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Monitoring Demand and Supply in Asia

An Industry Level Approach

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Monitoring Demand and Supply in Asia: An Industry Level Approach
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ABSTRACT: This paper provides a decomposition of GDP and its deflator into demand and supply driven components for 12 Asian countries, the US and Europe, following the forecast error-based methodology of Shapiro (2022). We extend that methodology by (1) considering a wide range of statistical forecasting models, using the optimal model for each country and (2) provide a measure idiosyncratic demand and supply movements. The latter provides, for example, a distinction between aggregate demand driven inflation and, inflation driven by large shocks in only a small number of sectors. We find that lockdowns in 2020 are explained by a mix of demand and supply shocks in Asia, but that idiosyncratic demand shocks played a significant role in some countries. Supply factors played an important role in the post-COVID recovery, primarily in 2021, with demand factors becoming more important in 2022. The mix of shocks during the sharp increase in inflation in 2021-22 differs by country, with large and advanced economies generally experiencing more supply shocks (China, Australia, Korea), while emerging markets saw significant demand pressures pushing up prices (Indonesia, Malaysia, Philippines, Vietnam, Thailand). We illustrate the usefulness of the industry level shocks in two applications. Firstly, we consider whether industry supply shocks have created demand-like movements in aggregate prices and quantities, so-called Keynesian supply shocks. We find evidence for this mechanism in a minority of countries in our Asia sample, as well for Europe and the USA, but that these results are driven by the COVID-19 event. Secondly, we use the granularity of the industry shocks to construct country-level GDP shocks, driven by idiosyncratic movements at the industry level, to study cross country growth spillovers for the three large economic units in our sample: China, Europe and the US.

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WORKING PAPERS

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[1] “The author(s) would like to thank” footnote, as applicable.

Contents

1. Introduction

Monitoring the balance between demand and supply is fundamental to monetary, fiscal and financial policy decisions. However, the shocks of that have buffeted the global economy since 2019, with very sharp, but mostly temporary, declines in real GDP growth during lockdowns, and multi-decade high increases in inflation subsequently, make this task both more difficult and more urgent. This paper provides a decomposition of GDP and its deflator into demand and supply for 12 Asian countries, the US and Europe, following the forecast error-based methodology of Shapiro (2022). This approach uses granular data on price and quantity indices at the industry level to classify each industry into supply or demand. Aggregate decompositions of GDP and inflation then follow as a weighted averages of industry growth rates. This differs from the dominant paradigm in empirical macroeconomics for such decompositions, Structural VAR (SVAR) models (see Ramey 2016), which would typically employ only aggregate data on GDP and prices.

The bottom-up sectoral approach to a demand/supply decomposition we pursue here has a number of advantages over the traditional SVAR approach. Firstly, Identification of supply and demand shocks at the industry level is important when studying the COVID-19 shock as this prevents the conflation of aggregate demand shocks with large sectoral supply shocks that induce demand like responses in aggregate prices and quantities due to complementarities between sectors - so called Keynesian Supply shocks (Guerrieri and others (2022)). Secondly, the granular nature of the data provides a natural narrative to the decomposition at the aggregate level, in that we can point to the specific sectors that explain the mix of demand or supply. Thirdly, we extend the methodology by distinguishing between idiosyncratic movements in demand or supply and movements that are representative of a majority of sectors. We show that this distinction is important for thinking about the shocks around the COVID-19 period. Finally, while Shapiro uses linear autoregressive models, we extend his approach considering a wide range of machine learning models, using the optimal model for each country. This approach allows us to automatically incorporate a large information set in an environment where it is difficult to have informative priors for each variable as well as to account for non-linearities[2].

Our results contribute to the understanding of economic consequences the COVID-19 shock and provide policy makers with useful information to calibrate polices in real-time. We find that lockdowns in 2020 are explained by a mix of demand and supply shocks in Asia, but that idiosyncratic demand shocks played a significant role in some countries (India and Indonesia). Supply factors played an important role in the post-COVID recovery, primarily in 2021, with demand factors becoming more important in 2022. We use our decompositions to study the sharp increase in inflation in 2021-22 finding that the mix of shocks differs by country, with large and advanced economies generally experiencing more supply shocks (China, Australia, Korea), while emerging markets saw significant demand pressures pushing up prices (Indonesia, Malaysia, Philippines, Vietnam, Thailand). However, most of the increase in Indonesia is idiosyncratic and driven by a single commodity related sector. This distinction is important since a central bank raising interest rates to reduce inflation in the face of

[2] Extending the Shapiro (2022) methodology to an environment with many countries entails producing industry level forecasts for a large number of industries where the econometrician may have little a priori idea about what predictors are important. Moreover, for maximum granularity we have different numbers of sectors for each country (since each statistical authority differs in how much detail they provide). In our case we have 218 sectors across 14 countries/regions to build forecasting models for. Machine learning models allow us to do that efficiently without applying the same set of predictors across all countries.

shocks that are asymmetric across sectors will face a larger sacrifice ratio than when it faces high demand in a wide swathe of sectors[3] (Guerrieri, Lorenzoni and Straub (2021)).

We illustrate the usefulness of the industry level shocks in two applications. Firstly, we consider whether industry supply shocks have created demand-like movements in aggregate prices and quantities, so-called Keynesian supply shocks. We find evidence for this mechanism in a minority of countries in our Asia sample, as well for Europe and the USA, but that these results are driven by the COVID-19 event. Secondly, we use the granularity of the industry shocks to construct country-level GDP shocks, driven by idiosyncratic movements at the industry level, to study cross country growth spillovers for the three large economic units in our sample: China, Europe and the US. We find limited evidence of short-term (within 1 year) growth spillovers emanating from China except for the case of spillovers to Asia. We estimate medium-term spillovers (2 years) in line with the literature at approximately a 0.3 percent decline in the level of GDP[4]. We find that growth spillovers from Europe and the US are important in both the short and medium term at 0.4 percent for one standard deviation, but this may reflect a shorter sample period for the latter[5].

1.1 Literature

There are two broad approaches to decomposing macroeconomic variables into demand and supply: Dynamic Stochastic General Equilibrium (DSGE) and SVAR models. The estimated DSGE models are a fundamental element of the policy toolkit of most central banks and economic policy institutions[6]. These models represent internally consistent representations of economic theory for policy experiments (Gürkaynak and Tille (2017)). However, that consistency comes at the cost of imposing a large set of modelling assumptions on the data some of which may not be well suited to novel shocks (e.g. COVID-19). Data driven approach such as SVAR models are thus useful complements to the decompositions obtained by DSGEs.

The empirical approach of this paper is most closely related to the SVAR tradition of extracting demand/supply shocks. Blanchard and Quah (1989) began this tradition with their influential idea of identifying supply shocks as those with a permanent effect on output while all temporary disturbances are attributed to demand. Many alternative identification schemes for SVARs have subsequently been proposed. However, the vast majority have been employed to identify more specific shocks without specific reference to whether they are demand or supply, such as monetary policy shocks, fiscal policy shocks, technology and oil shocks[7]. The most influential approach for identifying generic demand or supply shocks, after Blanchard and Quah (1989), is to use sign restrictions (popularized by Uhlig (2005)) to identify supply shocks as those that cause movements in prices and quantities that are the opposite in sign, and demand shocks as those with the same sign (recent examples

[3] The logic is similar to the case of a cost-push shock. If all other sectors have output gaps that are closed and only one sector has a large positive output gap then raising interest rates requires creating negative output gaps in a range of sectors to offset the excess demand in a single sector. Guerrieri, Lorenzoni and Straub (2021) show that asymmetric demand shocks across sectors breaks the divine coincidence in a simple New Keynesian model, akin to cost-push shocks in the standard model.

[4] One standard deviation for the granular shock is 94 basis points of growth in China and 60 basis points in Europe and the USA. Thus a 1 pp shock in the USA or Europe would imply spillovers that are close to double those from a 1pp shock in China.

[5] The spillover analysis for the US is inhibited by a short sample that covers a relatively placid time period in terms of business cycles, 2011-2019. The Europe and China samples start in 2006 and thus include the Global Financial Crisis in 2007-8 as well as the European debt crisis in 2009-10.

[6] Prominent examples include Laxton and other (2010), Board of Governors (2017), Del Negro et al. (2013), Burgess and others (2013), and Smets and Wouters (2003). See Gürkaynak and Tille (2017), for a recent review.

[7] See Ramey (2016) for a review.

include Buitron and Vesperoni (2015), Forbes and others (2018)). In line with this SVAR literature, the Shapiro methodology uses the sign of the forecast errors to assign a given quarters movements in output or prices as supply driven (price and quantity errors move in the opposite direction) or demand driven (errors move in the same direction). This approach has the benefit of easy application to single equation models without requiring cross-equation restrictions to the forecast errors in order to arrive at the interpretation of demand v supply (as is the case in the Blanchard and Quah (1989) approach). It is thus amenable to use across a large set of equations where identifying restriction between them (i.e. across all sectors) may not readily be found.

As noted above, we extend the linear autoregressive model of Shapiro (2022) using a range of statistical learning models, using the optimal model for each country. A nascent literature on the application of machine learning models in economics has provided evidence that these techniques have the potential to improve macro forecasting, see Coulombe and others (2019) for a review. Examples include Joseph and others (2021) for inflation, Smalter and Cook (2017) for unemployment and Sermpinis et al. (2014) for both unemployment and inflation forecasts. A number of papers have produced comparative analysis of different techniques in macro forecasting such as Chen (2019), Gianonne and others (2021) and Kalamara and others (2022). There is also a growing interest in leveraging these high-performance forecasting techniques to inform structural analysis such as Athey and Imbens (2015) and Joseph (2019). This paper aims to contribute to this literature by conducting a comparative model test for a set of countries that have received less attention in the literature, and to extract information about shocks using the same identification scheme used in sign restricted SVARs.

We pursue two applications of the industry level shocks derived from the above. Firstly, we consider whether Keynesian supply shocks have occurred in Asia and, secondly, we use the industry level shocks to construct instrumental variables to study growth spillovers from shocks in the USA, Europe and China.

Guerrieri and others (2022) introduce a theory of Keynesian supply shocks – large supply shocks in a few or even single sector that can induce demand-like responses in aggregate prices and quantities via complementarities as well as income effects. Cesa-Bianchi and Ferrero (2021) provide empirical evidence of this channel in the US and find that it is active even outside of the COVID-19 shock. The sectoral level shock produced in our analysis are well suited to investigating this question given that the demand and supply shocks are orthogonal for a given sector but not necessarily with respect to shocks in other sectors. This means they can potentially provide evidence that supply shocks in one sector induce demand shocks on aggregate. We find evidence for this mechanism in a minority of countries in our Asia sample, as well for Europe and the USA, but that these results are fully explained by the COVID-19 event.

The shocks identified at the industry level may be correlated with common shocks that influence all shocks, such as global shocks or shocks affecting an entire country[8]. Thus, they are not well suited to causal analysis as they stand. To address this short coming we use the industry level shocks to construct country level aggregate shocks that are purged of common shocks acting on all sectors. We do this by constructing granular instrumental variables following Gabaix and Koijen (2021). This method produces shocks that are driven by idiosyncratic movements in large sectors. We then use these shocks to study growth spillovers for the three large economic units in our sample: China, Europe and the USA.

[8] The model used to define the shocks will, in general, include controls for a range of global variables and to that degree will exclude common shocks. However, there may be a range of variables or shocks that are hard to measure or are simply not included which create common variation in our forecast residuals.

Growth spillovers from a 1 percentage point shock to growth in China tend to range from 0.15 to 0.4 percent. Maliszewski and others (2016) employ a Global VAR (GVAR) model finding a 0.2 pp, Furceri and others (2017) find 0.4 pp after 3 years while Barcelona and others (2022) find 0.3 pp from a 1 percent of GDP expansion of credit in China. Our estimate is in line with this literature, finding 0.3 pp In the medium term. A large literature studies the spillovers emanating from the US economy, especially to monetary policy (see Arbatli-Saxegaard and others (2022) and Caldara and others (2022) for recent estimates) and, relatedly, financial conditions (Rey (2013) and Miranda-Agrippino and Rey (2020)). Canova (2005) studying growth spillovers to Latin America finds these are 0.3-0.5 percent for US demand and supply shocks, far smaller than the spillovers associated with monetary policy shocks. Similarly, Feldkircher and Huber (2016), using a GVAR model, find that demand and supply shocks driving US GDP have only small real spillovers in other countries of approximately 0.1 percentage points (pp) whereas the US monetary shocks have effects more than twice that size. We find spillovers peaking at 0.4 pp after 6 quarters. Buitron and Vesperoni (2015) find large spillovers from real shock in the USA and Europe. They define a shock as leading to 100 bps rise in 10-year yields and that is associated with a 3.5 and 2.5 percent drop in Industrial production in other countries for real shock emanating from the USA and Europe, respectively. Kose and others (2017) estimate large growth spillovers form the US at 0.7 percent for a 1pp shock to USA growth. They also estimate significant spillovers to the USA from growth shock in other advanced economies at 0.3 percent for a 1 pp growth shock.

The remainder of the paper is organized as follows: section 2 described the data and empirical models used to construct the price and quantity shocks, and provides evidence that the GDP deflator is a useful indicator monitoring CPI; section 3 described the resulting decompositions of GDP and its deflator; section 4 presents the results on Keynesian supply shocks; section 5 describes the estimates for growth spillovers; section 6 presents some robustness checks while section 7 concludes.

2. Data and Empirical Models

2.1 Empirical Models

We build on the methodology of Shapiro (2022), who employed a linear autoregressive model to produce forecasts for each industry's price and quantity indices, but we considering a range of statistical learning models that have performed well in forecasting applications with economic datasets (see, for example, Coulombe and others (2019), Hellwig (2020), Kalamara and others (2022)). We estimate the following model for each country (c) and industry (i):

$$\hat{y}^{c}_{i,t+h} = f(\boldsymbol{\Gamma}, \boldsymbol{X}^{c}_{i,t}, \boldsymbol{X}^{c}_{i,t-1} \dots, \boldsymbol{X}^{c}_{i,t-4}) \tag{1}$$

$$\textit{where } \boldsymbol{X}^{c}_{i,t} = \{y^{c}_{i,t}, x^{c}_{-i,t}, x^{Global}_{t}\}$$

$\hat{y}^{c}_{i,t+h}$ is the forecast of the year-on-year change in the price or quantity index for industry (i) in country (c), h periods ahead. $f(.)$ is the forecasting function which will depend on the model used. $\boldsymbol{\Gamma}$ is the hyperparameters that need to be chosen when estimating the model. These parameters are optimally chosen based on out-of-sample forecasting performance, as is common in the machine learning literature. $\boldsymbol{X}^{c}_{i,t}$ is a matrix of variables used to predict the target variable $y^c_{i,t+h}$, which includes lags of the target variable, $y^c_{i,t}$; the values for target variables in industries other than *i*, denoted with *-i*, $x^c_{-i,t}$; and a set of global control variables that are the same for each country and industry, the specific data used in the above is described below. The addition of global controls reduces the role for global shocks in driving the forecast errors[9].

In order to use these models to decompose aggregate GDP, $y_t = \sum_i^N w_t^y y_{i,t}$, where w_t^y is the weight of industry i in real GDP, and the GDP Deflator, $\pi_t = \sum_i^N w_t^\pi \pi_{i,t}$, where w_t^π is the weight of industry i in nominal GDP, we use the forecast errors of the optimal models for each industry and country to determine whether demand or supply disturbance is responsible for the growth outcome in that variable for that quarter. We then can determine the share of demand and supply in the aggregate GDP or its deflator using the weights for each industry. We define the forecast error for industry i as $\varepsilon^Q_{i,t} = \hat{y}_{i,t} - y_{i,t}$ for GDP forecast errors and $\varepsilon^P_{i,t} = \hat{\pi}_{i,t} - \pi_{i,t}$ for GDP deflator forecast errors. For industry i we classify its output and deflator movements as demand if $\varepsilon^Q_{i,t}\ \varepsilon^P_{i,t} > 0$ and supply if $\varepsilon^Q_{i,t}\varepsilon^P_{i,t} < 0$. Thus, an when forecast errors move in the same direction then they signal demand and when they move in the opposite direction they are assumed to be

Eight different models are considered in the forecasting tests. The baseline model is the same as Shapiro (2022) denoted by OLS which includes lags of the target variable, i.e. $\boldsymbol{X}^c_{i,t} = \{y^c_{i,t}\}$, since including the additional predictors creates an overfitting problem (the performance of OLS is significantly higher if additional predictors are excluded). The remaining seven models are designed to handle datasets with many predictors and are thus fed the full matrices $\boldsymbol{X}^c_{i,t}$. A full description of these model scan be found in Hastie and others (2001), the following section provides a brief intuitive description of the forecasting models employed, which could be skipped by readers familiar with these models.

2.1.1 Description of Empirical Models

We use 3 linear models that are close relatives to OLS: Lasso, Ridge and their convex combination, Elastic-Net. Lasso, introduced by Tibshirani (1996), selects among predictors by adding an additional penalty term to the likelihood function of an OLS model where that term is the L1 norm of the parameters of the model[10]. That penalty function results in a sparse model – that is one where a few predators have positive weight. Thus, lasso is a method to automatically select relevant predictors. The weight on the L1 penalty function is a hyperparameter that needs to be selected.

Ridge is a closely related method, which uses the L2 norm for its penalty function (Hoerl and Kennard (2000)). In contrast to Lasso a ridge regression places positive weight on all predictors, but avoids overfitting but choosing parameters for those predictors that are generally smaller than those which OLS would choose (thus reducing out of sample forecast variance when new data is more volatile than in sample). More specifically, ridge shrinks together the coefficients of correlated predictors in much the same way a principal component regression does. Indeed, a ridge regression provides predictions that are almost identical to that of a principal components

[9] Cases where global shocks are capture by the model and where those shocks have large implications for GDP and inflation should imply that the model does not identify the shocks and the decomposition would then include those global shocks in the unknown or ambiguous category – see results section below. A good example where the model would not forecast a large global shock is COVID-19 which was unprecedented in recent times and thus hard to forecast with traditional data.

[10] The L1 norm is the sum of the absolute value of the components of a vector, $|\vec{x}| = \sum |x_i|$. The L2 norm is the standard Euclidean distance measure, the square root of the sum of squared components, $||\vec{x}|| = \sqrt{\sum x_i^2}$.

regression (see Hastie and others (2001)). Thus, ridge provides a natural comparator to factor models that are widespread in macroeconomic forecasting.

The final linear model employed is a convex combination of an L1 and L2 norm penalty function which is known as Elastic-Net and is due to Zou and Hastie (2005). The hyperparameter for the relative weight on the L1 and L2 norm needs to be selected and the model inherits the properties of the Ridge and Lasso models to the degree it places more weight on the L2 and L1 penalty, respectively.

We consider 4 non-linear models that are a substantial departure from OLS: Support Vector Regressions (SVR), Random Forest regressions, Ada-boosted trees and K-nearest-neighbor regressions. A linear SVR aims to minimize the absolute value of the distance of the predictions from a linear model subject to the constraint that the slope coefficients of the model remain small (using an L2 norm on the slope coefficients). Non-linearity is introduced through non-linear transformations of the predators using basis functions – similar to the way OLS can be extended to accommodate non-linearities e.g. through polynomial transformations of the predictors.

