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Unraveling the Exogenous Forces Behind Analysts' Macroeconomic Forecasts*

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Abstract

Modern macroeconomics focuses on the identification of the primitive exogenous forces generating business cycles. This is at odds with macroeconomic forecasts collected through surveys, which are about endogenous variables. To address this divorce, our paper uses a semi-structural general equilibrium model as a multivariate filter to infer the shocks behind economic analysts' forecasts and thus, unravel their implicit macroeconomic stories. By interpreting all analysts' forecasts through the same lenses, it is possible to understand the differences between projected endogenous variables as differences in the types and magnitudes of shocks. It also allows to explain market's uncertainty about the future in terms of analysts' disagreement about these shocks. The usefulness of the approach is illustrated by adapting the canonical SOE semi-structural model in Carabenciov et al. (2008a) to Colombia and then using it to filter forecasts of its Central Bank's Monthly Expectations Survey during the COVID-19 crisis.

Keywords: Macroeconomic expectations, Professional forecasters, Semi-structural model, Kalman smoother, Survey expectations.

JEL Codes: C53, E17, E27, E37, E32, E58, E47

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Desentrañando las fuerzas exógenas detrás de los pronósticos macroeconómicos de los analistas*

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Resumen

La macroeconomía actualmente se centra en la identificación de las fuerzas exógenas primitivas que generan los ciclos económicos reales. En contraste, las encuestas macroeconómicas recogen pronósticos sobre variables endógenas. Con el fin de reconciliar este divorcio, este trabajo usa un modelo semi-estructural de equilibrio general como un filtro multivariado para inferir los choques que estarían detrás de los pronósticos de los analistas de mercado y, por ende, desvelar sus historias macroeconómicas implícitas. Al interpretar los pronósticos de todos los analistas a través de los mismos lentes, es posible entender las diferencias entre las variables endógenas proyectadas a partir de las diferencias en los tipos y magnitudes de los choques implícitos en ellas. Del mismo modo, la incertidumbre del mercado respecto al futuro de la economía puede ser explicada en términos del desacuerdo de los analistas frente a estos choques. La utilidad de este enfoque es ilustrada mediante un caso de estudio, en el cual se adapta a Colombia el modelo semi-estructural canónico de Carabenciov et al. (2008a) para una economía pequeña y abierta, y se utiliza luego para filtrar los pronósticos registrados en la Encuesta Mensual de Expectativas del Banco de la República durante la crisis de la COVID-19.

Palabras Clave: Expectativas macroeconómicas, pronósticos profesionales, Modelo semi-structural, Suavizado de Kalman, Expectativas de encuestas.

Códigos JEL: C53, E17, E27, E37, E32, E58, E47

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1 Introduction

"We are pattern-seeking story-telling animals."
— Edward E. Leamer,
Macroeconomic Patterns and Stories

The bulk of macroeconomic expectations comes from surveys made to households, firms, researchers, or financial markets' analysts, who report forecasted endogenous aggregate macroeconomic variables offering little understanding of the narratives behind them. Of course, survey expectations of the endogenous variables are still useful, for example, as benchmarks for other forecasters and analysts, or for central banks to measure how close inflation expectations are to the target (Wieland and Wolters, 2013). Nonetheless, most surveys do not ask to report a qualitative story of the projected endogenous variables. That is, surveys do not normally collect *foredictions*, a term defined by Castle et al. (2016) as "[...]a **fore**cast made alongside a story(**diction**) describing that forecast verbally". Since projections usually lack those accompanying narratives, the assessment of forecasts as foredictions has not been studied yet.

To unravel the story describing the short-run fluctuations present in forecasts, the causes explaining the endogenous variables projections need to be identified. What is more, to compare the differences across agents' expectations or pinpoint their sources of variation over time, forecasts must be assessed by changes in exogenous forces and not by the reported endogenous variables. To assess forecasts as a forediction, this paper proposes to filter forecasts with a model to estimate the shocks that constitute an economic outlook consistent with a given macroeconomic framework.

This novel approach is used to processes a survey of macroeconomic expectations using a New Keynesian semi-structural DSGE model as the forecasts' "interpreter". Analysts' forecasts are filtered through the model using the Kalman Smoother to estimate the shocks behind them. In this way, every analyst's forecasts can be understood from a general equilibrium perspective and the extracted shocks used to study the respondents' implicit economic stories. Specifically, we extract the macroeconomic outlooks and narratives about the evolution of the COVID-19 pandemic of analysts in Colombia and complete the assessment of reported variables with stories of how much the market considered that the recession affected local supply and demand.

