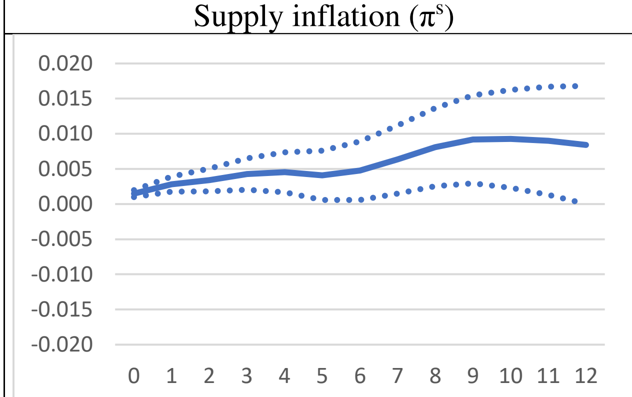


Demand inflation (π^d)



Emerging economies' responses

Supply inflation (π^s)



Demand inflation (π^d)