Random forest regressions (Breiman (2001)) and Ada-boosted trees (Freund and Schapire (1997)) are models that are based on a decision tree, which sequentially finds the optimal split points in the predictor set that makes the average of the target variable within that subset of the predictors, close to the actual values for the target variable. Decision trees are appealing in that they are easily interpreted however their primary drawback is that tend to overfit the data if the trees have many split points (high out-of-sample forecast variance) but poorly represent the true model with only a few split points (a biased, overly simplistic model). The solution has been to aggregate the predictions of many simple tree models. Random forest does this via a bootstrap procedure where trees are fitted on a random subset of the full predictor set, with the final prediction an average of the prediction of all the trees. This bootstrapping acts to decorrelate the individual trees since the initial split point in a tree model will typically be based on the variable in the predictor set that is most predictive, which would result in many similar tree models. Ada-boosted trees aggregate individual tree models by sequentially by reweighting the individual models and taking a weighted average of the all the simple models as a final prediction. One starts with a simple model where each out-of-sample target variable has equal weight. In the next iteration the target variables are re-weighted so that values of the target variable where there were large errors receive a higher weight – thus increasing the models effort to improve the fit for these observations. The econometrician chooses how many models to fit and a learning rate (for how quickly the models change at each step).

Our final model is the K- nearest-neighbors regression. This method is analogous to a factor model in the sense that the algorithm summarizes the information in the predictor set by reducing the dimensionality of that set via clustering the data. K is the number of clusters to use. The clusters are centered so as to reduce the within-cluster variance. The means of the clusters can then be used to make a prediction for data in that cluster (much like a regression tree).

2.1.2 Forecasting Exercise

For each country, industry and price or quantity measure we train the above models for a period of 4 years (16 quarters) and begin the out-of-sample forecasting exercise on the following quarters prediction. For simplicity we base the model choice on the average root mean squared error (RMSE) over all industries, prices and quantities to arrive at a RMSE metric for each country (c) and model (m):

$$RMSE_{c,m} = \sum_j \sum_{i=1}^{N} \left(\hat{y}^c_{i,j,t+h} - y^c_{i,j,t+h}\right)^2 \tag{2}$$

Where N is the number of industries and $j \in \{Price, Quantity\}$, i.e. the deflator or real value-added growth rate. $\hat{y}^c_{i,t+h}$ is the forecast of the year-on-year change in the price or quantity index whereas $y^c_{i,t+h}$ is the actual value.

2.2 Data

We collect real and nominal GDP value-added data by industry for 12 Asian countries, covering 74 percent of GDP in the Asia-Pacific Region. Data is collected from Haver. Quantity growth is calculated as the year-on-year percentage change in the value of the real GDP value-added data for each industry, the deflator is calculated as the growth rate in the nominal GDP less the growth rate in the corresponding real data. The industries are selected based on availability for each country with the median being 16 industries. In the case of China approximations are required to decompose GDP into industry value-added as one of the industry level data series have not been published since the fourth quarter of 2017. The details of how the data is imputed is outlined in annex I.

The global predictors include aggregate measures of GDP growth, investment, unemployment and policy rates in advanced economies; global share price returns (Dow Jones and MCSI); global industrial production growth; export and import growth aggregates for the USA, Euro Area and advanced Asia; Global policy uncertainty based on GDP weighted measures from Baker, Bloom and Davis (2016); consumer confidence measures for the US and the EU from the conference board and the European Commission; global PMI composite, manufacturing and services from JP Morgan; and, finally, global liquidity measures covering local and cross-border claims on the nonfinancial sector from the Bank for International Settlements. This broad set of global indicators is intended to summarize economic conditions besides the industry level changes in prices and quantities that may be predictive for the latter. The data sources and transformations are detailed in annex II.

Table 1: Data Coverage

Country	Start Date	End Date	Number of Industries
AUS	12/31/2008	12/31/2022	20
BRN	6/30/2016	12/31/2022	24
CHN	6/30/1999	12/31/2022	9
IDN	6/30/2014	3/31/2023	17
IND	9/30/2002	3/31/2023	8
KOR	6/30/2006	12/31/2022	15
MNG	6/30/2016	12/31/2022	9
MYS	6/30/1997	12/31/2022	6
PHL	6/30/2006	12/31/2022	16
SGP	6/30/1981	12/31/2022	11
THA	6/30/2006	12/31/2022	17
VNM	6/30/2016	3/31/2023	20

2.2.1 GDP Deflator

The methodology of Shapiro (2022) depends on reliable signals of the direction of quantity and price movements. While real GDP data at the industry common in practice, industry level deflators are less common. Thus, we focus on checking whether the implied deflators at the industry level are consistent with the aggregate GDP deflator when aggregated using the nominal expenditure weights. If the industry level deflators were completely consistent with the aggregate nominal GDP deflator then these methods should be identical. However, if inaccuracies are present at the industry level we would expect to see aggregation errors. We test the following error term $\varepsilon_t = \pi_t^{NGDP} - \sum_i^N w_{i,t}\,\pi_{i,t}^{VA}$, where π_t^{NGDP} is the aggregate nominal GDP deflator, $\pi_{i,t}^{VA}$ is the industry level deflator derived as described above and $w_{i,t}$ are the nominal GDP weights for industry i. Table 2 outlines the error metrics relating to ε_t expressed in terms of root mean square error (RMSE) and mean absolute error (MAE) as well as the correlation between the GDP deflator and the weighted average deflator. The errors are moderate for most countries with the exception of BRN and MNG – however those countries have deflator based inflation that is on average 2 and 3 times higher, respectively, than the other countries in the sample. Importantly, the correlations are all very high and given the methodology only requires that the *direction* of price changes are reliable this supports the claim that the deflator data is sufficiently reliable for this approach.

Table 2: Deflator Aggregation Errors

Country	RMSE	MAE	Correlation*
AUS	0.88	0.63	0.98
BRN	2.24	1.48	0.99
CHN	0.76	0.40	0.97
IDN	0.69	0.37	0.98
IND	0.55	0.31	0.98
KOR	0.26	0.17	0.99
MNG	3.50	2.34	0.95
MYS	0.81	0.54	0.99
PHL	0.20	0.15	1.00
SGP	0.65	0.45	0.99
THA	0.18	0.13	1.00
VNM	0.66	0.45	1.00

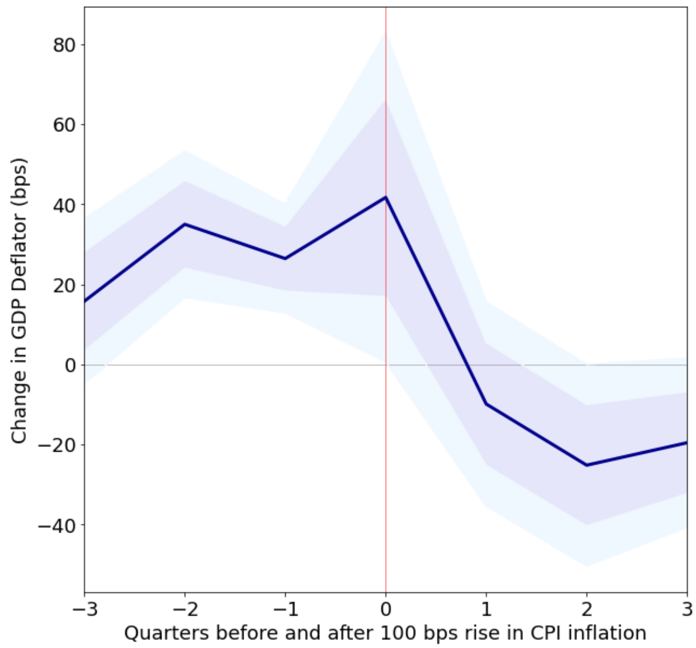
* Correlation between π_t^{NGDP} and $\sum_i^N w_{i,t}\,\pi_{i,t}^{VA}$

The relationship between CPI inflation and GDP deflator-based inflation varies significantly by country, but the most noteworthy feature is the movements in the deflator appear to lead those of CPI. This is most striking in the recent spike in inflation starting in 2021 (see figure A3, in the annex). To evaluate this leading relationship over on average we compute an event study chart based on the below equation:

$$\Delta y_{i,t+h} = \alpha_i + \gamma_t + \beta^h \Delta\pi_{i,t} + \varepsilon_{t+h} \qquad (3)$$

Where $y_{i,t}$ is the GDP deflator-based inflation rate in country i, π is the consumer price index-based inflation rate and $h = -3, .., 3$. The results indicate that GDP based inflation has been a significant leading indicator for rises in CPI inflation in Asia. The deflator increases by around 77 bps in the lead-up to a typical 100 bps increase in CPI inflation. Moreover, the signal is positive and statistically significant in the 3 quarters preceding the CPI increase. These results suggest that monitoring the GDP deflator is useful even if CPI inflation is of primary interest. Annex III provides results where additional controls for lags of other potential leading indicators for CPI are included in equation (3) including Consensus Economics current year CPI inflation expectations, PPI inflation rates, wage inflation and import prices. Adding these additional controls reduces the increase in the GDP deflator in the quarters leading up to a rise in CPI by around half on average but remains significant and positive for all cases except that of adding lags of wage inflation[11].

Figure 1: The GDP Deflator is a leading indicator for CPI inflation in Asia.



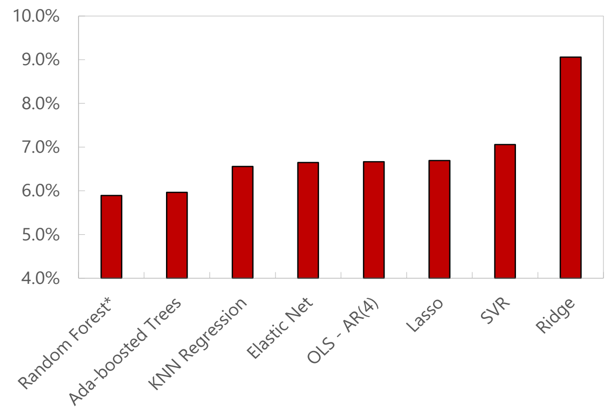
Source: IMF staff, Haver. Shaded region are 68 and 90 percent confidence intervals.
Sample includes AUS,CHN,KOR,MYS,NZL,PHL,SGP,THA for period 2005Q1-2022Q4.
Includes controls for country and time fixed effects and 2 lags of variable after + sign

2.3 Optimal Forecasting Models

The optimal forecasting model is found for each country (c) by selecting the model with lowest RMSE, i.e. $m^* = min_m RMSE_{c,m}$. In general, we find that the tree-based models which implement model averaging perform the best (Random Forest and Ada-boosted Trees) in terms of average RMSE. A baseline version of OLS (where no additional predictors are available to the model besides lags of the target variable) is competitive and actually optimal in a few important cases: China, India, Malaysia, Singapore. Random Forest and Ada-boost are optimal for 4 countries, the same as the baseline OLS model but with lower average RMSE. These results suggest that while OLS is not the optimal forecasting model for a majority of cases it is unlikely to lead to very large differences in results (see below Robustness section).

[11] The latter data is sparse, roughly halving the sample of countries, and thus conflates information from labor markets with a change in the sample of countries. Here we are only claiming that a decomposition of the GDP deflator is useful for thinking about the movements in CPI aside from being interesting in its own right, the existence of competing leading indicators does not negate this.

Figure 2: Average RMSE



Note: Average RMSE error for each model over 13 countries in sample.

Table 3: Optimal Model by Country

Country	Optimal Model
AUS	Ada-boosted Trees
BRN	Ada-boosted Trees
CHN	OLS
IDN	Random Forest
IND	OLS
KOR	Ada-boosted Trees
MNG	KNN Regression
MYS	OLS
PHL	Random Forest
SGP	OLS
THA	Random Forest
VNM	Ada-boosted Trees

3. Results: GDP and Inflation Decompositions

As highlighted by Shapiro (2022), this method of decomposing an aggregate into demand and supply based on categorizing its components movements as demand or supply implicitly assumes that small forecast errors provide an equally reliable signal as do large forecast errors. Unlike in the case of competing empirical methodologies, such as, SVARs, where the forecast error itself is combined with the model coefficients to arrive at a decomposition of the dependent variable. Thus, the size of the forecast error is implicitly accounted for in its role in explaining movements in the dependent variable. To address this and account for uncertainty in the decomposition, I apply a rule used by Shapiro's where I assume that if the forecast error is close to zero then the decomposition is unknown. Specifically, I assume a parameter α, where for a given value of $x = \varepsilon_{i,t}^{Q}\ \varepsilon_{i,t}^{P}$, if that value falls within the range between the $Q(q = 0.5 \pm \alpha)$,where $Q(q = p)$ defines the p^{th} percentile, then the decomposition into demand and supply is treated as unknown. The baseline results use $\alpha = 0.1$ which implies that 20 percent of forecast errors where the errors are close to zero result in an unknown classification. In annex we present results with high values for α as a test of the narrative that emerges in the baseline results.

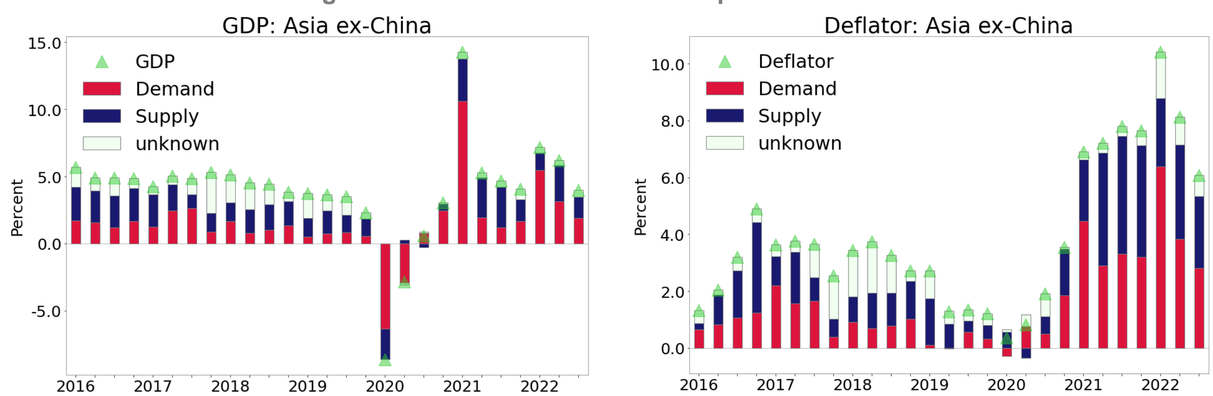
Figure 3 presents the results of the decompositions from the aggregate perspective of Asia. The results cover three periods of interest, the four years prior to the COVID-19 shock in 2020, the lockdowns during the COVID-19 shock in 2020, and the post-COVID recovery in 2021-22[12]. Due to the very large weight of China in the aggregate results we also present the Asia aggregates excluding China and discuss China separately. Full results for each country are provided in the annex.

For GDP we see that supply accounted for a significant share of growth prior to the COVID-19 shock. This is pronounced in Indonesia, Korea and the Philippines. The lock down where the major drop comes in 2020Q2

[12] The data for VNM and BRN only start in 2016, hence the full Asia aggregate results are limited to starting in 2016.

with a majority of the decline in GDP attributed to demand. Demand driven drops during lockdowns is seen in Indonesia, India, Malaysia, the Philippines, Singapore, and Thailand. The result that a number of lockdowns are associated with demand shocks is in contrast to the narrative that lockdowns are predominantly supply shock (Brinca and others (2020)). Moreover, since these results are based on granular industry level attribution of the shocks this result is not driven by Keynesian supply shocks that are incorrectly attributed to demand due to strong complementariness in other sectors (Guerrieri and others (2022)). The recovery in the latter stages of 2020 and early 2021 was predominately demand-driven, however a significant role for supply growth in Australia, Malaysia and especially Korea, with the latter primarily driven by supply[13].

Figure 3: GDP and Inflation Decompositions for Asia



Note: Deocmpositions for Asia based on GDP weighted average of individual country results, excluding China. Uncertinaty parameter $\alpha = 0.1$ *implying that 20 percent of observations are unclassified. Sample exlcudes BRN and VNM to allow for longer time period.*

Inflation broadly mirrors the results for GDP[14], where supply factors are more prominent in 2021 and demand picking up in 2022. The greater role for supply in 2021 aligns with the common narrative that supply chain disruptions following lockdowns had a substantial impact in driving up global prices (Carriere-Swallow and others (2023)). However, the demand component remains significant and, on its face, suggests that demand-supply mismatches may have affected several industries leading to demand-pull elements to the 2021-22 rise in prices. We investigate four countries in the sample where demand-pull inflation appears to be strong, specifically Indonesia, the Philippines, Malaysia, Vietnam. Despite ostensibly similar inflation experiences within the group from the aggregate perspective, industry level price movements show that much of the demand-pull inflation in Malaysia and Indonesia is driven by price movements in primary commodities, whose values are typically determined internationally. Whereas in the case of the Philippines and Vietnam there is more evidence of a broad-based increase in prices across sectors, which is more likely to map into domestic conditions.

We formally measure the idiosyncratic component of demand and supply based on cross-sectional outliers relative to the median over industries in each quarter. To flag outliers, we normalize the industry level components of demand and supply to be mean 0 and standard deviation 1 using the pre-COVID sample values, to be of comparable scale. We then define outliers for a given industry and quarter pair as where the

[13] The finding that supply shocks have increasing relevance in Australia accords with the recent findings of Beckers and others (2023) who apply the Shaprio methodology to headline CPI in Australia.

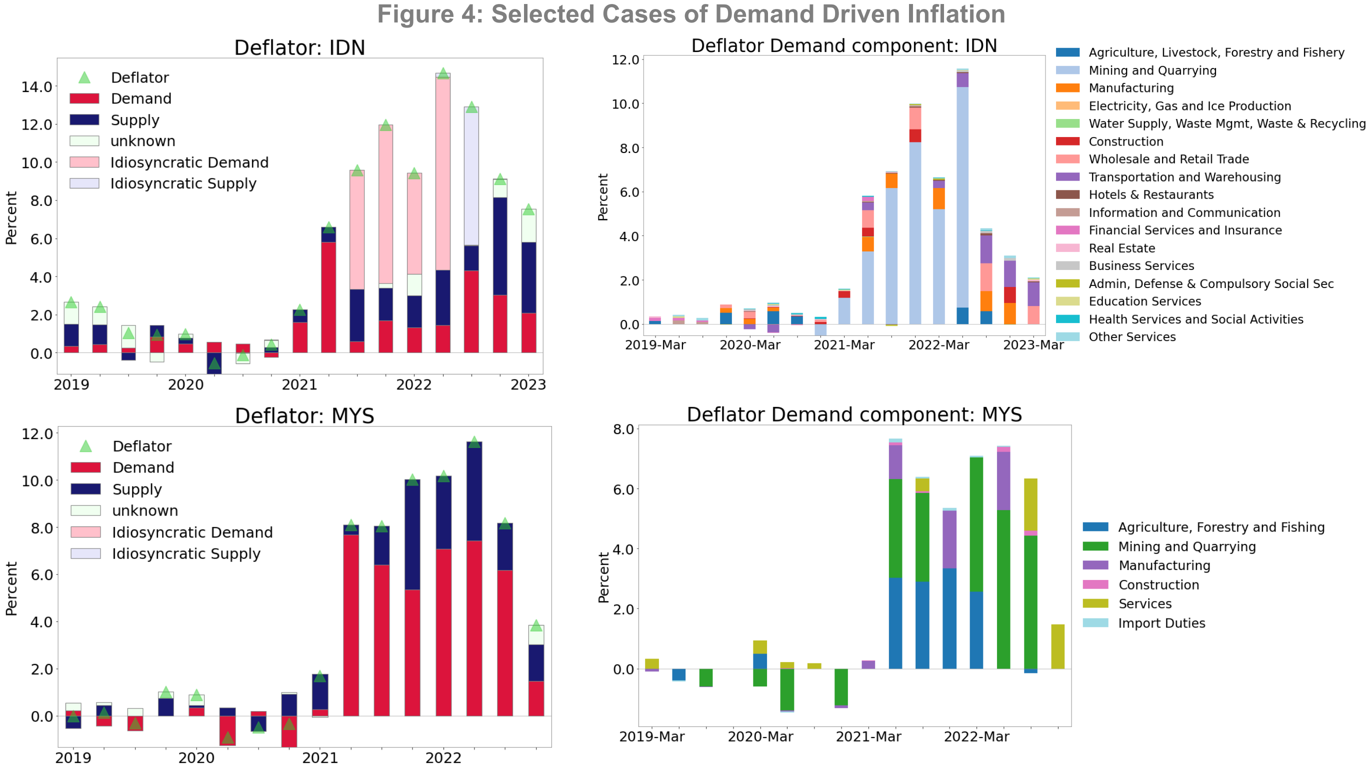
[14] The categorization of demand and supply at the industry level is the same for GDP and the deflator, the difference in results is driven by the (1) different growth rate in the price components v. quantity components, and (2) for GDP, real GDP share weights are used whereas for the deflator nominal GDP share weights are used for aggregation at the country level.

value is 4 standard deviations above the cross-sectional median. In those cases, we assign a value to the industry quarter pair equal to the pre-COVID mean for that industry.