The methodology enables to assess all survey respondents' forecasts through the same lenses, where macroeconomic narratives emerge from the implicit shocks found by filtering expectations with the same model. Analysis is therefore conducted to assess variations across analysts dispersion among different implicit shocks. Also, the methodology allows studying the evolution of those shocks and thus, the changes through time of macroeconomic perspectives. Moreover, this approach enables to track market's uncertainty about the future general macroeconomic outlook by identifying its sources, that is, it explains the mentioned uncertainty in terms of the disagreement about shocks.

Therefore, this approach leads to macro-consistent foredictions in light of a theoretical model whose impulse response functions allow to tell a story of economic causality. In those terms, forecasts are a function of a model explaining the economic outlook in response to some underlying forces driving macroeconomic fluctuations. The recovered shocks and stories, however, are not necessarily the ones analysts considered but the ones that conform to an economically rigorous framework one believes in. In other words, the methodology attempts to make sense of analysts' forecasts guided by an economic theory one deems credible, rather than to actually figure out how analysts produced their forecasts. Consequently, all the shocks and latent variables estimated per analyst are a *subjective* interpretation of her forecasts but obtained through a consistent, rigorous, and invariant interpreter (both across analysts and through time).

Furthermore, putting forecasts through the lenses of an economic framework to the unravel shocks behind expected macroeconomic variables enriches surveys assessment because it exploits the reported information by understanding expectations as macroeconomic narratives. In particular, this procedure makes easier the understanding of forecasts by encompassing the quantitative analysis of a survey with a qualitative background that explains the reported numbers through narratives consistent with an economic theory. As explained by Fuhrer (1988), the standard assessment of surveys can sometimes be insufficient, since the use of survey's projections allows to capture a more complete information set of agents' macroeconomic stories and perspectives.

As a case study, our approach is applied to Colombia in order to examine the evolution of market's expectations and macroeconomic narratives during the outbreak and unfolding of the COVID-19 pandemic. More specifically, the interpreter used in the paper is the canonical SOE semi-structural model of the IMF, proposed in Carabenciov et al. (2008a), which is here adapted, calibrated and estimated for Colombia. An adventitious feature of this model is that it allows to calculate the implicit output gap in each analyst's forecasts as an estimate of her balance between supply and demand shocks. The model is estimated up to 2019Q4, which marks the last quarter in the sample without any clear effect of the pandemic.

After the estimation, the model is fed with the Monthly Expectations Survey (MES) carried out by Colombia's Central Bank, which gathers the forecasts reported by economic research departments of financial institutions participating in the local market. This survey favors our approach because analysts report a sufficient amount of variables to depict a very stylized macroeconomic equilibrium in a SOE: GDP growth, inflation, exchange rate and monetary policy interest rate. On top of that, the MES respondents are unchanged, facilitating an examination of the market's macroeconomic perspectives and their implicit shocks through time.

Recent work along these lines is found in Gómez-Pineda (2020), who uses a univariate filter to gauge the depth and size of the COVID-19 recession by filtering output forecasts. In contrast, our paper employs a general equilibrium model to extract the shocks implicit in analysts' forecasts for multiple macroeconomic variables. Since these shocks depict the macroeconomic narratives explaining said forecast, we are able to understand projections with their accompanying stories, translating the reported forecasts into foredictions.

This paper contributes with a nontraditional methodology to assess economic forecasts. This is particularly useful for central banks or policy-makers as a way to understand the macroeconomic outlook projected by any other agent. The methodology enriches a policy-marker's information about expectations for improving her communication or policy actions. As settled by Wieland and Wolters (2013), policy-makers react to expectations. Then, understanding the narratives behind forecasts and knowing the magnitudes about shocks driving those projections fosters more accurate reactions from policy-makers to agent's expectations. For instance, central banks can better understand changes in expectations to sharpen their messages to what they find relevant in face of private agents' macroeconomic stories and make their policies more effective. Likewise, it is useful for any researcher or analyst to assess others' macroeconomic outlooks and find the shocks explaining potential discrepancies among them.

The methodological approach we propose has not been used before, even though there is some research aiming to extract implicit information from forecasts. For example, Yoko et al. (2013) constructed a model to decompose the total factor productivity into supply/productivity, demand and other shocks using the gap between the actual amount of production and productive capacity. In addition, Bhandari et al. (2016) aim to identify ambiguity shocks as exogenous fluctuations to test the rational expectation hypothesis and prove that the large and systematic pessimistic biases observed in household survey responses are due to agents using a misspecified model when forming their expectations. Although they quantify the magnitude and economic channels through which misspecification concerns affect aggregate outcomes, they do not extract a set of shocks underlying households' expectations nor the entire macroeconomic narrative explaining forecasts' biases.

The remainder of the paper is organized as follows. Section 2 contains a more detailed description of the methodology proposed. Section 3 briefly summarizes the model and explains its calibration and estimation process. This section also includes detailed information about the MES. Afterwards, the usefulness of the methodology is illustrated through the case study in Section 4. Section 5 concludes.

2 Interpreting Survey Expectations

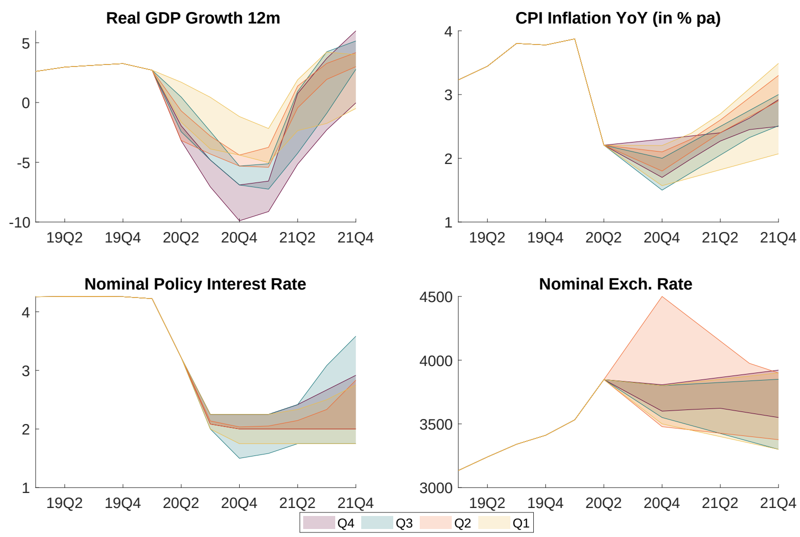
The interpreter used in the case study is a canonical SOE semi-structural model based on Carabenciov et al. (2008a). The model is adapted, calibrated and estimated for Colombia as described in Section 3. Once the model is ready, it is employed to interpret the forecasts of the MES and obtain the implicit macroeconomic stories in them. The method through which this is possible, as well as the analysis tools built to interpret the results, are laid out below.

First, the set of variables reported by each analyst is filtered through the model using the Kalman Smoother. This yields estimates of the analyst's shocks and latent variables, such as the output gap. Each analyst's set of estimates is used to compute her shock decompositions for annual GDP growth, annual inflation, monetary policy interest rate and output gap. In turn, this translates forecasts into shocks explaining the macroeconomic dynamics projected by each analyst. Note that these shocks are not necessarily the ones analysts considered but the ones that conform to an economically rigorous framework one believes in (i.e. the interpreter). For simplicity and to avoid knotty writing, throughout the paper the interpreter's output would be used and analyzed as if it was really what is behind analysts' forecasts.

Secondly, to carry out the analysis in a more compact fashion, these calculations are averaged across analysts to characterize the market's mean macroeconomic outlook. Note that each analyst has a complete set of macroeconomic variables reflecting a unique macroeconomic assessment. For example, analyst A can report the highest GDP growth forecast and the lowest inflation forecast, while analyst B can report the second highest GDP growth forecast but with the highest inflation forecast. This suggests analysts have two very different perspectives about the economy, since analyst A might be perceiving a positive supply shock and analyst B a positive demand shock. Hence, filtering the average forecast is not equivalent to filtering each analyst's forecast and then computing the average. Throughout the document, the analysis will be performed using the mean shock decompositions for each of the variables considered.

Thirdly, distributions of the shock decompositions are computed for a given survey release to evaluate the cross-section volatility of analysts' macroeconomic assessments at every period of the forecast horizon. Even though analyzing the mean shock decompositions offers a general overview of the market's implicit perspective and macroeconomic story, it hides the dispersion of the macroeconomic perspectives implied by the forecasts reported in the survey. Limiting the analysis only to the average macroeconomic perception is especially problematic during the COVID-19 shock, since uncertainty has risen significantly during this period as documented by Baker et al. (2020) and as shown in Figure 1. This figure orders by quartile the GDP growth projections for 2020Q4 reported in the July20 release and shows that the same order does not hold for the other variables. Therefore, studying the distributions of each of the reported variables alone would lack the economic consistency provided by our method. Instead, performing the analysis with the distributions of the shock decompositions stemming from a general equilibrium model provides such consistency and enables a straightforward identification of the sources of disagreement among analysts.

Figure 1: Forecasts in July20 MES release



Graph depicts forecasts reported in the July20 Monthly Expectations Survey (MES) release organized by quartiles (Q) which are ordered according to Real GDP 12m growth projection for 20Q4.