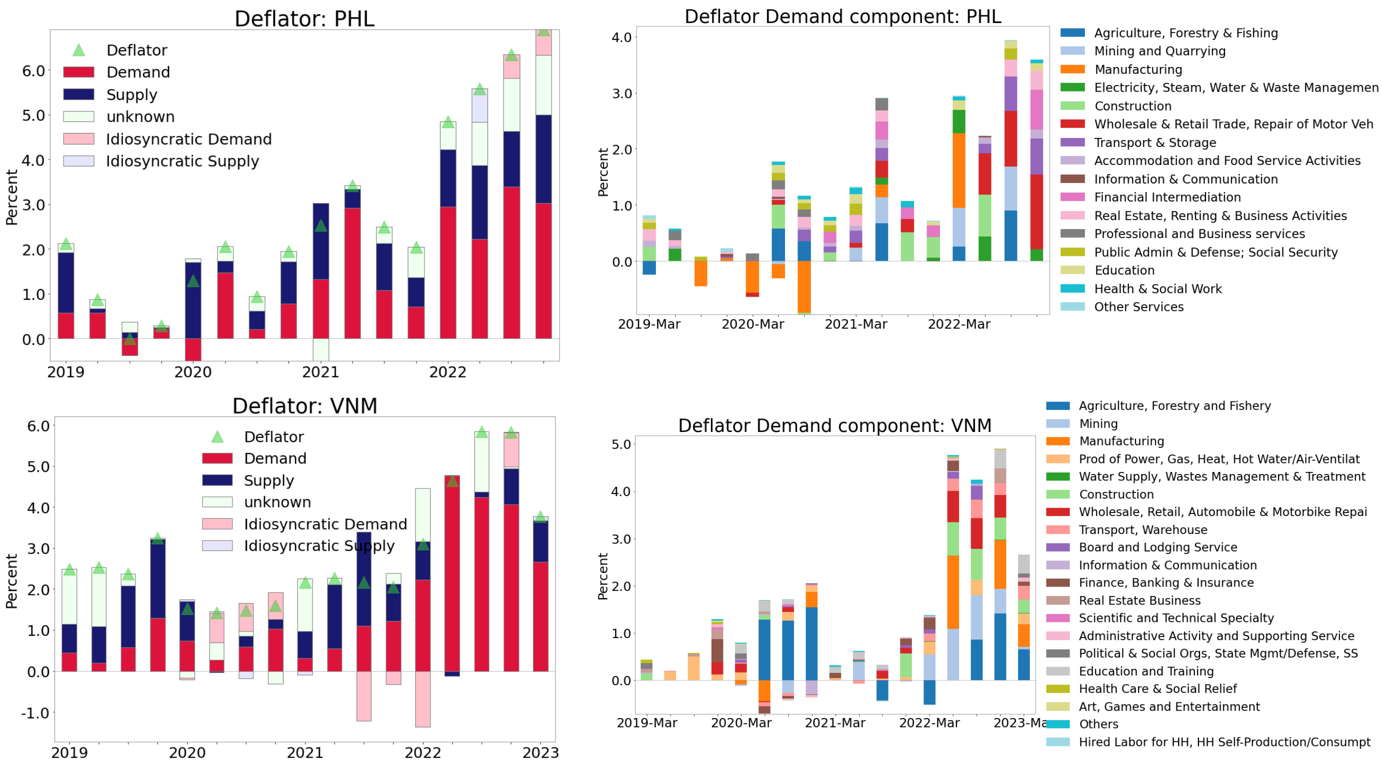
Alternative approaches such as using the simple median or expenditure weighted median over industries were considered. While these methods in general do work for removing the influence of outliers, they are not consistent with the demand supply decomposition that the main methodology employs. This is because the (cross-sectional) median or weighted median of industry level deflators are not necessarily equal to the expenditure weighted sum over industry deflators and thus will not provide a decomposition of the headline GDP deflator (which is an expenditure weighted sum of industry deflators). Moreover, we found the weighted median to be volatile in this application where in some quarters only a few industries are allocated to demand (or supply), leading to excessive volatility in the median over time. Instead, the outlier methodology adopted here only departs from the main demand/supply decomposition when there are very high levels of cross-sectional variance.

From this definition we can see the much of the commodity price driven inflation seen in Indonesia during 2021/22 is classified as idiosyncratic. However, the method does not apply the same conclusion to Malaysia, which may in part be driven by the small number of available sectors. Inflation seen the Philippines and Vietnam is demand pull inflation in the typical sense in that idiosyncratic shocks play a relatively small role. Idiosyncratic inflation is less likely to be a useful signal to central banks that the economy is overheating, barring strong downstream effects on other sectors[15].

Figure 4: Selected Cases of Demand Driven Inflation

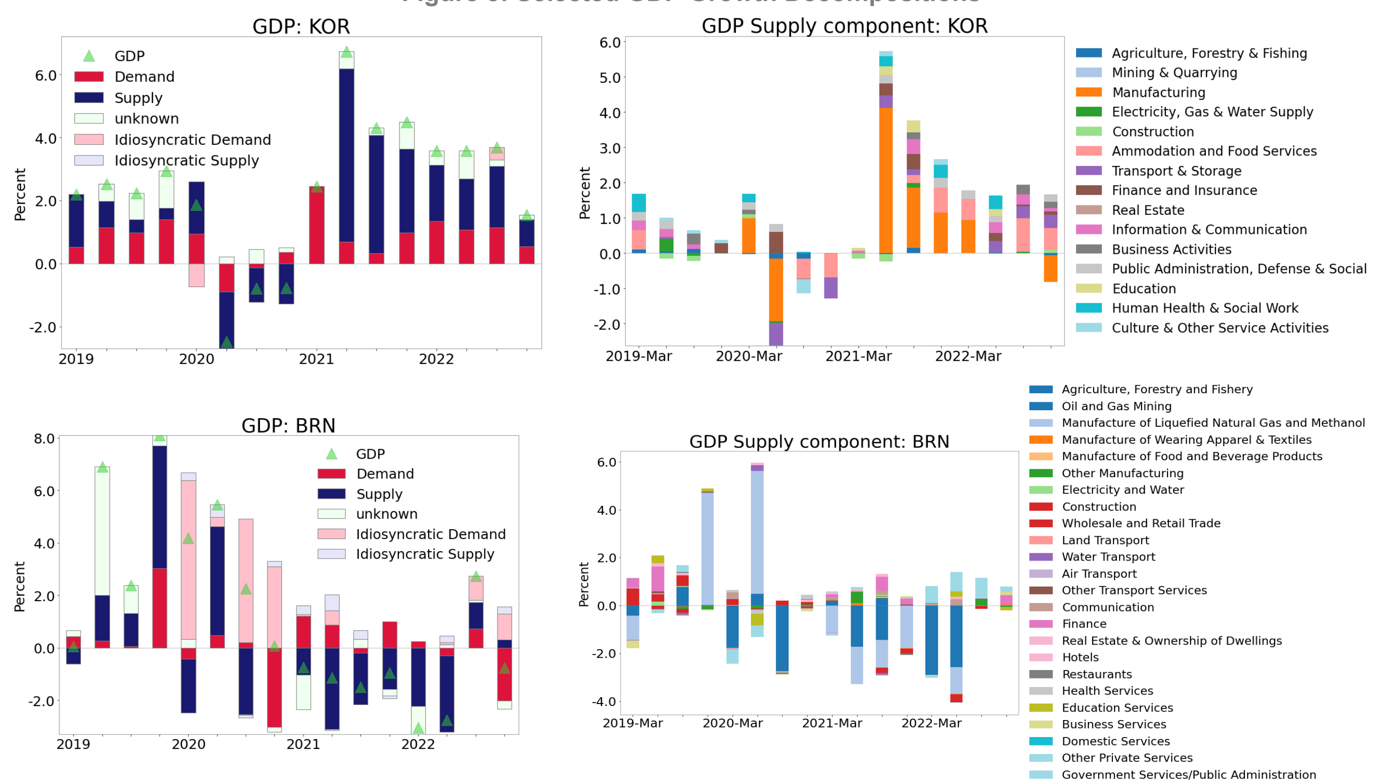


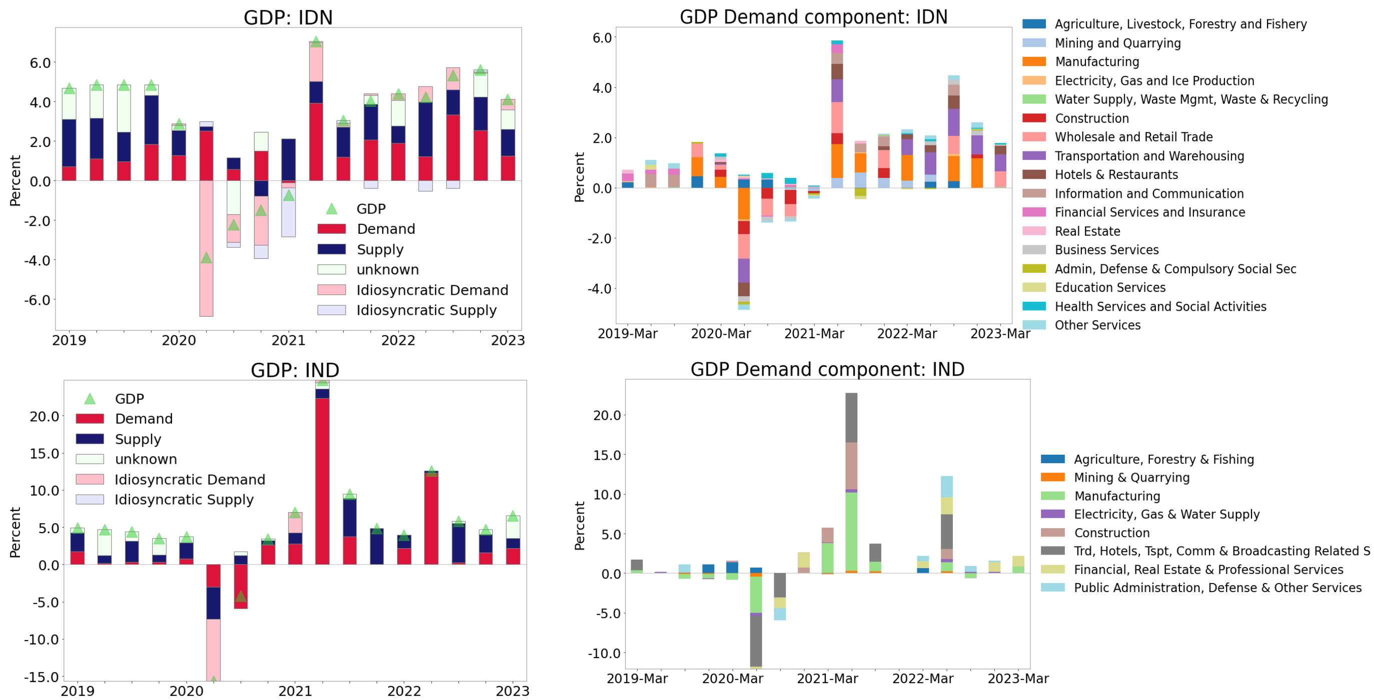
[15] For example if sharp price rises in mining leads to higher prices in manufacturing because a significant share of manufacturing raw materials are sourced domestically. Whether this is likely could be measured from input-output tables.



Note: Uncertinaty parameter $\alpha = 0.1$ implying that 20 percent of observations are unclassified.

Figure 5: Selected GDP Growth Decompositions





Note: Uncertinaty parameter $\alpha = 0.1$ *implying that 20 percent of observations are unclassified.*

Figure 5 presented selected examples of growth decompositions. Korea's GDP growth has been heavily driven by supply movements, primarily relating to the manufacturing sector which drove the recovery in growth following the pandemic but subsequently suffered from sharp declines in semi-conductor prices in 2022 (IMF (2022)) Brunei is a further case of idiosyncratic shocks driven by fluctuations in two sectors related oil and gas: mining, and manufacturing of Liquefied Natural Gas. Supply movements have been primary in explaining the majority of growth outturns but large idiosyncratic demand shocks (driven the manufacture of LNG) in 2020. In Indonesia, outside of the 2020Q2 lockdown induced drop in growth, demand driven components of GDP are not dependent on a single sector but instead driven a wider group of sectors including Manufacturing, Wholesale and Retail trade and Transportation and Warehousing.

Finally, India's slump and recovery around the pandemic was primarily demand driven with a significant role for manufacturing and the transport and hospitality related sectors – with the latter representing an idiosyncratic drop in demand during lockdowns of 2020Q2. However recent growth outturns (excluding 2022Q2) have had more sizable supply components, with trade, transport, communication and broadcasting playing a large role (not shown in the chart).

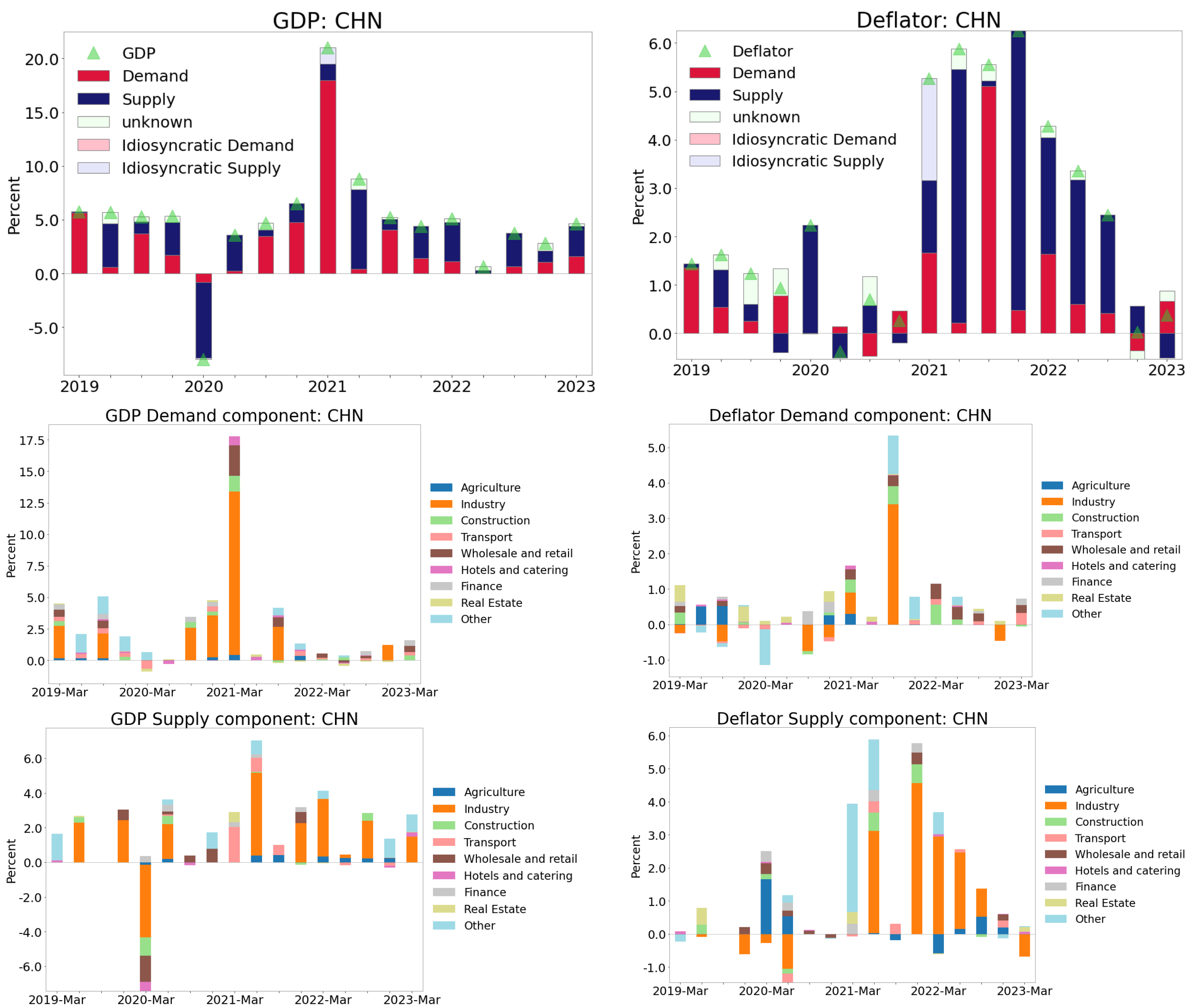
China is the largest country in the Asia Pacific region by GDP and its interlinkages with the rest of the region mean shocks in China have will have significant spillovers to the rest of the region (Barcelona and others (2022)) and those spillovers may depend on the kind of shock affecting Chinese activity (Copestake et al. (2023)). Chinese GDP fell sharply in 2020Q1, one period prior to most other Asia nations, as lockdowns began in Hubei province in January-April 2020[16]. Those lockdowns resulted in a severe supply shock in most sectors of the economy. The recovery initially took the form of a rebound in supply, in 2020Q2, in all sectors except Hotel and Catering, but form the second half of 2020Q3-2021Q1 a demand driven recovery, especially in

[16] https://en.wikipedia.org/wiki/COVID-19_lockdown_in_China

manufacturing took place. Growth in 2022Q2 onward has been primarily driven by supply in the manufacturing sector.

Chinese CPI showed mild deflation during the latter half of 2020 and early 2021 but have since then remained relatively close to its historic average rate in the last decade of 2 percent despite the sharp rise in prices seen in most other countries in the 2021-2022 period[17]. The GDP deflator's behavior is much more in line with other countries experience and rose sharply in early 2021 based on supply shocks. With the exception of an aberrant 2021Q3, the GDP deflator-based inflation has been supply driven and have decelerated sharply in 2022 from a peak of over 6 percent to zero in 2022Q4 despite relatively stable GDP growth over this time. Much of the inflation movements, as with the GDP growth movements are driven by the manufacturing or industry sector.

Figure 6: GDP and Inflation Decompositions for China



Note: Uncertinaty parameter $\alpha = 0.1$ implying that 20 percent of observations are unclassified.

[17] There has been some weakness in the very recent CPI data for 2023 with cpi inflation touching zero in 2023Q2.

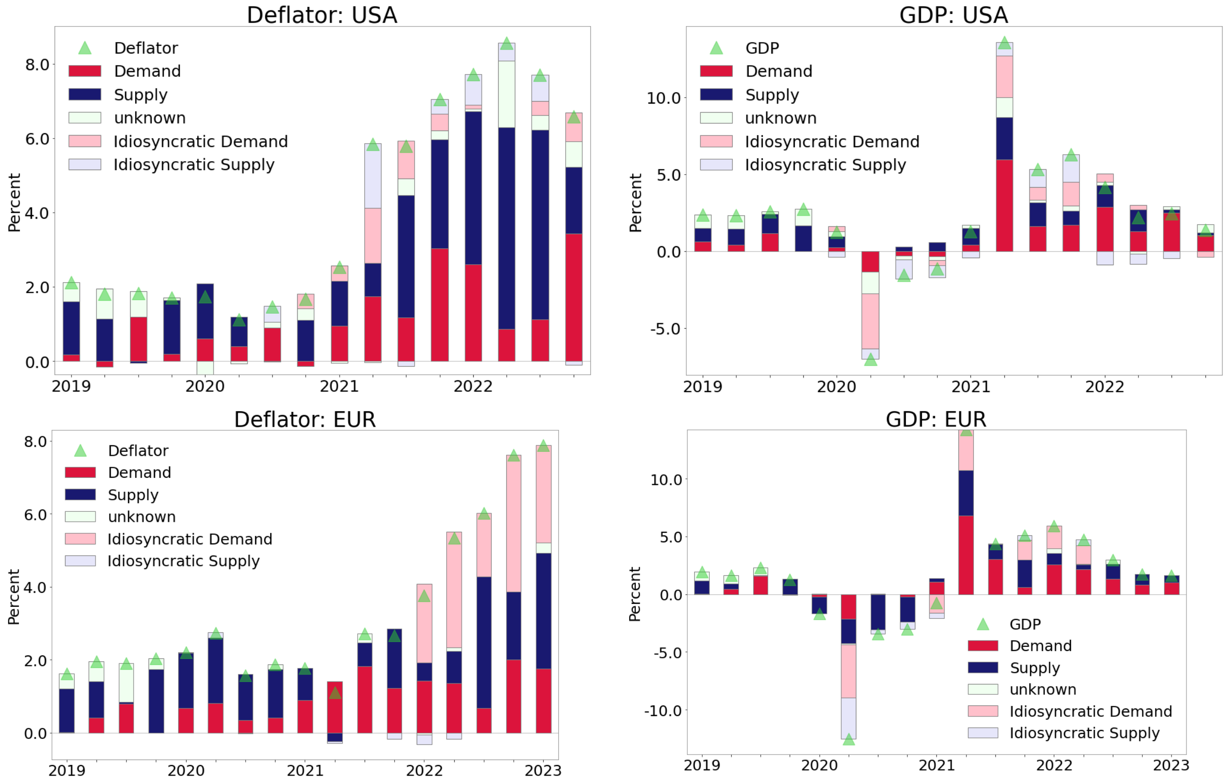
Finally, we compare the aggregate results for Asia with those for the USA and Europe (the EU 27 countries), see Figure 7. High inflation in the USA and Europe has been the primary reason for increases in policy rates from the Federal Reserve and the ECB (IMF (2023)). Differences in the drivers of inflation in other regions may motivate a different monetary policy response than pursued in Europe or the USA. For example, if supply shocks or idiosyncratic demand shocks predominate, then policy makers may face higher costs in terms of lost output from reducing inflation with higher policy rates.

The results for the USA indicate a significant role for supply shocks in driving the increase in inflation in 2021/22. While half of the initial increase in inflation rates in 2021Q2 is explained by idiosyncratic shocks, supply shocks broadened to cover a number of sectors including Manufacturing, Wholesale & Retail Trade, Transportation and Warehousing which account for 40 percent of inflation in 2022. Idiosyncratic shocks played a more significant role in driving output, particularly during lockdowns in 2020Q2 but also in a non-trivial way during the recovery from COVID-19, fading only in the latter part of 2022. In 2020 those idiosyncratic supply shocks hit those sectors most directly impacted by lockdowns: Retail; Transport and Warehousing; and the Arts ,Entertainment, Food and Accommodation sector. Idiosyncratic demand shock in 2020 included Transportation and Arts etc. sectors too, but also extended to health care and the government sectors. As noted above in 2021-22 the shocks broadened to include more sectors but still included large idiosyncratic shocks to Construction; Retail; Professional, Scientific and Technical Services.

The inflation results for Europe are markedly different: almost half of the run-up in inflation can be explained by idiosyncratic demand shocks in two sectors: manufacturing and Trade, Travel, Accommodation and Food. These take place from 2022Q1 onward and given the timing and the sectors involved, we interpret this as related to the unwinding of the COVID-19 shock which resulted in a large rebound in hospitality related sectors as well as the shift in demand from services to goods during and directly after the pandemic[18]. The role of supply becomes more noteworthy from 2022Q3 onward, which is dominated by Industry excluding construction – a sector that includes the production of electricity and gas. Thus, this spike is likely related to the sharp rise in European gas prices in 2022 following the war in Ukraine. The movements in output are comparable to those seen in the USA, with a significant role for idiosyncratic shocks during the lockdowns of 2020 and, to a lesser extend the recovery 2021 and 2022, but they fade out from the second half of 2022 onwards.

[18] Tauber and van Zandweghe (2021) provide evidence of the shift into durable goods in the 5 quarters following the pandemic. They show that this was both sizable and unusual in terms of past business cycles. They conclude that changes consumer tastes combined with increased disposable incomes following fiscal stimulus played an important role in explaining the surge.

Figure 7: GDP and Inflation Decompositions for the USA and Europe



Note: Uncertinaty parameter $\alpha = 0.1$ *implying that 20 percent of observations are unclassified.*

4. Application I: Keynesian Supply Shocks

The sharp declines in GDP growth seen during the lockdowns of the first half of 2020 entail a clear supply shock: businesses and workers in high contact industries had to sharply reduce or even stop production. (Dingel and Nieman (2020), Barrot and others (2020), OECD (2020)). Indeed, the results in the presented in the preceding section indicated a role for supply shocks (see figures 3 and 6), especially in China. However, excluding the case of China, there is also a substantial role played by aggregate demand. In the case of the aggregate results for Asia (ex China) demand played a larger role than supply.

Guerrieri and others (2022) propose a theory to help explain how sectoral supply shocks can have aggregate demand-like results on GDP growth. They show in a two-sector model with nominal wage rigidity where a large negative supply shock in one sector leads to declines in income and thus demand that are sufficient to induce declines in aggregate demand that are larger than the declines in aggregate supply. They show that whether or not this effect will obtain depends on the substitutability between sectors (demand may rise in sectors that are substitutes for the shutdown sectors and decline in those that are complimentary with them), the strength of the income effect from reduced supply in sectors suffering negative supply shocks. The latter being stronger in the face of incomplete markets and borrowing constraints which act to raise the Marginal Propensity to Consume (MPC) of households and thus creates a larger decline in their spending on all sectors when income declines.

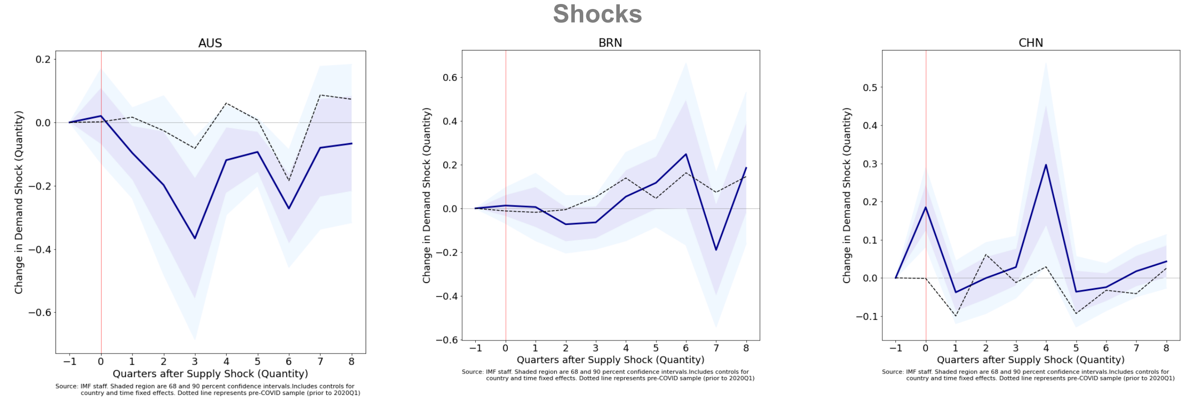
The industry level price and quantity shocks, classified into demand or supply provide a simple way to analyze the correlations between industry level supply shocks and the subsequent response in demand. Specifically, we estimate the following local projections model country-by-country[19]:

$$\varepsilon_{i,t+h}^{Demand} - \varepsilon_{i,t-1}^{Demand} = \alpha_i + \gamma_t + \beta^h \varepsilon_{i,t}^{Supply} + \Delta\varepsilon_{i,t-1}^{Demand} + v_{t+h} \tag{3}$$

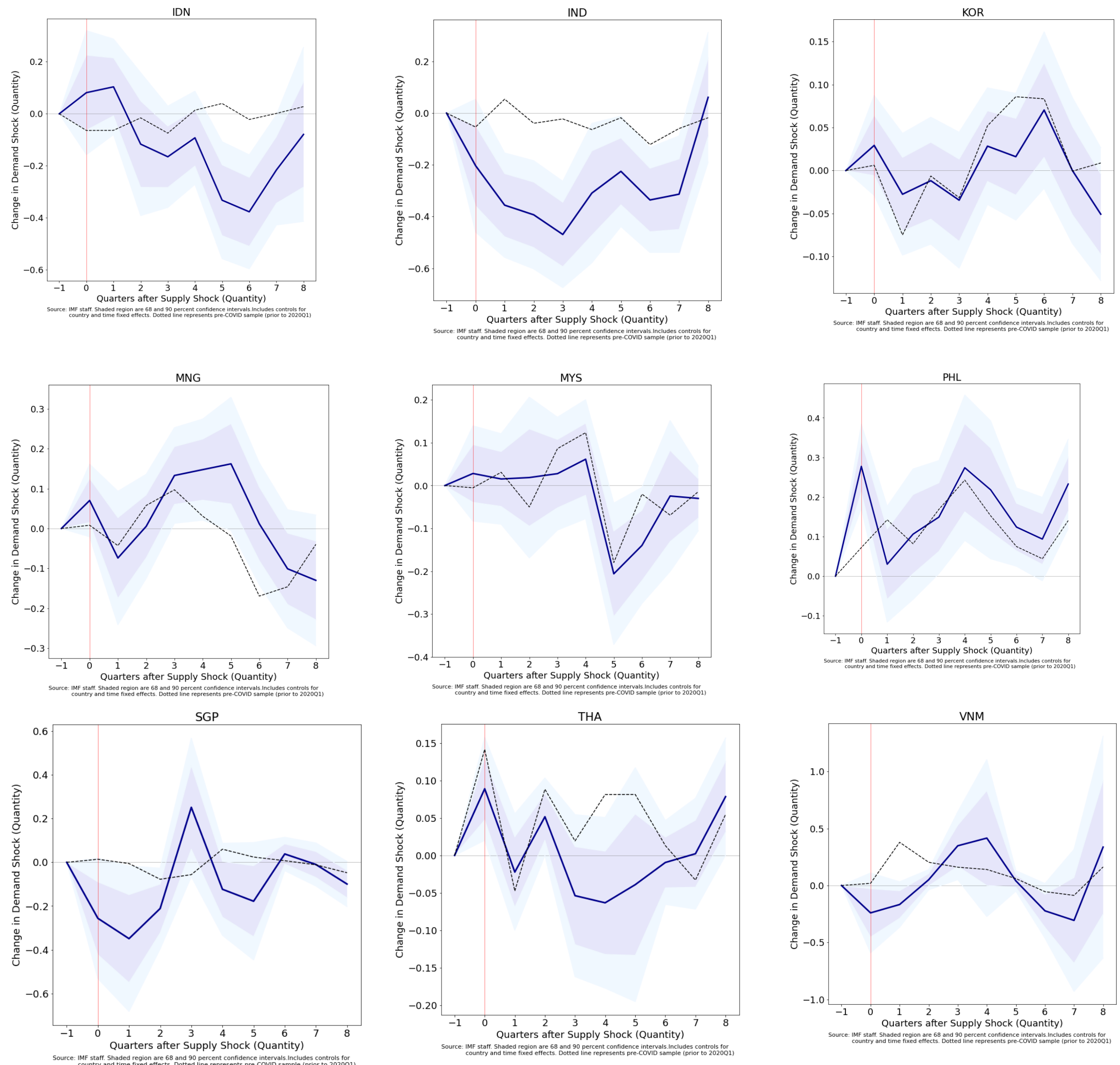
Where $\varepsilon_{i,t+h}^{Demand}$ is the demand shock affect real quantity growth in the i^{th} sector, $\varepsilon_{i,t}^{Supply}$ is defined similarly with respect to supply. α_i is an industry fixed effect and γ_t a time fixed effect. β^h measures the cumulative change in demand shocks following a supply disturbance at the sectoral level. A negative β^h is consistent with the presence of Keynesian supply shocks as described by Guerrieri and others (2022) whereby negative supply shocks in a subset of sectors is associated with a decline in demand at the aggregate level. A positive β^h is consistent with substitutability between sectors where demand is reallocated from sectors with constrained supply to those without.

We find evidence of the Keynesian Supply mechanism leading to negative aggregate demand movements in the quarters following an asymmetric supply shock for Australia, Indonesia, India, and to a lesser degree, Singapore and Vietnam (see Figure 9). In the remaining 7 Asian countries in our sample we find limited evidence declines in aggregate demand following supply shocks at the industry level. Moreover, the COVID-19 shock plays an important role in the cases where we do find evidence of Keynesian supply shocks. The dashed line indicates the average response in the pre-2020 sample which generally show a limited role for Keynesian supply shocks. These findings suggest that very asymmetric and large supply shocks are likely needed for supply shocks to generate aggregate shocks that have the properties of aggregate demand shocks.

Figure 8: Keynesian Supply Shocks in Asia: the response of Aggregate Demand to negative Supply Shocks

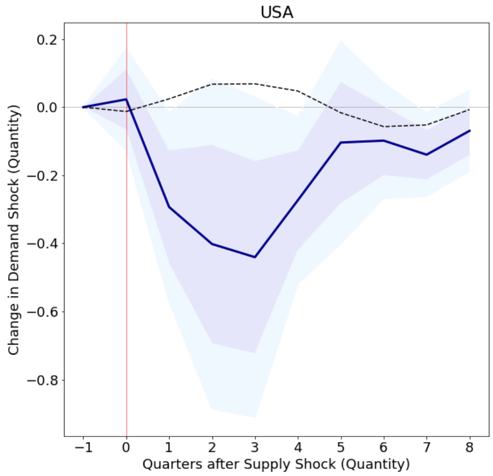


[19] This specification is unusual in that it relates two different sets of shocks, an alternative would be to use the level of industry output (and prices directly) rather than the demand shocks themselves. However, the demand shocks avoid conflating the effect of the supply shock itself on output and prices and the demand shocks are residuals from the model estimated in equation (1) where a number of global and domestic control variables were employed.

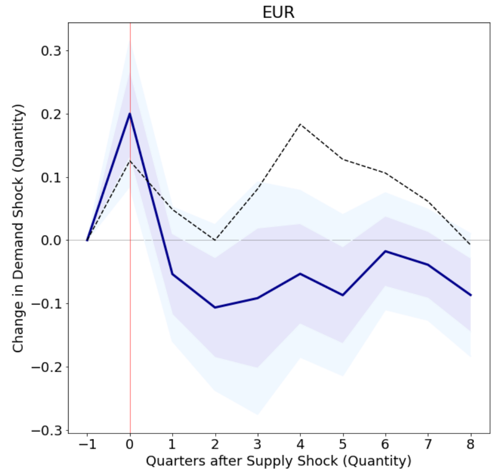


For comparison purposes we repeat this exercise for the USA and Euro Area (see Figure 9). Cesa-Bianchi and Ferrero (2021) find evidence of a Keynesian supply shock mechanism using a factor augmented VAR model. Studying the US,they find evidence of supply shocks with aggregate demand effects even outside of the COVID-19 shock period. We find evidence of this mechanism in both the USA and Europe, where the effect is significantly stronger in the USA, whereby a negative supply shock is followed by negative aggregate demand shocks. However, as in the case of the sample of Asian countries this result is dependent on the inclusion of the COVID-19 period and once excluded this negative correlation is no longer evident.

Figure 9: Keynesian Supply Shocks in USA and EU



Source: IMF staff. Shaded region are 68 and 90 percent confidence intervals.Includes controls for country and time fixed effects. Dotted line represents pre-COVID sample (prior to 2020Q1)



Source: IMF staff. Shaded region are 68 and 90 percent confidence intervals.Includes controls for country and time fixed effects. Dotted line represents pre-COVID sample (prior to 2020Q1)

5. Application II: Growth Spillovers

The methodology of section provides estimates of the shocks to real GDP growth at the industry level, $\varepsilon_{i,t}^{Q}$. Here we exploit the granularity of these shocks to construct a shock estimate for GDP growth at the country level which excludes the influence of common or aggregate shocks following Gabaix and Koijen (2022), hereafter GK. We assume that $\varepsilon_{i,t}^{Q} = \theta_i \mu_t + u_{i,t}$, where $\varepsilon_{i,t}^{Q}$ is affected by aggregate shocks, μ_t , and idiosyncratic shocks, $z_{i,t}$. The goal of the is to isolate the idiosyncratic shocks. We define the aggregate country level shock as $\varepsilon_t = \varepsilon_t^{w} = \sum_{i=1}^{N} w_{i,t}\, \varepsilon_{i,t}^{Q}$, which is the real GDP weighted average of industry level shocks to real quantities. Following, GK we also define an equally weighted version of the aggregate shock: $\varepsilon_t^{E} = \frac{1}{N}\sum_{i=1}^{N} \varepsilon_{i,t}^{Q}$. Given the assumed structure of shocks we can isolate the idiosyncratic shocks using the difference in these two aggregate shocks:

$$z_t = \varepsilon_t^{w} - \varepsilon_t^{E} = (\mu_t + u_t^{w}) - (\mu_t + u_t^{E}) = u_t^{w} - u_t^{E} \tag{4}$$

Where z_t is the difference between the size weighted and equally weighted idiosyncratic shocks. Since this granular residual removes common shocks that affects all sectors it is a good candidate to measure the impact of the spillovers of shocks from one country to others. GK use this methodology to measure the spillovers applied to sovereign yield spreads. Here, we will apply this to growth spillovers for 3 large economic units in our sample: China, the United States and Europe. Specifically, we construct z_t for each of these using the industry level quantity shock estimates from section 3.

We use the granular residual, z_t , as an instrumental variable for the aggregate quantity shocks, ε_t. We implement the first stage regression using the post-lasso procedure of Chernozhukov and others (2015). This procedure easily allows us to include a range of controls, lags of the endogenous variable and lags of the instrument. The predicted value for z_t, which we denote $\hat{z}_t$ is estimated using OLS but including only the predictors that are selected by the lasso estimation[20].

[20] Joint F statistics on the granular instruments in the post-lasso OLS estimation are 9.5 (USA), 14 (EUR), 11.8 (China).