Up to this point, the output obtained from steps 1 to 3 is useful for doing an intra-temporal analysis of the market's macroeconomic overview according to what is reported in a given survey release. Nonetheless, an inter-temporal analysis of how forecasts change over time shows the evolution of the market's central macroeconomic perspective and reveals shifts in dissension among analysts between releases. To that end, the last step is to repeat this process for every survey release considered.[1] In particular, this inter-temporal analysis is divided into two stages. The first centers the attention on the outbreak of the pandemic and its impact on the analysts' macroeconomic views. The second part goes on to examine the evolution of the pandemic, how projections changed as more information was available, and what shocks explained these viewpoints revisions.

[1]Note that this procedure yields a fourth-dimensional database (survey release, analyst, variable, forecast period).

3 The Interpreter

3.1 Model structure

The interpreter is a semi-structural New-Keynesian model for a small open economy based on the canonical model of IMF Carabenciov et al. (2008a). It is divided into four blocks, in line with the four macroeconomic variables reported in the Monthly Expectations Survey (MES):[2] the first block considers the IS Curve and the potential output; the second one shows a Phillips Curve for total inflation; the third block explains how the foreign exchange rate is determined; and the fourth describes the monetary policy rule.

IS Curve and potential output

The output y_t is defined in terms of a cyclical component $\hat{y}_t$ (output gap), and a trend $\overline{y}_t$ (potential output). Therefore, output is defined as:

$$y_t = \overline{y}_t + \hat{y}_t \tag{1}$$

The annualized potential output growth and the quarterly output level can be expressed as:

$$\Delta\overline{y}_t = \rho_{\Delta y}\Delta\overline{y}_{t-1} + (1-\rho_{\Delta y})\Delta\overline{y}_{ss} + \epsilon_t^{\Delta\overline{y}} \tag{2}$$

$$\overline{y}_t = \overline{y}_{t-1} + \frac{\Delta\overline{y}_t}{4} + \epsilon_t^{\overline{y}} \tag{3}$$

Equation (2) describes the law of motion of potential growth. It depends on its past $\Delta\overline{y}_{t-1}$, the long-term growth rate $\Delta\overline{y}_{ss}$, and shocks to potential growth $\epsilon_t^{\Delta\overline{y}}$. Furthermore, equation (3) describes the level of potential output, contemplating an additional shock to the output level $\epsilon_t^{\overline{y}}$ that is useful to capture permanent effects on potential output. The latter is particularly relevant in times of crisis, when productive capacity might be harmed. Henceforth, these two shocks would be called supply shocks.

The cyclical component is modeled through an IS curve:

$$\hat{y}_t = \beta_1\hat{y}_{t-1} - \beta_2 MCI_t + \beta_3\hat{y}_t^* + \epsilon_t^{\hat{y}_t} \tag{4}$$

The output gap $\hat{y}_t$ has inertia, hence $\hat{y}_{t-1}$, and depends on a demand shock $\epsilon_t^{\hat{y}_t}$. It is also a function of the foreign output gap $\hat{y}_t^*$, that captures the dynamic of foreign demand, and of a real monetary condition index MCI_t. The MCI captures changes in the business cycle derived from both, the real interest rate gap $\hat{r}_t$, and the real exchange rate gap $\hat{z}_t$ according to the following equation:

[2] The reported variables are GDP growth, annual inflation, monetary policy interest rate and exchange rate.

$$MCI_t = \beta_4 \hat{r}_t + (1-\beta_4)\hat{z}_t \tag{5}$$

The real interest rate gap measures the effects of monetary policy on aggregate demand, while the real exchange gap takes into account the expenditure switching as a consequence of changes in the real exchange rate.

The output gap reflects the dynamic of the aggregate demand and it is an indicator of the business cycle. Thus, a negative gap indicates economic slack, while a positive one signals an overheating economy. It is worth noting that together, equations 1 and 4, imply that the output gap summarizes the net balance between supply and demand shocks.

Phillips Curve

The short-term aggregate supply is modeled through a New Keynesian Phillips Curve that link inflation rate with the real marginal costs.

$$\pi_t = \alpha_1 \pi_{t-1} - (1-\alpha_1)\mathbb{E}_t \pi_{t+1} + \alpha_2 RMC_t + \epsilon_t^{\pi}\,, \tag{6}$$

$$RMC_t = \alpha_3 \hat{y}_t + (1-\alpha_3)\hat{z}_t\,. \tag{7}$$

The annualized quarterly inflation π_t depends on inflation inertia π_{t-1}, expected inflation $E_t \pi_{t+1}$, the real marginal cost RMC_t, and a cost shock ϵ_t^{π}. The real marginal cost responds positively to the output gap and the real exchange rate gap.