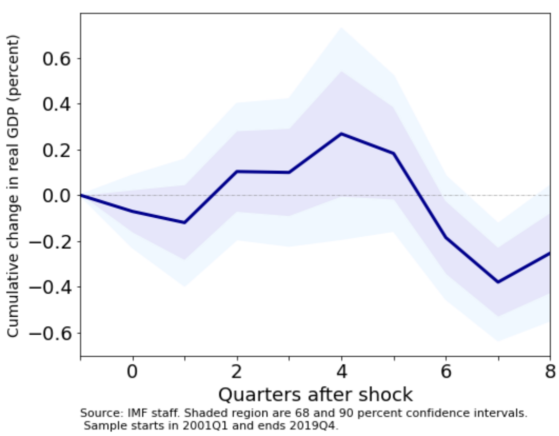
To measure spillovers from shocks to $\widehat{z_t}$ we use the framework of Copestake and others (2023) which follows the local projections panel model approach of Furceri, Jalles, and Zdzienicka (2017). In particular, we estimate the following IV panel regression model for each quarter h=0…6:

$$y_{i,t+h} - y_{i,t-1} = \alpha_i + \rho t + \beta^h \widehat{z_t} + \gamma z_{t-1} + +\kappa \Delta y_{i,t-1} + \Gamma' X_{i,t} + v_{i,t+h} \quad (5)$$

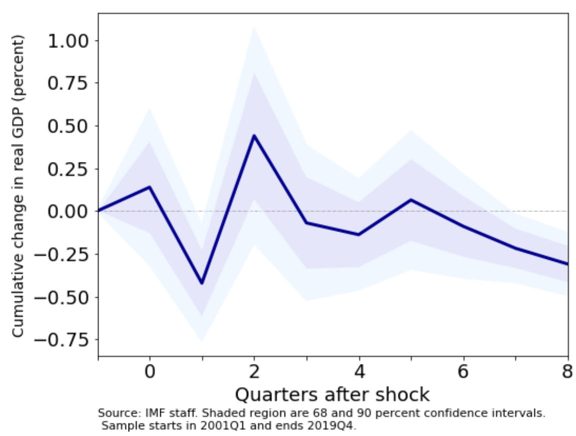
$y_{i,t+h}$ is the log of GDP in country i, α_i are country fixed effects, t captures a linear time trend, and X_t is a set of control variables. Controls include financial conditions indices for advanced and emerging economies. The Chicago Board Options Exchange Volatility Index as well as two lags of world export-weighted GDP growth for a given country. GDP and financial conditions data is from the IMF (2023). We control for the impact of shocks in the preceding quarter, captured in γ. This specification is a minor simplification of the model used in Copestake and others (Forthcoming) due to the shorter sample available here for z_t. For China and Europe the sample starts in 2006Q2 and the USA sample starts in 2011Q2. We end the sample in 2019Q4 to avoid spurious spillover results due to the very large and global covid lockdown shocks affecting GDP growth.

Figure 10: Growth spillovers from idiosyncratic growth shocks in China, USA and Europe

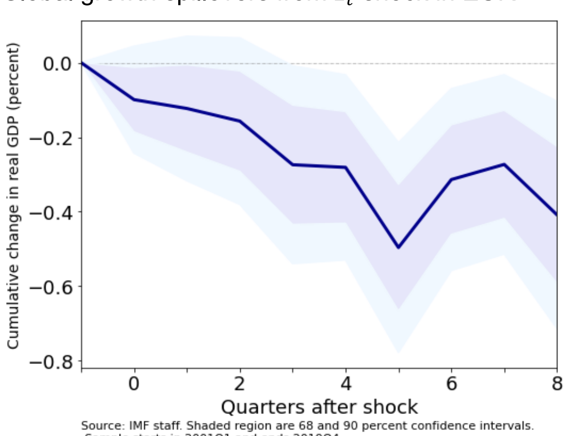
Spillovers from idiosyncratic growth shock in China



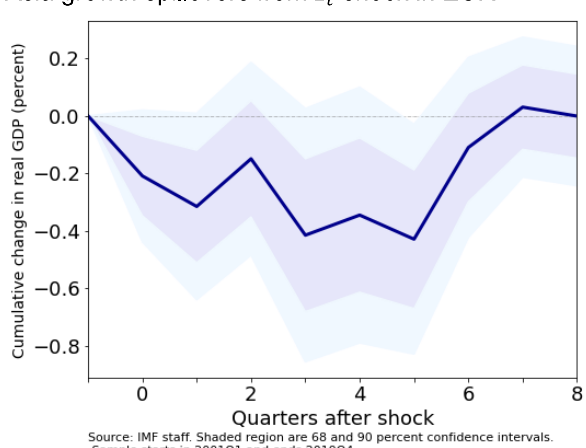
Restricting sample to Asia



Global growth spillovers from z_t shock in EUR

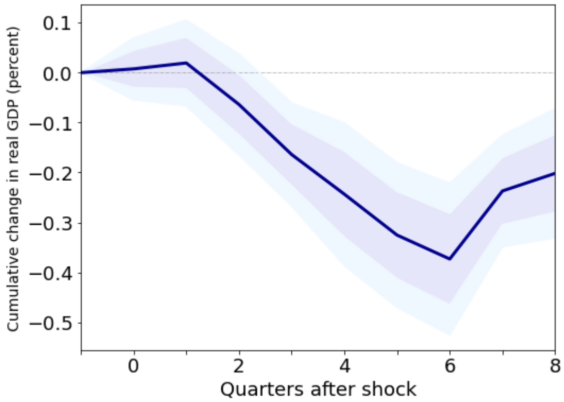


Asia growth spillovers from z_t shock in EUR

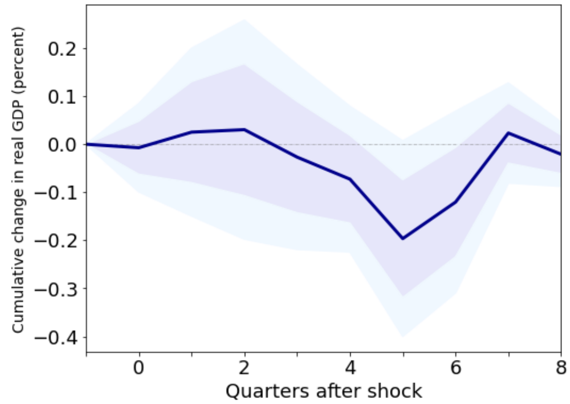


Global growth spillovers from z_t shock in USA

Asia growth spillovers from z_t shock in USA



Source: IMF staff. Shaded region are 68 and 90 percent confidence intervals.
Sample starts in 2001Q1 and ends 2019Q4.



Source: IMF staff. Shaded region are 68 and 90 percent confidence intervals.
Sample starts in 2001Q1 and ends 2019Q4.

Using the model in (5) we measure the average impact of a one standard deviation shock to z_t on the rest of the world[21] as well as on Asia excluding the country where the shock originates.

We find limited evidence of growth short-term spillovers from China globally from these idiosyncratic shocks. There is some medium run evidence of spillovers of approximately 0.3 percent of GDP. The finding of small spillovers in the short term and more significant spillovers in the longer term is broadly in line with the literature such as Furveri and others (2017). Restricting the results to Asia only we see more evidence of a short-term spillovers on the order of 0.4 percent but this shock is short lived and is fully offset by the end of the first year, medium-term spillovers remain approximately 0.3 percent. Global growth spillovers from Europe are slightly larger than the peak found for China at 0.4 percent but notably more persistent and larger in the short term. Spillovers to Asia are broadly similar to the rest of the world however spillovers are more short-term and approximately zero of 1.5 years . The spillover results for shocks from the USA indicate a significant drop in global (ex-USA) growth in the short-term peaking around 0.4 percent after 6 quarters. The impact on Asia is significantly more moderate at around 0.2 percent. A few important caveats should be noted regarding the results for the USA. Firstly, that data availability implies that the sample for z_t only begins in 2011 and thus the sample covers only the comparatively stable period after the Global Financial Crisis and before the COVID-19 shock. This will likely contribute to a smaller estimates for global spillovers. Secondly, the shock we consider here only includes idiosyncratic shock affecting the real economy and will thus exclude import financial channels such as US monetary policy and financial conditions that are known to have significant global spillovers. Both these channels may contribute to the moderate effects on Asia.

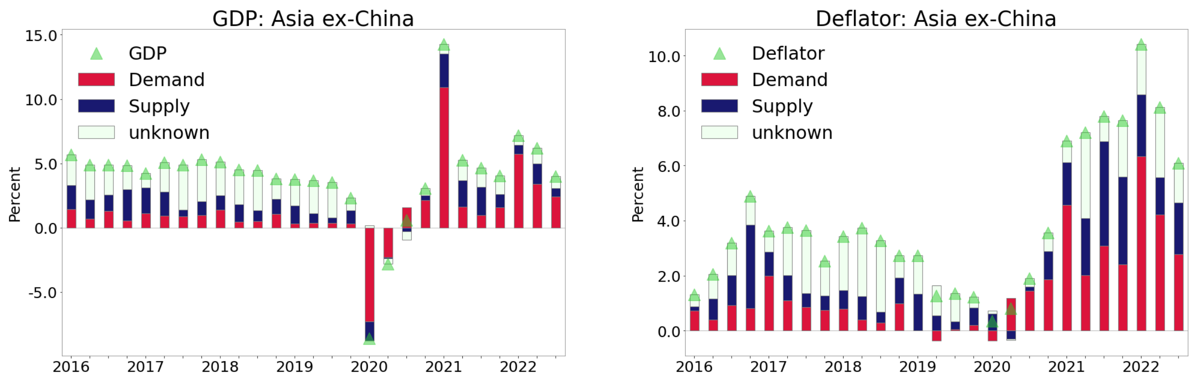
6. Robustness

6.1 GDP Growth and inflation decompositions

[21] The quarterly dataset is from Copestake and others (Forthcoming) and covers 51 economies. The Asia only sample includes 12 economies: Japan, Australia, New Zealand, Taiwan Province of China, Hong Kong SAR, India, Indonesia, Korea, Malaysia, Philippines, Singapore, and Thailand. One standard deviation is 94 bps in China and 60 bps in EUR and USA.

The baseline decompositions in section 3 assumed an uncertainty parameter of $\alpha = 0.1$ to account for the fact that forecast errors that are close to zero. Here we check the robustness of those decompositions with a higher level of uncertainty to check whether the same broad conclusions reached above hold. We double the uncertainty parameter to $\alpha = 0.2$ which entails that on average, 40 percent of observations will remain unclassified over the sample[22]. The aggregate results for Asia indicate that uncertainty is higher outside of periods with large shocks, specifically the pre-2020 sample. This is because forecast errors are larger during periods of large shocks or structural breaks.

Figure 11: Robustness: GDP and Inflation Decompositions for Asia with high model uncertainty



Note: Deocmpositions for Asia based on GDP weighted average of individual country results, excluding China. Uncertinaty parameter $\alpha = 0.2$ implying that 40 percent of observations are unclassified.

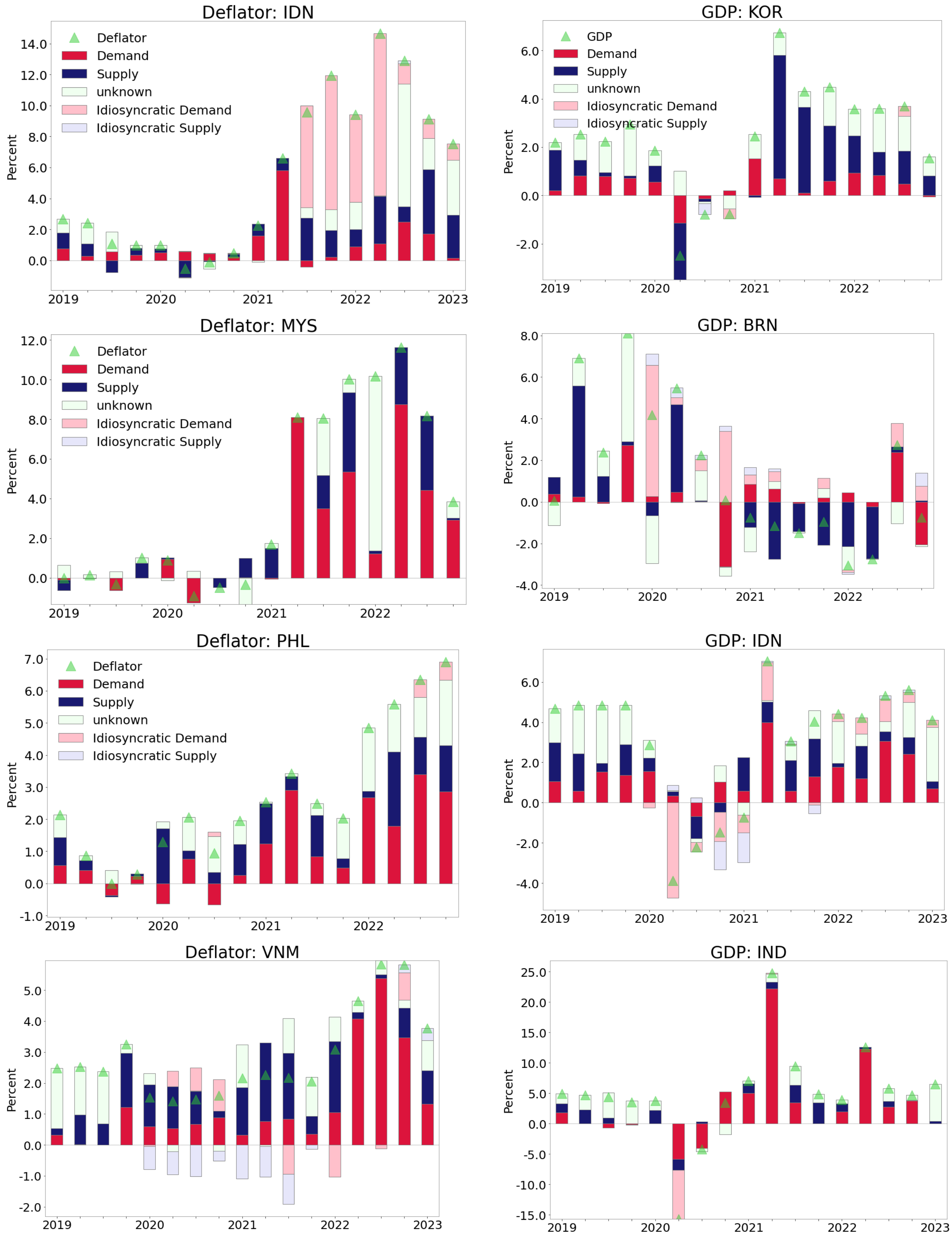
However, the additional uncertainty does not substantively alter the decomposition of demand/supply. For GDP the pre-2020 share of explained output (i.e. excluding the unknown component) attributed to demand is 41.3 percent in the high uncertainty case whereas this 38 percent in the baseline. For the deflator, demand explains 41.7 percent of pre-2020 inflation under high uncertainty with a figure of 43 percent in the baseline.

The full set of decompositions with $\alpha = 0.2$ is provided in Annex III. Here we focus on the analysis of the demand driven inflation examples (figure 4) and selected growth decompositions (figure 5). Those results are reproduced with $\alpha = 0.2$ in Figure 11. We highlighted four countries as suffering from demand driven inflation in the post-pandemic periods: Indonesia, Malaysia, Philippines and Vietnam. The conclusions draw on Indonesia and the Philippines are broadly unchanged. For Malaysia, there is some additional volatility in the demand component of inflation, especially for 2022Q1, however the conclusion that aggregate demand is primarily responsible for the increase inflation. Similarly, the role of aggregate demand in Vietnam's rise in inflation in 2022 remains, but there is an additional role for supply pressures in 2020-21 (which is somewhat offset by idiosyncratic elements in supply). Similarly for the growth decompositions presented in Figure 5, Bahrain, Korea and Indonesia look broadly similar (with a somewhat larger role for idiosyncratic demand during the initial lockdown period in Indonesia under the higher uncertainty case). The narrative for India is broadly unchanged up to 2022. However, the higher uncertainty case suggests that supply growth is significantly more uncertain than demand growth.

[22] This level of uncertainty may be impractical for use when analyzing a new quarter of data since a significant share of the data may be unclassified. However, raising α provides a way to quantify uncertainty in a given quarter's results where no change in the decomposition provides a measure of robustness.

Figure 12: Robustness: Selected Deflator and Growth Decomposition

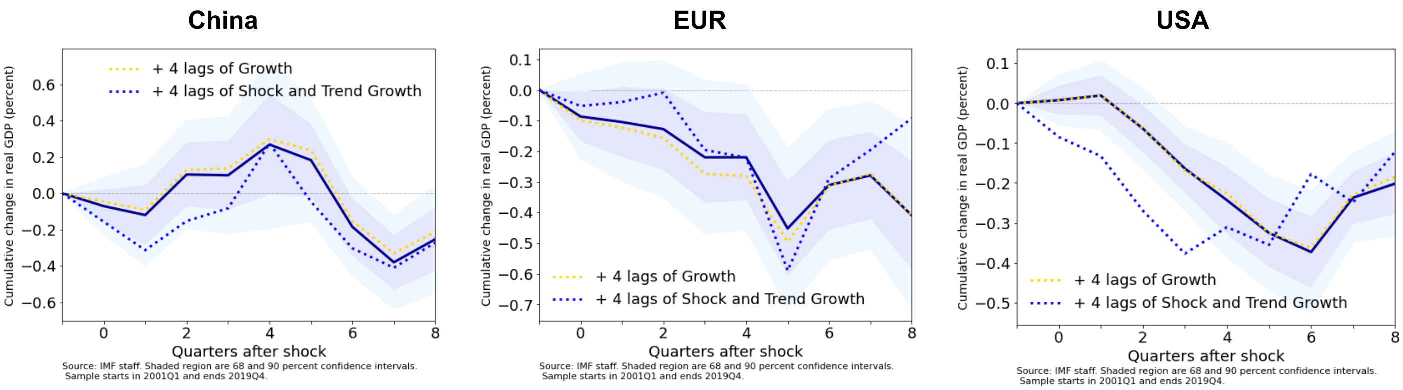
(i) Selected Cases of Demand Driven Inflation: **(ii) Selected GDP Growth Decompositions:**



6.2 Growth Spillovers

We consider alternate specifications of the panel local projections results presented in section 5. Two alternative specifications are considered (i) adding additional lags of the target variable in the regress, GDP growth for countries that are not the source of the shock and (ii) lags of the shock variables as well as trend growth in the country. We find that the conclusions reached above are broadly unchanged. Specification (ii) provides a more compelling case for near-term spillovers from China and the USA but similar conclusions relating to the medium term. For the case of Europe, specification (ii) suggests that spillovers may be more slow to build, slightly larger at peak and potentially weaker in the medium term.

Figure 13: Robustness: Global Growth Spillovers



7. Conclusion

This paper presents a demand and supply decomposition of GDP and its deflator for Asia and compares the results to Europe and the USA. The methodology is an extension of the industry level approach of Shapiro (2022) which allows us to incorporate a larger information set and potential non-linearities. We distinguish between idiosyncratic drivers of demand and supply from movements that are reflected in a broad swathe of industries – an aggregate shock. This distinction is important as it can affect the optimal response of monetary policy. We find that idiosyncratic shocks were important in a number of countries during in the sharp movements in output in early 2020 as well as the recovery in early 2021. We also find this distinction important for studying the sharp rise in prices in 2021-22 where idiosyncratic demand played an outsized role in Europe and Indonesia. In terms of aggregate shocks, we find that demand pressures are important for a number Emerging Markets in Asia (Malaysia, Philippines, Vietnam, Thailand). Supply shocks are more prominent in China and some more advanced economies (Australia and Korea).

We illustrate the usefulness of the industry level shocks in two applications. Firstly, we consider whether industry supply shocks have created demand-like movements in aggregate prices and quantities, so-called Keynesian supply shocks. We find evidence for this mechanism in a minority of countries in our Asia sample, as well for Europe and the USA, but that these results are driven by the COVID-19 event. Secondly, we demonstrate how to use the granular shocks produced in the decomposition for causal analysis. We combine the granular instrumental variables framework of Gabaix and Koijen (2022) with the estimation procedure of

Chernozhukov and others (2015). This allows us to produce country-level GDP shocks, driven by idiosyncratic movements at the industry level, to study cross country growth spillovers for the three large economic units in our sample: China, Europe and the US. We find limited evidence of short term global growth spillovers from China but meaningful spillovers from Europe and the US. China spillovers have more short term impact in Asia and, globally, in the medium term.

Future research could further refine the definition of idiosyncratic shocks to ground the definition in modern model-based welfare analysis. The distinction between idiosyncratic and aggregate shocks could then be used to define output gaps that ignore idiosyncratic shocks.

Annex I. Imputation of Data for China

The China National Bureau of Statistics publishes nominal GDP by industry in levels (billions of RMB) but does not publish real GDP disaggregated by industry in levels. They do publish the y/y growth rates for real GDP by industry which in principle would allow computation of the deflator growth as done in this paper as the difference in the growth rates of nominal GDP and real GDP growth rates. However, since 2018Q1 the agency has ceased publication of a single sectors growth rates (a catch-all category called "other", labelled y_t^{OTHER}).

To proceed with the methodology outlined in section 2, I estimate the growth rates of this missing sector subject to trying to match the growth rates for the aggregate GDP deflator and aggregate GDP growth assuming stability in the share of this sector in real GDP. A simple alternative approach would be to choose the growth rate for the missing sector to match the GDP growth rate but doing so entails large errors for the GDP deflator (see figure A1a. Similarly choosing this sequence of growth rates to match the GDP deflator errors in the implied real GDP growth figures – although substantially less so than in the case of the deflator (see figure A1b). Thus, to proceed I balance these two errors by choosing the growth rate in y_t^{OTHER}in the following minimization problem:

$$min_{y_t^{OTHER}} \sum_{j=1}^{N} \left(\omega_y \left[\pi_{t+j}(y_t^{OTHER}) - \pi_{t+j}^{True}\right]^2 + \left(1-\omega_y\right)\left[y_{t+j}(y_t^{OTHER}) - y_{t+j}^{True}\right]^2\right)^2 \quad \text{(A1)}$$

This objective function puts a weight ω_y on departures from the true deflator (π_t^{True}), where $\omega_y = \frac{\sigma_y^2}{\sigma_\pi^2+\sigma_y^2}$ and $1-\omega_y$ for departures of from the true real GDP growth rate (y_t^{True}). The weight functions to put a higher weight on the sector with *lower* variance over the estimation period. In this case the deflator has much lower variance than GDP growth and thus we put more weight on departures from the true aggregate rate of inflation, π_{t+j}^{True}, since large departures are more unusual in the data. Errors are substantially reduced compared to the extreme choice of only match one aggregate quantity with small overshoots relative to the official figures for both the deflator and real GDP as the economy emerged from COVID-19 in 2021Q1.

Figure A1a: China GDP Deflator if real GDP growth is matched when choosing y_t^{OTHER}

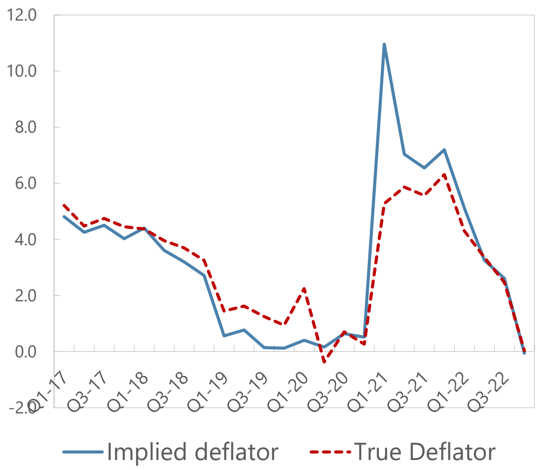


Figure A1b: China real GDP growth if GDP Deflator is matched when choosing y_t^{OTHER}

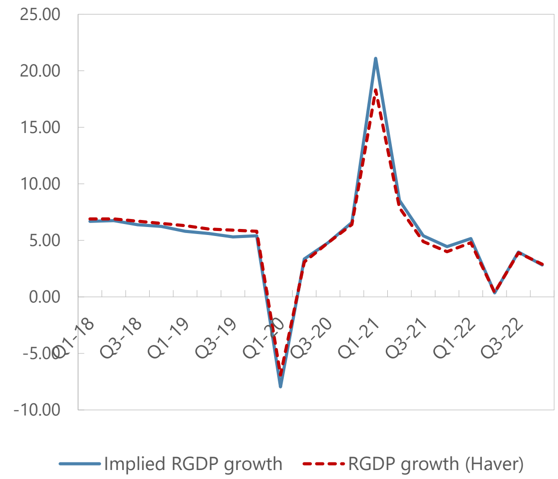


Figure A1c: Implied GDP deflator used based on optimal choice of y_t^{OTHER}

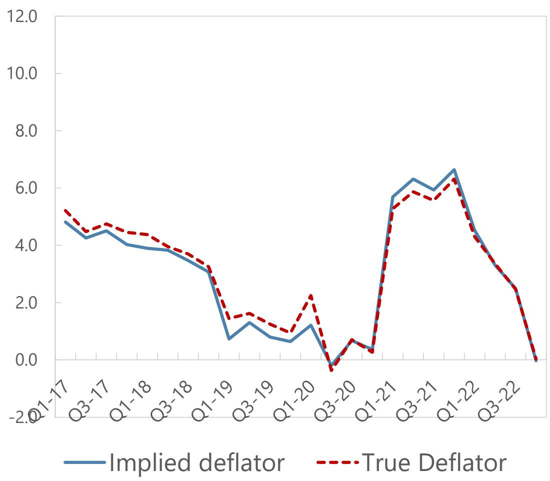
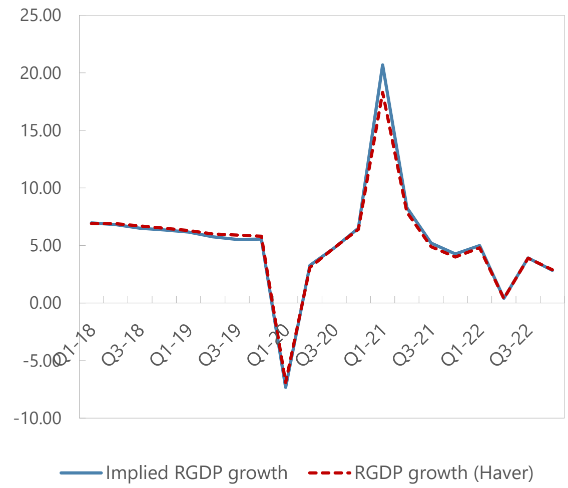


Figure A1d: Implied real GDP growth based on optimal choice of y_t^{OTHER}



Annex II. Data Sources

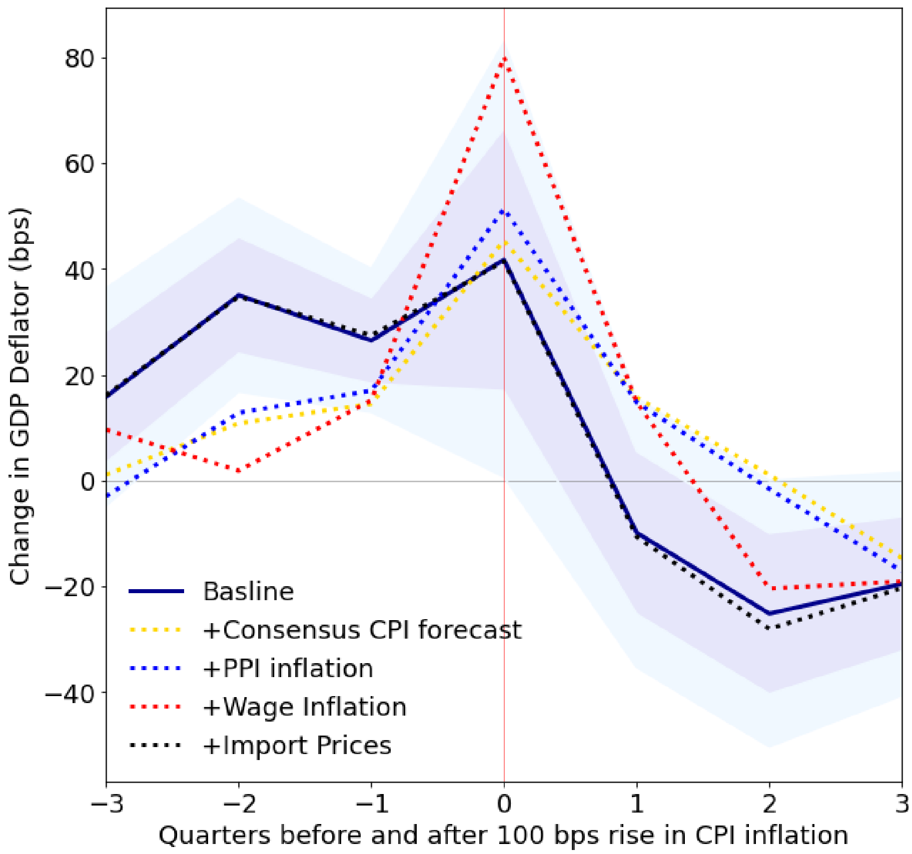
Table A1: Global Data Used for Controls

Data	Transformation
Advanced Economies: GDP at 2010 Prices & Exchange Rates (SA, Bil.2010.US$)	y/y percentage change
Advanced Economies: Gross Fixed Capital Formation (SA, 2015=100)	y/y percentage change
Advanced Economies Policy Rate (EOP, %)	level
Dow Jones Global Index: World (Avg, Dec-31-91=100)	y/y percentage change
The World: MSCI Shr Price Index with Gross Div, US$ (EOP, Dec-69=100)	y/y percentage change
World: Industrial Production ex Construction [Production-Wghtd](SWDA,2010=100)	y/y percentage change
Advanced Economies Unemployment Rate (Average, %)	level
EA 19: Export Volume (SA, 2010=100)	y/y percentage change
U.S.: Export Volume (SA, 2010=100)	y/y percentage change
Japan: Export Volume (SA, 2010=100)	y/y percentage change
Advanced Asia excl Japan: Export Volume (SA, 2010=100)	y/y percentage change
EA 19: Import Volume (SA, 2010=100)	y/y percentage change
U.S.: Import Volume (SA, 2010=100)	y/y percentage change
Japan: Import Volume (SA, 2010=100)	y/y percentage change
Advanced Asia excl Japan: Import Volume (SA, 2010=100)	y/y percentage change
Global Real Economic Activity Index in Industrial Commodity Markets (NSA, %)	level
Global Economic Policy Uncertainty Index [PPP-Adjusted GDP Weights] (Mean=100)	level
EU 27: Consumer Confidence Indicator (SA, % Balance)	level
U.S.: Conference Board: Consumer Confidence (SA, 1985=100)	level
U.S.: Conference Board: Consumer Expectations (SA, 1985=100)	level
EU 27: Consumer General Economic Situation, Next 12 Months(SA, % Bal)	level
U.S.:NFIB: Small Business Optimism Index (SA, 1986=100)	level
EU 27: Industrial Confidence Indicator (SA, % Balance)	level
Global Manufacturing PMI Using Markit Mfg for U.S. (SA, 50+=Expansion)	level
Global PMI: Services Business Activity (SA, 50+=Expansion)	level
Global PMI: Composite Input Prices (SA, 50+=Expansion)	level
Global PMI: Composite New Orders (SA, 50+=Expansion)	level
Global Liquidity: Local Claims on Private Nonfinancial Sector (% of GDP)	level
Global Liquidity: Cross-border Claims on Private Nonfinancial Sector (% of GDP)	level
Global Liquidity: Local Claims on Emerging Asia (% of GDP)	level
Global Liquidity: Cross-border Claims on Emerging Asia (% of GDP)	level

Source: Haver.

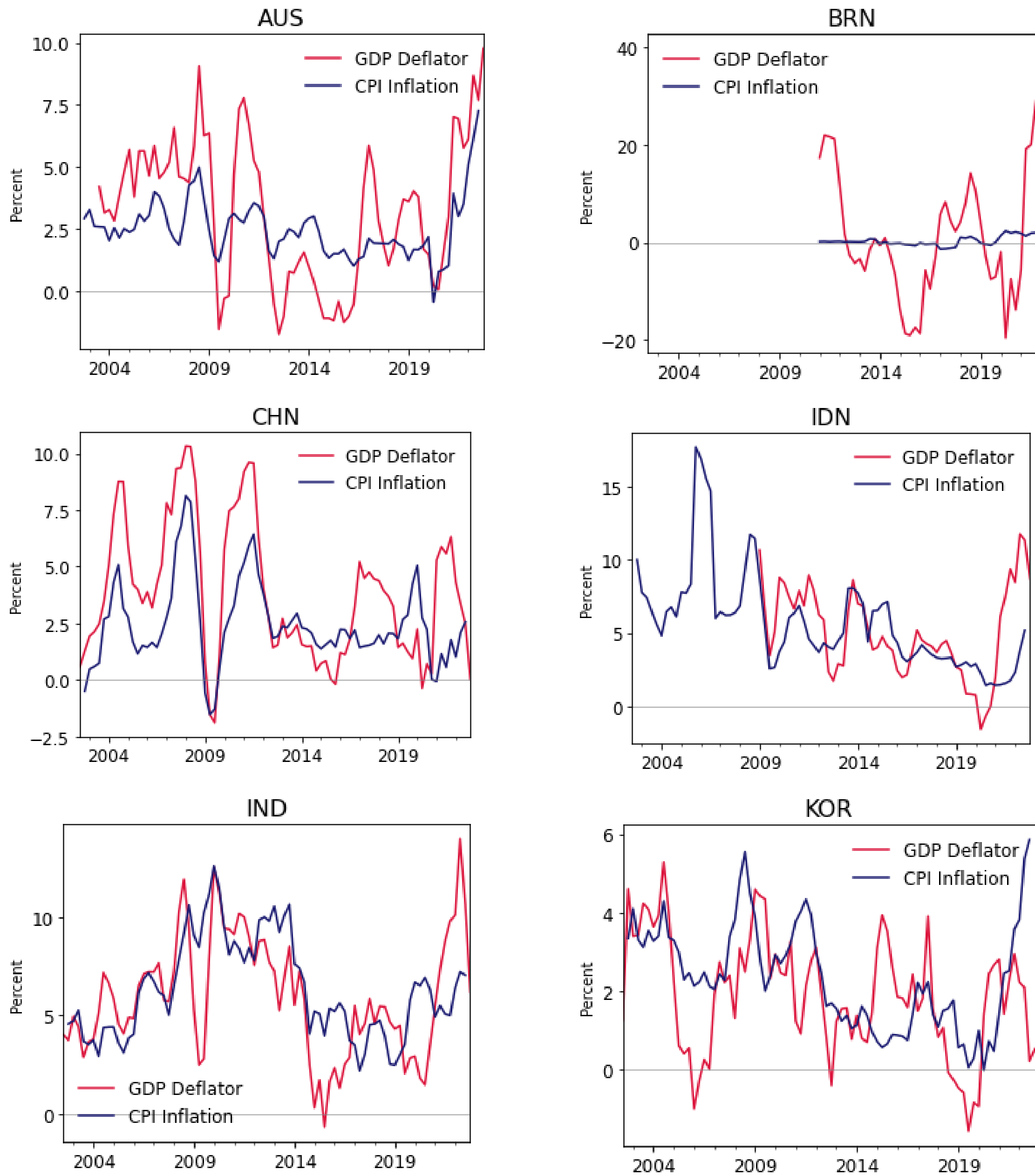
Annex III. Additional results on GDP and CPI based inflation rates.

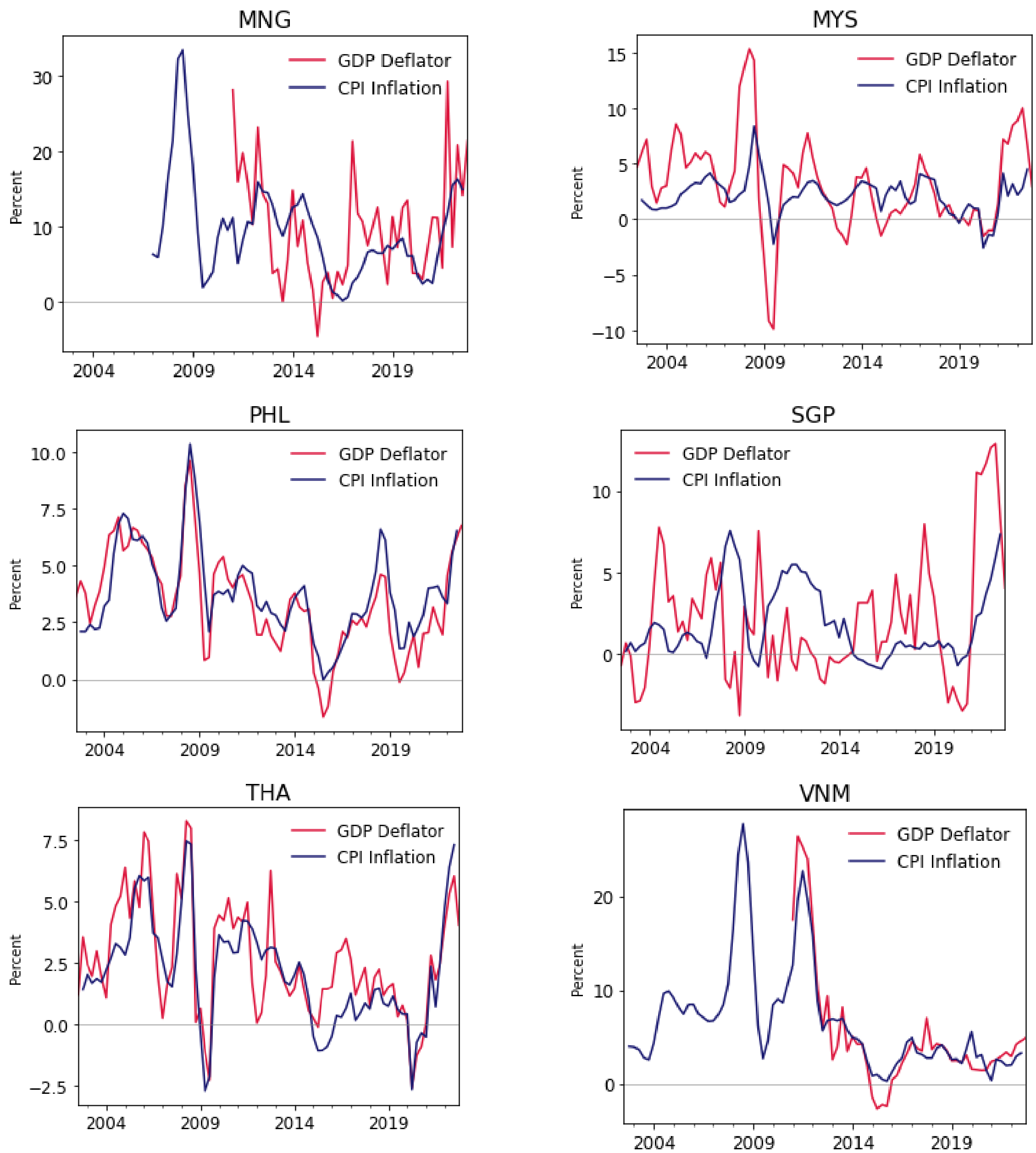
Figure A2: Robustness: GDP Deflator is a leading indicator for CPI inflation in Asia.