Determination of the Nominal and Real Exchange Rates

Nominal depreciation is modeled using the UIP condition:

$$\Delta s_t = i_t^* - i_t + prem + \varepsilon_t^{ls} \tag{8}$$

Where Δs_t is the nominal depreciation, i_t^* is the FED funds rate, i_t is the monetary policy interest rate, $prem$ is a constant risk premium, and ε_t^{ls} is an idiosyncratic shock to the UIP condition.

Regarding the real exchange rate, z_t one can identify a trend $\overline{z}_t$ and a cyclical component $\hat{z}_t$ following: $z_t = s_t + \pi_t^* - \pi_t$

$$z_t = \overline{z}_t + \hat{z}_t \tag{9}$$

$$\Delta\overline{z}_t = \rho_{\Delta z}\Delta\overline{z}_{t-1} + (1-\rho_{\Delta z})\Delta\overline{z}_{ss} + \epsilon_t^{\Delta\overline{z}} \tag{10}$$

Lastly, the nominal and real depreciation are related through $\Delta z_t = \Delta s_t + \pi_t^* - \pi_t$.

Monetary Policy Rule and Interest Rates

The monetary policy rate depends on its lag i_{t-1}, the neutral nominal interest rate $\bar{i}_t$, the output gap, the deviation of annual inflation expectations from its target one year ahead $E_t\pi^A_{t+4} - E_t\overline{\pi}^A_{t+4}$, and a monetary policy shock ϵ^i_t. The parameter ρ_i is the smoothing coefficient, ψ_π and $\psi_{\hat{y}}$ are the weight of the expectations deviation and output gap, respectively, in the reaction function:

$$i_t = \rho_i i_{t-1} + (1-\rho_i)\left[\bar{i}_t + \psi_\pi(E_t\pi^A_{t+4} - E_t\overline{\pi}^A_{t+4}) + \psi_{\hat{y}}\ \hat{y}_t\right] + \epsilon^i_t\,. \quad (11)$$

The neutral nominal interest rate is defined by Fisher equation $\bar{i}_t = \overline{r} + \pi_{t+1}$, where $\overline{r}$ is the neutral real interest rate and π_{t+1} is the inflation expectations. Therefore, the long depreciation will be constant and given by:

$$\Delta\overline{z} = \overline{r} - \overline{r}^* + prem$$

Where $\overline{r}^*$ and $\Delta\overline{z}_t$ are the US neutral real interest rate, and the depreciation of the real exchange rate trend, respectively.

Foreign variables

The rest of the world is considered in the model through four macroeconomic US variables. These variables follow the exogenous processes:

$$\hat{y}^\star_t = \rho_{\hat{y}^\star} * \hat{y}^\star_{t-1} + \epsilon^{\hat{y}}_t \quad (12)$$

$$\pi^\star_t = \rho_{\pi^\star} * \pi^\star_{t-1} + (1-\rho_{\pi^\star}) * \overline{\pi}^\star + \epsilon^{\pi\star}_t \quad (13)$$

$$i^\star_t = \rho_{i^\star} * i^\star_{t-1} + (1-\rho_{i^\star}) * (\overline{r}^\star_t + \pi^\star_{t+1}) + \epsilon^{i\star}_t \quad (14)$$

$$r^\star_t = i^\star_t - \pi^\star_t \quad (15)$$

Where $\pi^\star_t$ is the US CPI headline inflation and $r^\star_t$ the ex-post real interest rate.

3.2 Calibration and Estimation

The parameters of the model are divided into two groups, ones that are calibrated and other that are estimated. Among the first group, there are three types of parameters related to the steady state, the exogenous processes and the Taylor Rule. The former account for long-run growth rates, inflation targets and natural interest rates. The second set includes the persistences of the exogenous processes, which are calibrated to match the Impulse Response Functions (IRF) that characterize the macroeconomic transmission channels depicted in González et al. (2020).[3] And the latter set were calibrated

[3]The IRF's of the calibrated model of this paper are presented in Appendix A.

taking into account the posterior values in González et al. (2020) and Carabenciov et al. (2008a) for their Taylor Rules. The values for these parameters are presented in Table 1.