Source: IMF staff, Haver, Refinitiv. Shaded region are 68 and 90 percent confidence intervals.
Sample includes AUS,CHN,KOR,MYS,NZL,PHL,SGP,THA for period 2005Q1-2022Q4.
Includes controls for country and time fixed effects and 2 lags of variable after + sign

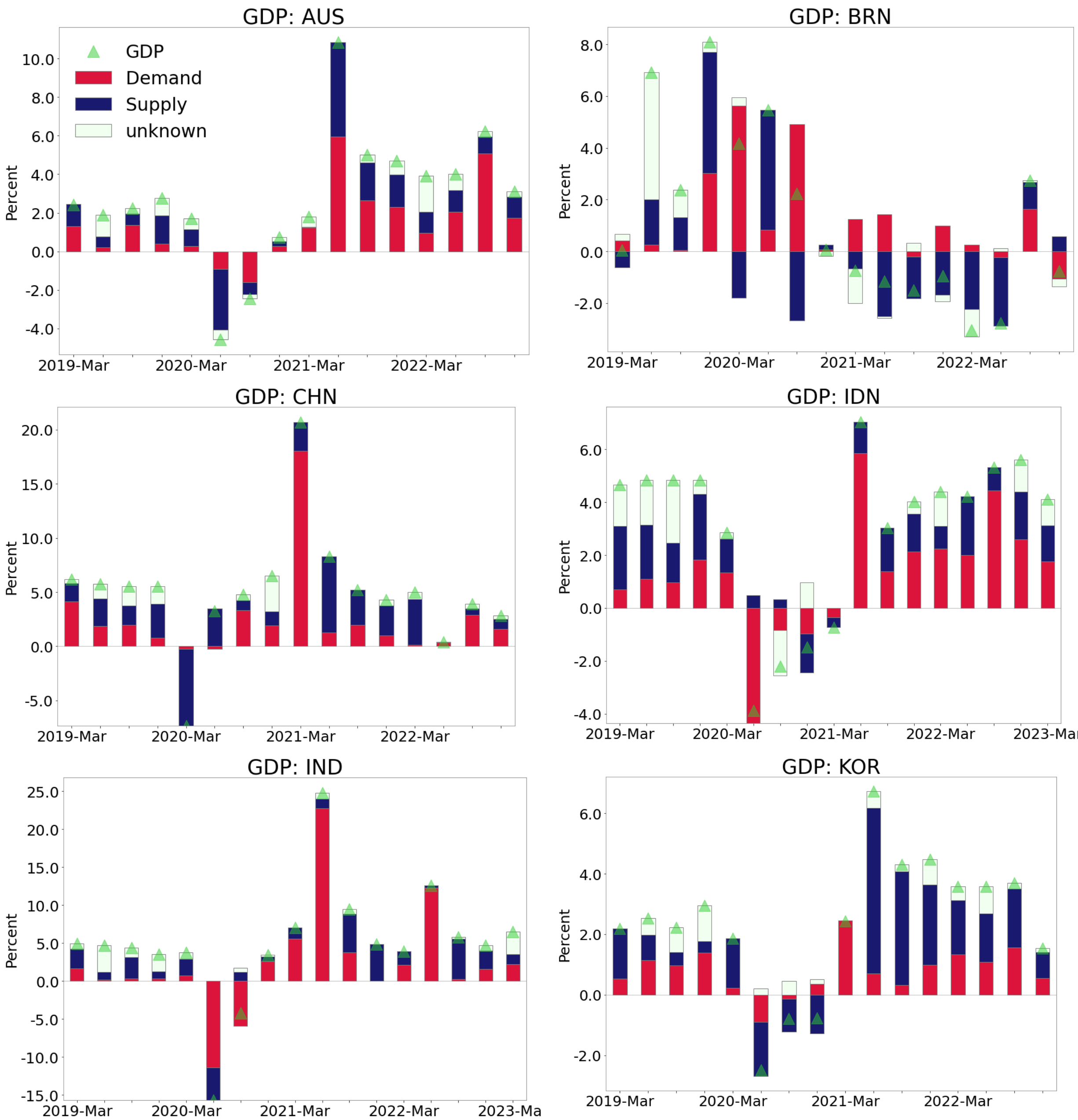
Figure A3: GDP Deflators and CPI Inflation




MNG
GDP Deflator
CPI Inflation
Percent
2004
2009
2014
2019
MYS
GDP Deflator
CPI Inflation
Percent
2004
2009
2014
2019
PHL
GDP Deflator
CPI Inflation
Percent
2004
2009
2014
2019
SGP
GDP Deflator
CPI Inflation
Percent
2004
2009
2014
2019
THA
GDP Deflator
CPI Inflation
Percent
2004
2009
2014
2019
VNM
GDP Deflator
CPI Inflation
Percent
2004
2009
2014
2019

Annex IV. GDP and Inflation Decompositions by Country

Figure A2: GDP Decompositions



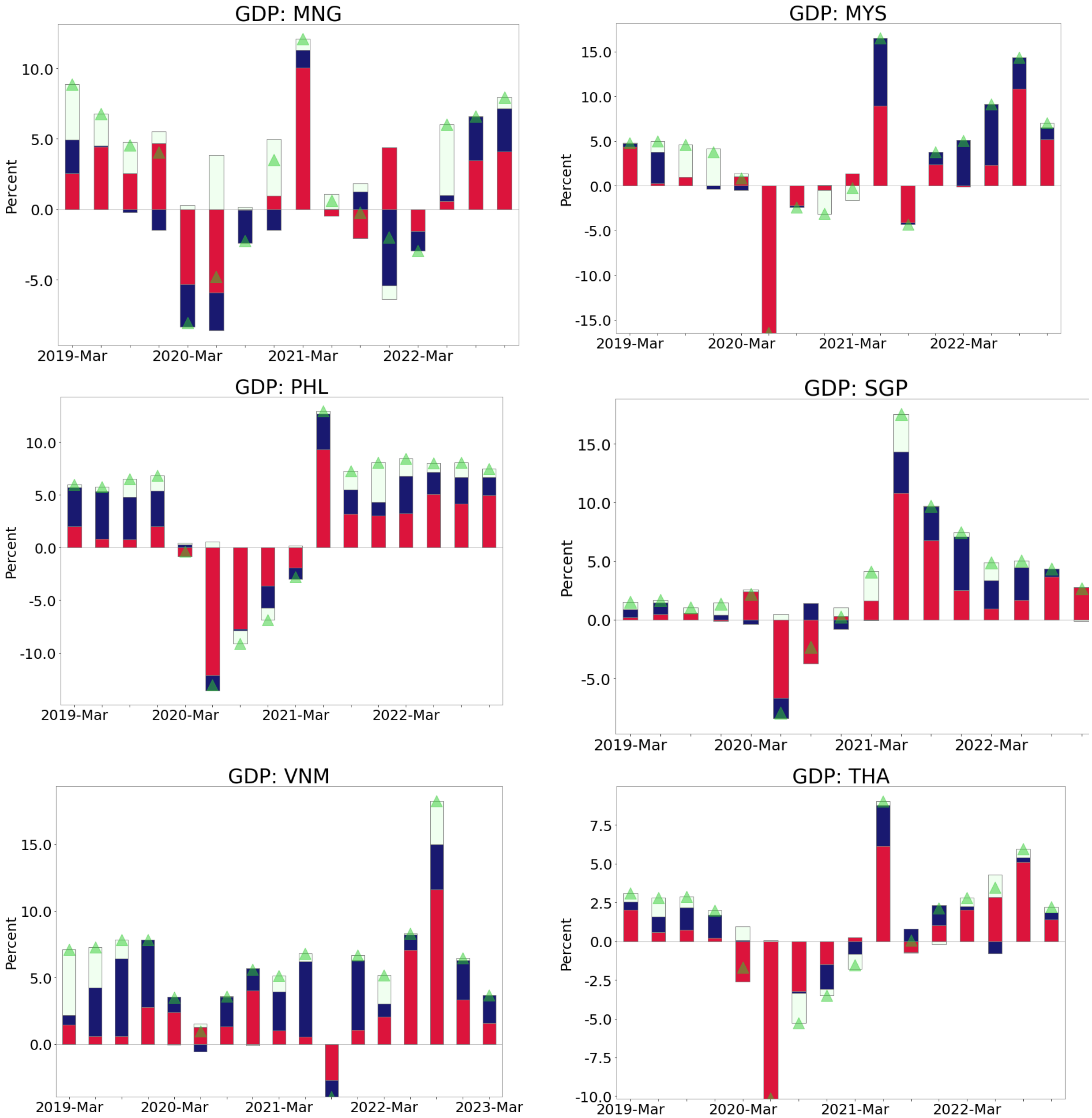
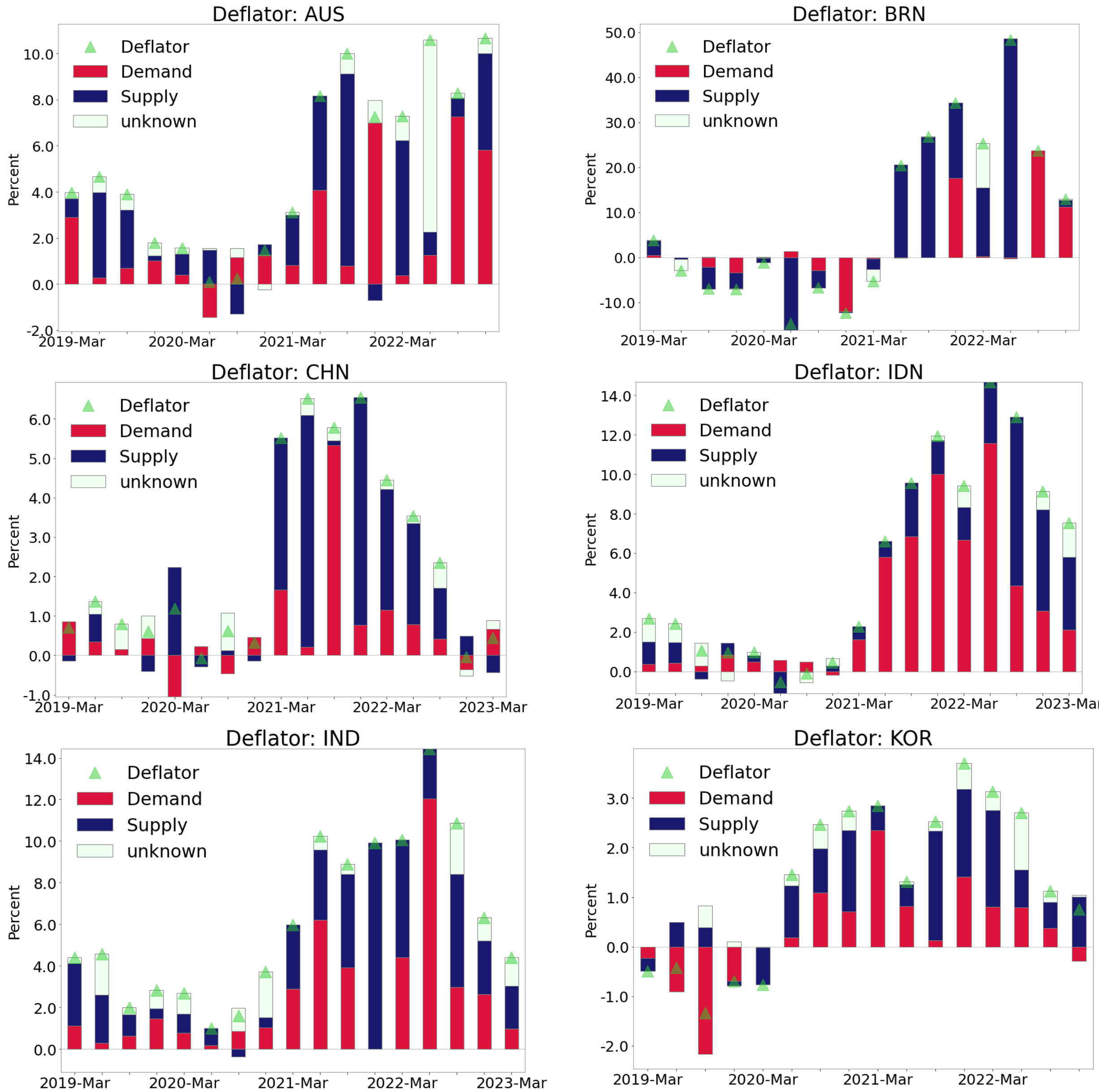
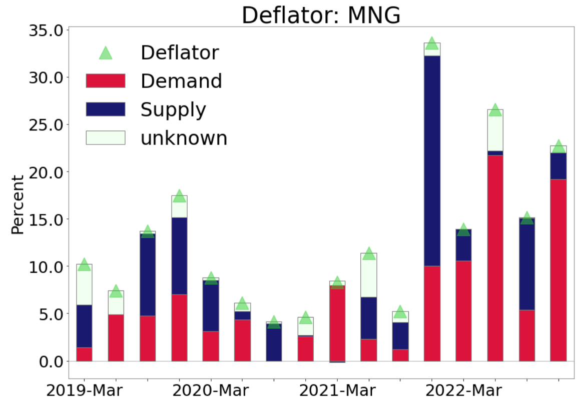
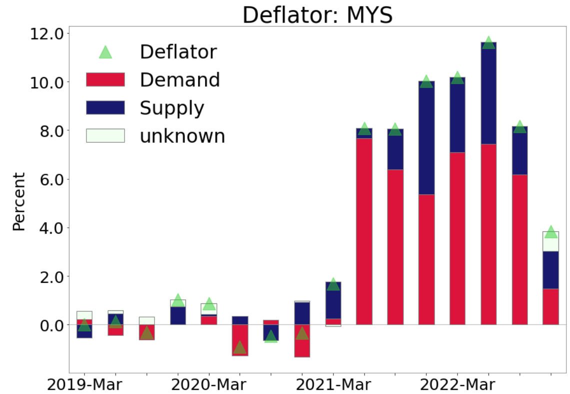
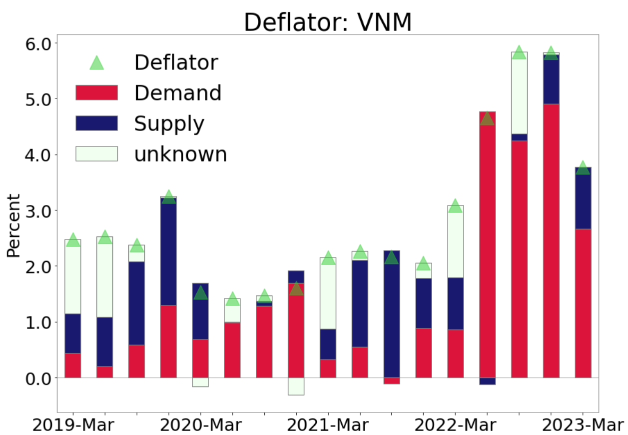

GDP: MNG
Percent
10.0
5.0
0.0
-5.0
2019-Mar
2020-Mar
2021-Mar
2022-Mar
GDP: MYS
Percent
15.0
10.0
5.0
0.0
-5.0
-10.0
-15.0
2019-Mar
2020-Mar
2021-Mar
2022-Mar
GDP: PHL
Percent
10.0
5.0
0.0
-5.0
-10.0
2019-Mar
2020-Mar
2021-Mar
2022-Mar
GDP: SGP
Percent
15.0
10.0
5.0
0.0
-5.0
2019-Mar
2020-Mar
2021-Mar
2022-Mar
GDP: VNM
Percent
15.0
10.0
5.0
0.0
2019-Mar
2020-Mar
2021-Mar
2022-Mar
2023-Mar
GDP: THA
Percent
7.5
5.0
2.5
0.0
-2.5
-5.0
-7.5
-10.0
2019-Mar
2020-Mar
2021-Mar
2022-Mar

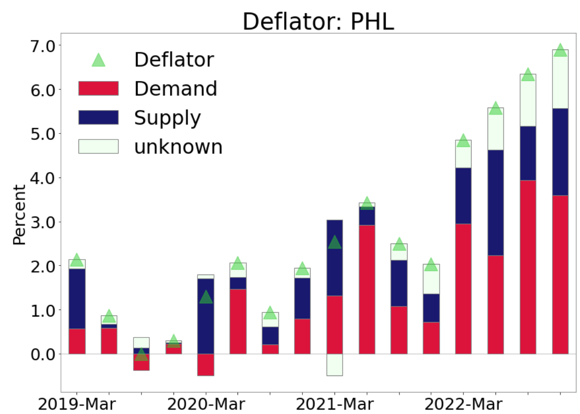
Figure A3: Inflation Decompositions

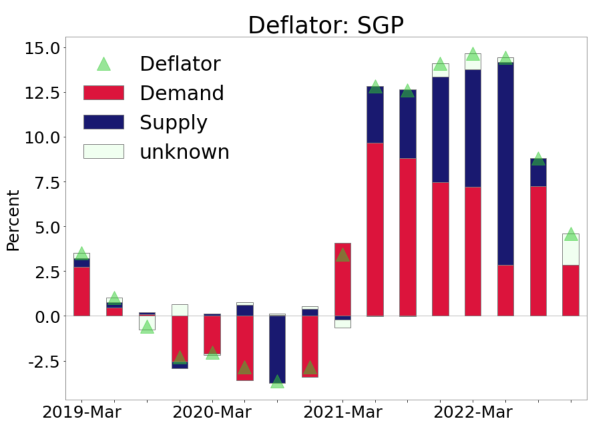



Deflator: MNG
Deflator
Demand
Supply
unknown
Percent
35.0
30.0
25.0
20.0
15.0
10.0
5.0
0.0
2019-Mar
2020-Mar
2021-Mar
2022-Mar


Deflator: MYS
Deflator
Demand
Supply
unknown
Percent
12.0
10.0
8.0
6.0
4.0
2.0
0.0
2019-Mar
2020-Mar
2021-Mar
2022-Mar


Deflator: VNM
Deflator
Demand
Supply
unknown
Percent
6.0
5.0
4.0
3.0
2.0
1.0
0.0
2019-Mar
2020-Mar
2021-Mar
2022-Mar
2023-Mar


Deflator: PHL
Deflator
Demand
Supply
unknown
Percent
7.0
6.0
5.0
4.0
3.0
2.0
1.0
0.0
2019-Mar
2020-Mar
2021-Mar
2022-Mar


Deflator: SGP
Deflator
Demand
Supply
unknown
Percent
15.0
12.5
10.0
7.5
5.0
2.5
0.0
-2.5
2019-Mar
2020-Mar
2021-Mar
2022-Mar

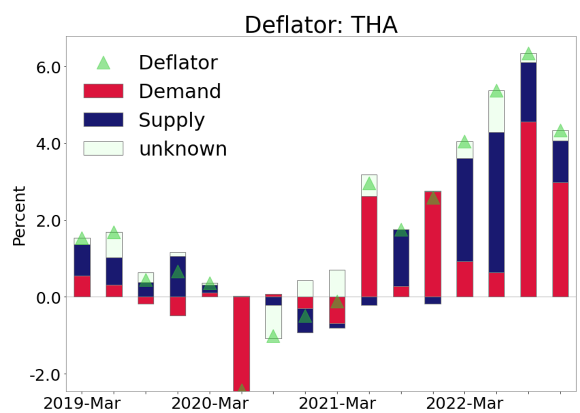
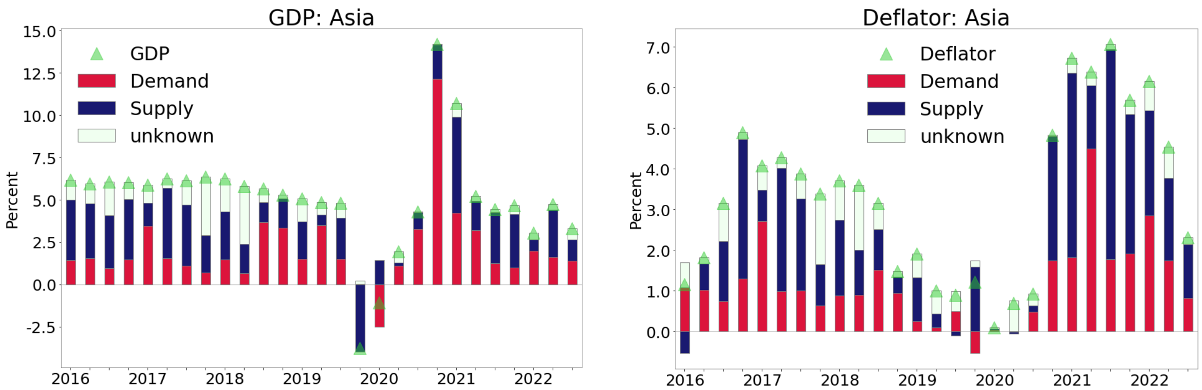