Table 1: Calibrated Parameters Values and Description

Parameter	Value	Description
Steady State		
$\Delta\overline{y}$	3.3%	Long run Potential Output Growth
$\overline{\pi}$	3%	Long run inflation
$\overline{r}$	2%	Long run neutral real interest rate
$\overline{\pi}^{\star}$	2%	Long run US inflation
$\overline{r}^{\star}$	0.5%	Long run US neutral real interest rate
$\Delta\overline{z}$	0%	Long run depreciation
$\overline{\omega}$	1.5%	Constant risk premium
Taylor Rule		
ρ_i	0.7	Backward component
ψ_π	1.5	Inflation weight
$\psi_{\hat{y}}$	0.3751	Output gap weight
Persistences		
$\rho_{\overline{z}}$	0.1	Persistence of the Real Exchange Rate Trend Depreciation
$\rho_{\Delta\overline{y}}$	0.75	Persistence of Real GDP Trend Growth
$\rho_{\hat{y}*}$	0.5	Persistence of foreign output gap
$\rho_{i^\star}$	0.6	Persistence of foreign interest rates
$\rho_{\pi^\star}$	0.5	Persistence of foreign inflation
Standard Deviation		
$\sigma\epsilon_t^{\overline{y}}$	0.2407	Standard Deviation of potential GDP shock level

To set the rest of the parameters, the model is estimated using a Bayesian approach that approximates the posterior distribution through the MCMC Metropolis-Hastings algorithm. However, this algorithm is modified to take into account that during high volatility episodes, there is also higher volatility for potential output level. To avoid the identification problem that may arise between the potential output level and potential output growth shocks, the former is used only during volatile periods (2008Q2-2008Q4), while the latter is turned off. Therefore, following Gómez-Pineda (2020) the standard deviation of the potential output level shock is set with an iterative process that goes as follows. The parameter is calibrated before the Bayesian estimation. Given that this estimation might change the initial calibration, the process must be repeated until it converges. We obtain a 0.2407 value that fits inside the 0.175-0.75 range proposed by Gómez-Pineda (2020). This range covers plausible values for the share of the standard deviation of the potential output level shock relative to the sum of the standard deviations of the potential growth shock and the potential output level shock.

In this process, quarterly data containing 5 domestic variables and 4 foreign variables from 2003Q1 to 2019Q4 is employed. The first set of variables includes GDP (constant prices, chained and seasonally adjusted), annual headline inflation, monetary policy rate, annual inflation target, and nominal exchange rate (USD-COP). The second set includes foreign variables such as US GDP (constant prices, chained and seasonally adjusted), the FED funds rate, US annual headline CPI inflation and the Colombian average risk premium before 2020, measured through the 5-year CDS spread on sovereign debt. The model also observes estimates of the foreign output gap which is calculated using a Hodrick-Prescott filter. Data sources are documented in Appendix B. Table 2 summarizes the estimation results.

Table 2: Estimated Parameters Description

Parameter	Value	Description
Phillips Curve		
α_1	0.3748	Backward component weight
α_2	0.2836	Real marginal cost weight
α_3	0.6001	Output gap weight
IS Curve		
β_1	0.6736	Backward component weight
β_2	0.0445	MCI weight
β_3	0.1483	Foreign output gap weight
β_4	0.4516	Real interest rate gap weight
Standard Deviations		
$\sigma\epsilon^{\hat{y}}$	0.3792	Demand shock SD
$\sigma\epsilon^{\Delta y}$	0.1249	Potential growth shock SD
$\sigma\epsilon^{\pi}$	0.7644	Phillips curve shock SD
$\sigma\epsilon^{ls}$	1.7585	UIP shock SD
$\sigma\epsilon^{i}$	0.2843	Monetary policy shock SD
$\sigma\epsilon^{\overline{z}}$	5.6372	Real exchange rate trend depreciation SD
$\sigma\epsilon^{\hat{y}*}$	0.4731	Foreign demand shock SD
$\sigma\epsilon^{i*}$	0.5153	Foreign monetary policy shock SD
$\sigma\epsilon^{\pi*}$	1.7839	Foreign inflation shock SD

The parameters obtained for the IS and Phillps Curve are in line with those obtained by Andrle et al. (2013); Carabenciov et al. (2008a,b); Charry et al. (2014). Also, the historical shock decompositions, presented in Appendix A, tell a story similar to the one presented in González et al. (2020) about the main drivers of the macroeconomic dynamics of Colombian economy.

3.3 Survey

The Monthly Expectations Survey (MES) designed by Colombia's Central Bank, query the research departments of financial institutions participating in the local market and economic research centers about their GDP growth, inflation, exchange rate and monetary policy interest rate forecasts for a given horizon. Despite the frequency of the survey, the researchers report their GDP growth forecast only at the end of each quarter. For that reason, the forecast set is complete only in the survey conducted during the first month after each quarter ends. These are the months that are taken for the analysis. A useful characteristic of the MES is that most of the respondents are unchanged, allowing us to do an assessment of the evolution of the market's macroeconomic perspectives throughout time.

With the survey and the observable data we construct a balanced panel from 2003Q1 to 2021Q4 for a total of 25 analysts. For each survey release (January20, April20, July20, October20 and January21), historic data is updated to include the new information of the observed variables such as GDP growth and inflation. It is important to mention that we exclude those researchers that do not report forecasts in every release or do not report sufficient information in a particular release.[4] A balanced panel is desired for two reasons. First of all, to do a general equilibrium assessment is necessary to have the complete set of variables that describe said equilibrium for a small open economy. Secondly, to do a proper inter-temporal analysis of the market's macroeconomic outlook one wants to keep the sample constant. This prevents that, between releases, macroeconomic outlooks vary due to new analysts or old analysts that do not report forecasts in a given release. The information in each survey release is summarized in Table 3. [5,6]

Table 3: Survey Data

Variable reported in survey	**Survey release in which are included**
Annual inflation: 2020Q4 and 2021Q4	All
Exchange rate Level: 2020Q4 and 2021Q4	All
GDP growth(YoY): Fourth quarter of the present and next year	All
Annual GDP growth: 2020Q4 and 2021Q4	January20 and April20
quarterly GDP growth(YoY):	July20, October20 and January21

Foreign Variables Assumptions

The MES does not ask analyst to report forecast of foreign variables, but these are an important source of information for the model. Therefore, some assumptions

[4] Analysts that do not report information for the 2020 or 2021 in one or more variables are excluded.

[5] The complete information of the MES survey is found in https://www.banrep.gov.co/es/estadisticas/encuesta-mensual-expectativas-analistas-economicos.

[6] For the releases of October20 and January21, analysts were also asked to report the yearly GDP forecast for 2020Q4 and 2021Q4, which was used if analyst did not report data for GDP YoY growth forecast for each quarter.

about the US observed variables are needed. Specifically, the consensus of the quarterly reported Bloomberg survey is taken by assuming that this information is common for all analysts.[7]

Local Historic Output Gap

Finally, to conserve the macroeconomic story before the COVID-19 shock, the same domestic and foreign output gaps series (03Q1-19Q4) estimated by the model prior to the first MES release are observed in every survey.[8]

4 Macroeconomic Stories During the Pandemic

The COVID-19 pandemic was an atypical shock that brought about a great deal of uncertainty among private and public agents. At first, there was too little information on the virus characteristics to properly estimate the time to develop a vaccine or treatment or assess the policy actions needed to mitigate it. Then, as people gained more knowledge about the virus and public authorities learned better ways to combat the epidemic, uncertainty slowly waned. Therefore, in this section, the analysis of the five MES releases is broken down into two parts. The first subsection examines how analysts' implicit outlooks dramatically changed with the pandemic outbreak in Colombia while laying out the main analysis tools considered in the methodology proposed. The second subsection goes on to study the evolution of the analysts' macroeconomic narratives implicit in their forecasts as the pandemic unfolded throughout 2020 and as the general public acquired more information about the sanitary and economic consequences of the virus.

4.1 The outbreak

The first case of COVID-19 in Colombia was confirmed on March 6 of 2020, but its first nationwide quarantine was declared 14 days later, with only a third of the month left. The virus continued to spread throughout the country in the months to come, and with it, policy actions to slow down the epidemic. Thus, it was really during the second quarter of 2020 that the epidemic took root in the country. Moreover, this timeline implies that the January20 MES release could not have captured any effects of the pandemic. And by the time the April20 survey was conducted, analysts could only have had a very incipient assessment of the size and nature of the pandemic's