Deflator: THA
Deflator
Demand
Supply
unknown
Percent
6.0
4.0
2.0
0.0
-2.0
2019-Mar
2020-Mar
2021-Mar
2022-Mar

Figure A4: GDP and Inflation Decompositions for Asia including China

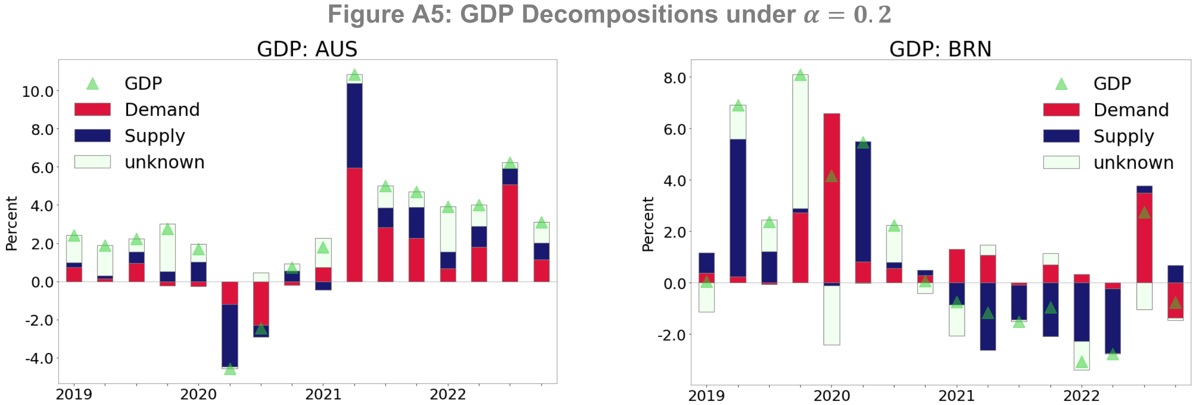


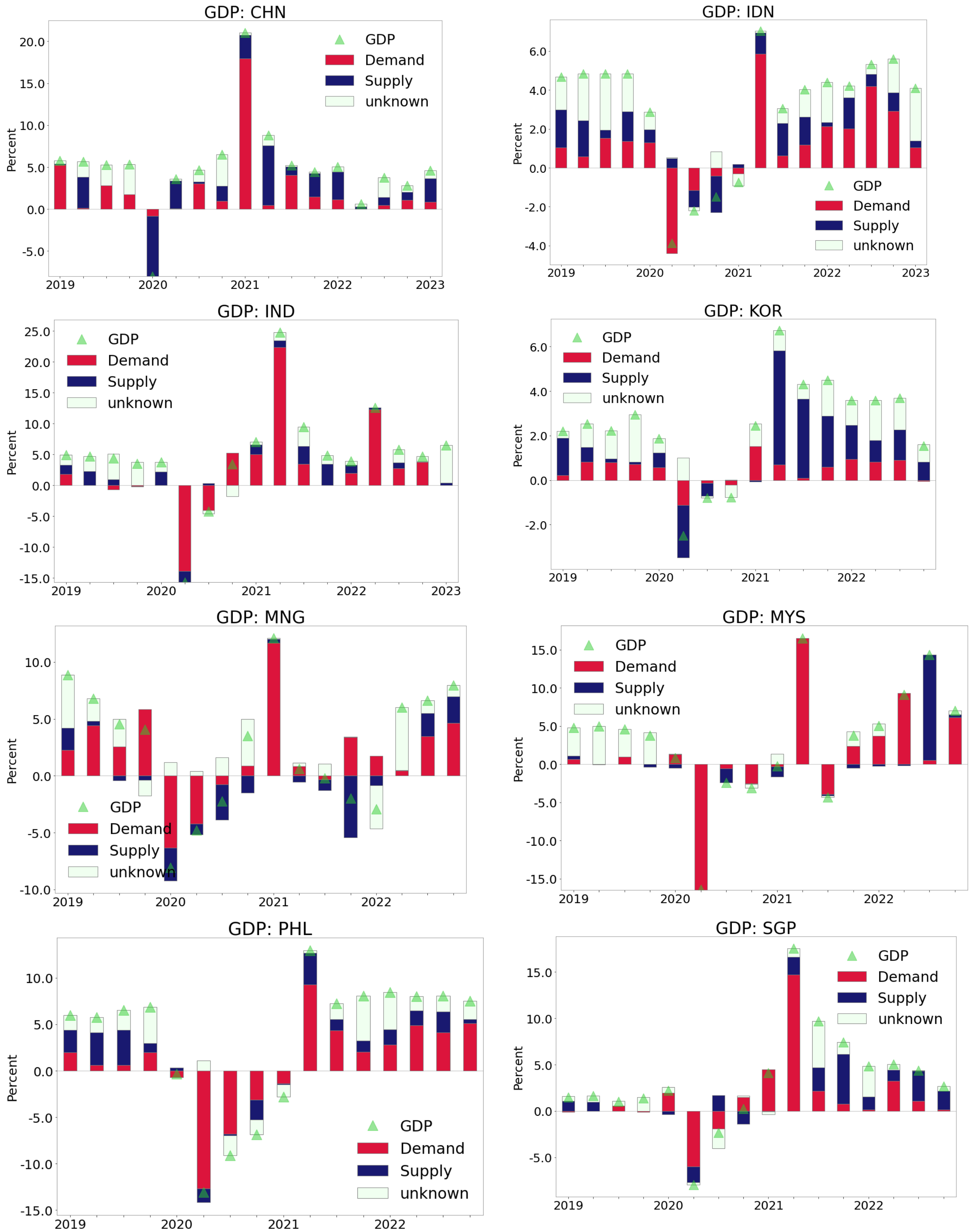
Note: Deocmpositions for Asia based on GDP weighted average of individual country results. Uncertinaty parameter $\alpha = 0.1$ *so that 20 percent of observations are unclassified. Asia sample exlcudes BRN and VNM to allow for longer sample.*

Annex V. GDP and Inflation Decompositions Assuming Higher Model Uncertainty

Results from main narrative but with alpha = 0.2.

Figure A5: GDP Decompositions under $\alpha = 0.2$




GDP: CHN
GDP: IDN
GDP: IND
GDP: KOR
GDP: MNG
GDP: MYS
GDP: PHL
GDP: SGP
Percent
GDP
Demand
Supply
unknown
2019
2020
2021
2022
2023

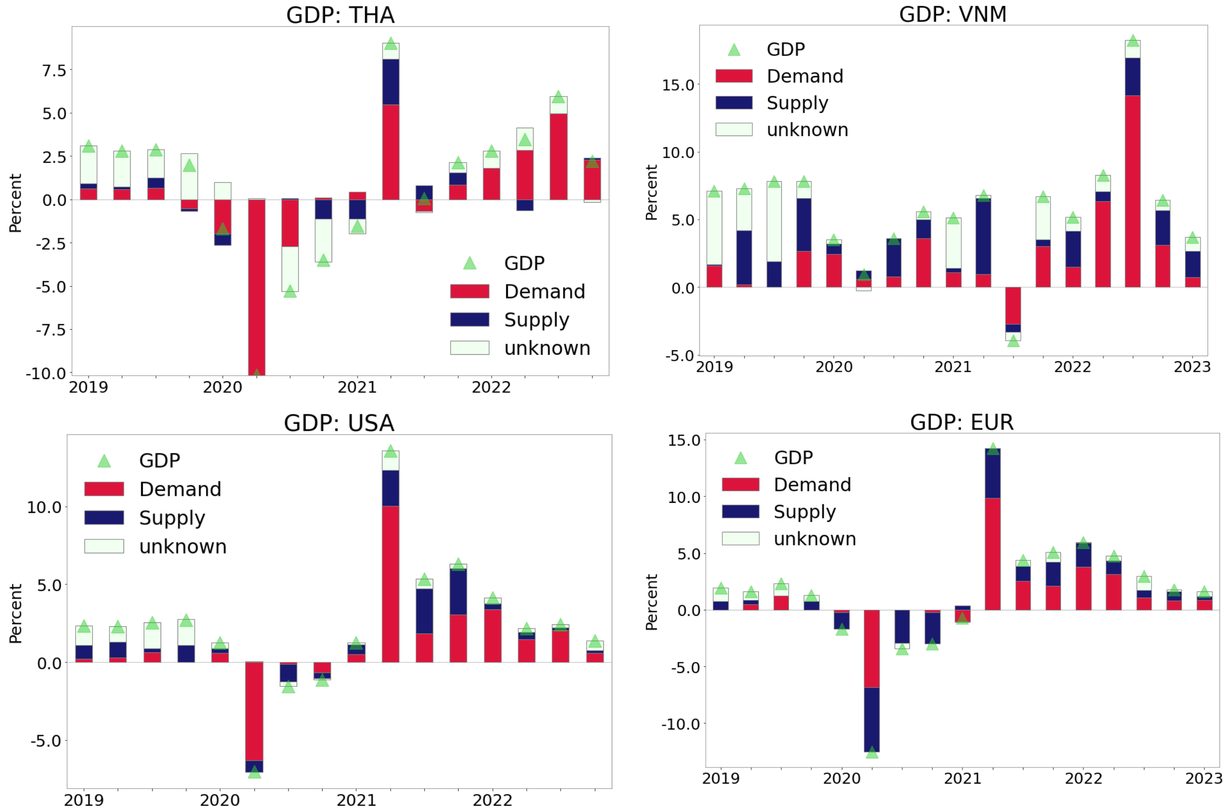
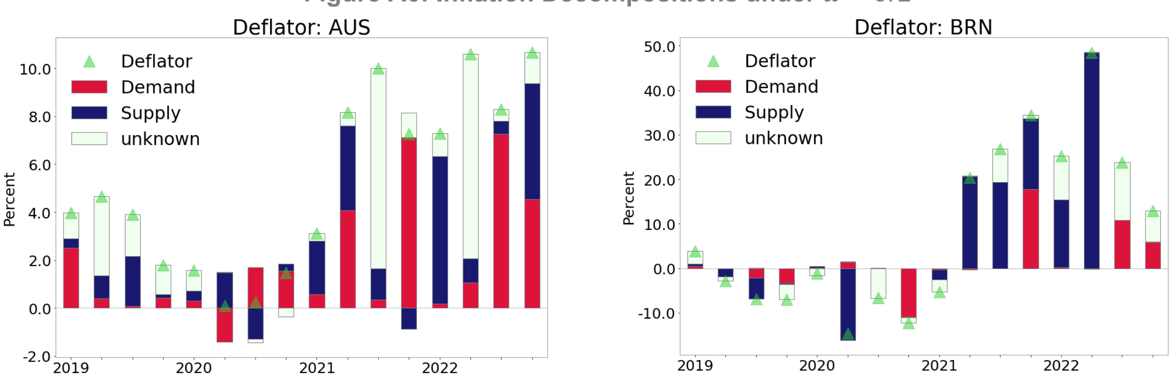
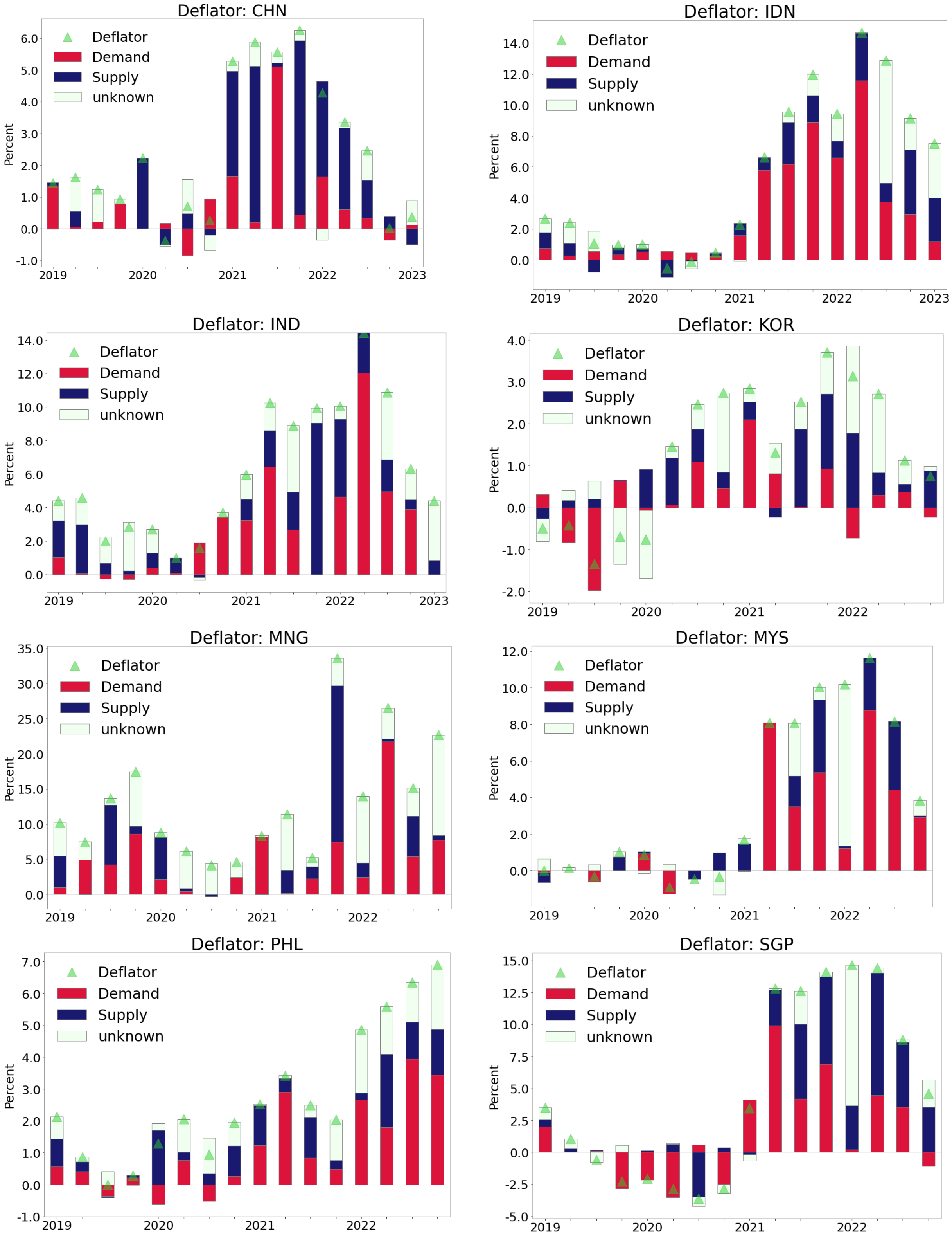
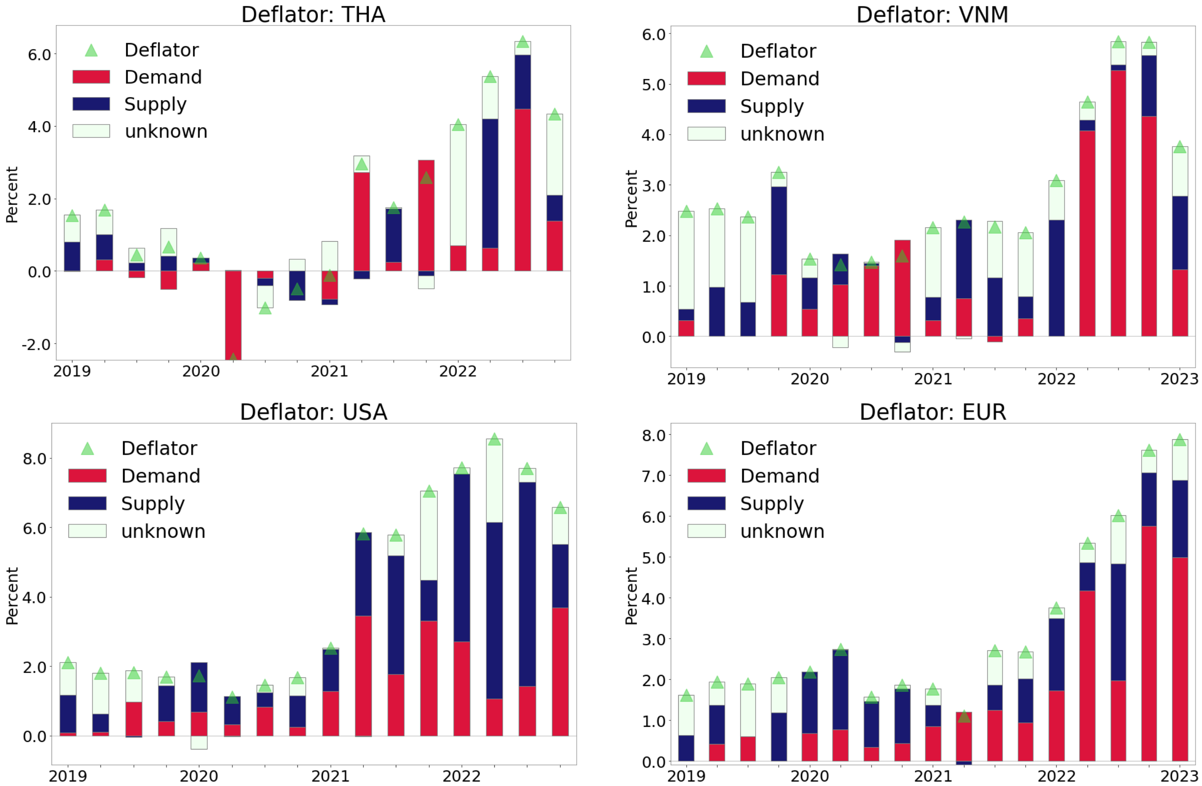


Figure A6: Inflation Decompositions under $\alpha = 0.2$




Deflator: CHN
Deflator
Demand
Supply
unknown
Percent
2019
2020
2021
2022
2023
Deflator: IDN
Deflator
Demand
Supply
unknown
Percent
2019
2020
2021
2022
2023
Deflator: IND
Deflator
Demand
Supply
unknown
Percent
2019
2020
2021
2022
2023
Deflator: KOR
Deflator
Demand
Supply
unknown
Percent
2019
2020
2021
2022
Deflator: MNG
Deflator
Demand
Supply
unknown
Percent
2019
2020
2021
2022
Deflator: MYS
Deflator
Demand
Supply
unknown
Percent
2019
2020
2021
2022
Deflator: PHL
Deflator
Demand
Supply
unknown
Percent
2019
2020
2021
2022
Deflator: SGP
Deflator
Demand
Supply
unknown
Percent
2019
2020
2021
2022


Deflator: THA
Deflator
Demand
Supply
unknown
Percent
6.0
4.0
2.0
0.0
-2.0
2019
2020
2021
2022
Deflator: VNM
Deflator
Demand
Supply
unknown
Percent
6.0
5.0
4.0
3.0
2.0
1.0
0.0
2019
2020
2021
2022
2023
Deflator: USA
Deflator
Demand
Supply
unknown
Percent
8.0
6.0
4.0
2.0
0.0
2019
2020
2021
2022
Deflator: EUR
Deflator
Demand
Supply
unknown
Percent
8.0
7.0
6.0
5.0
4.0
3.0
2.0
1.0
0.0
2019
2020
2021
2022
2023

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