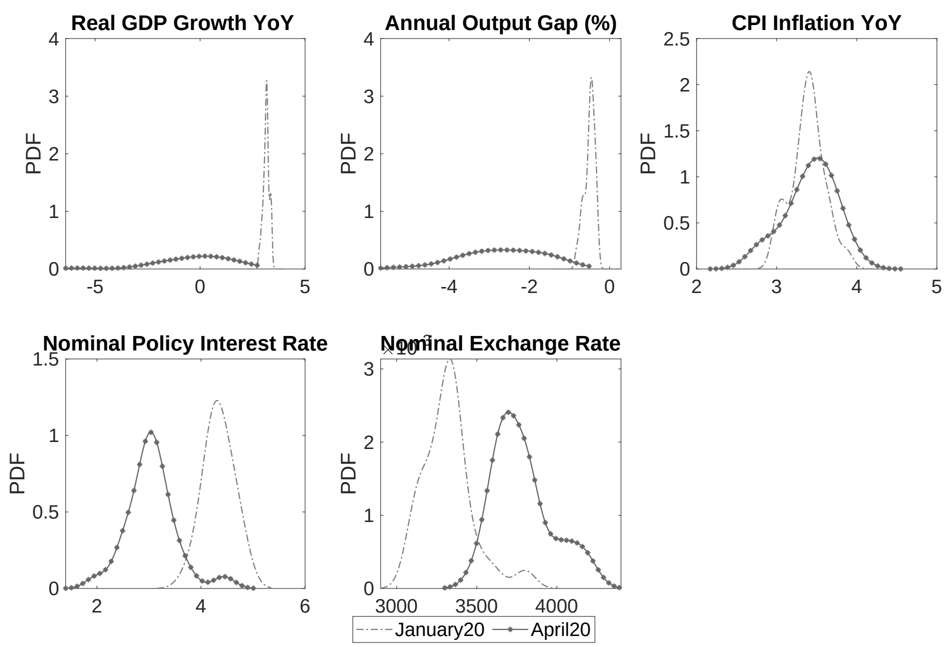
[7]We took the consensus forecasts reported in Bloomberg at the beginning of the month to assure that this external information can be used to generate the forecasts of the MES.

[8]We update the estimation (03Q1-19Q4) of the output gaps with every GDP release.

implications. Consequently, focusing on these two releases helps reveal how analysts' implicit macroeconomic outlooks transformed with the onset of the pandemic.

Before the outbreak, dissension among analysts was modest as seen in Figure 2. In the January20 release, forecasts of annual GDP growth and inflation narrowly revolved around the long-run values reported in Section 3. The distribution of the interest rate was centered almost at its 2020Q1 level (4.25%) and showcased as little disagreement as inflation. Forecasts about the nominal exchange rate feature more dissension, ranging from \$3000 to \$4.000, which is consistent with the fact that it is the most volatile of the variables reported. Although this description of reported variables provides an overview of analysts' responses dispersion, it offers little information about their macroeconomic assessment. Perhaps a more useful indicator is the output gap estimated by the model per analyst, whose distribution reveals a lot of consensus about it being close to zero by the end of 2020.

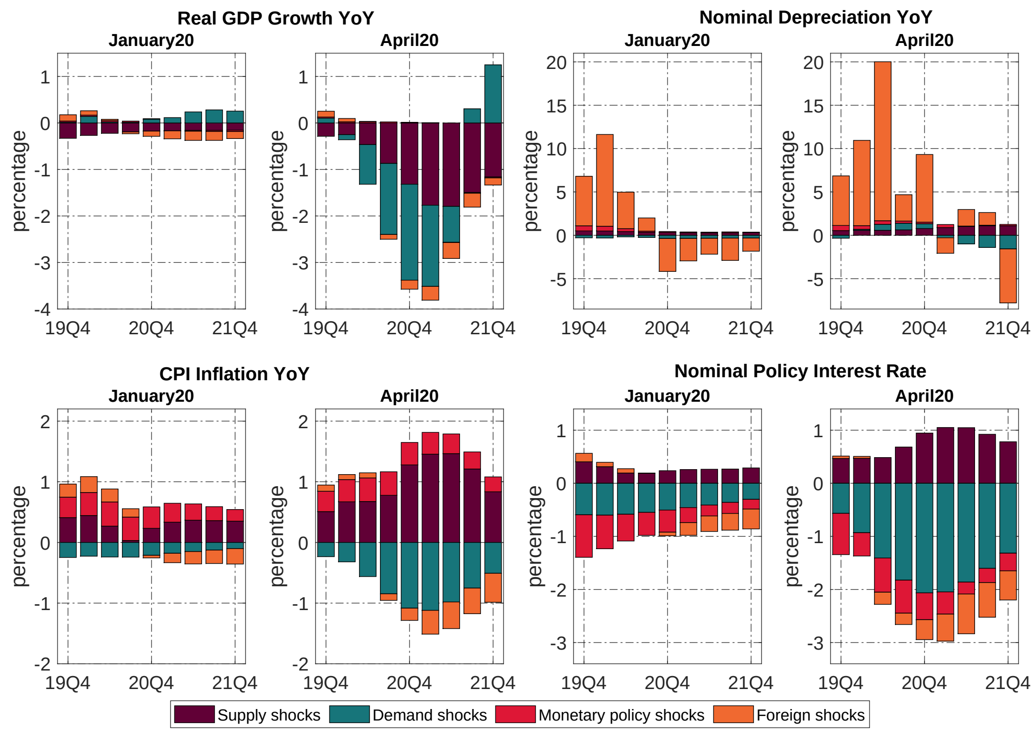
Figure 2: Variables Distributions at 20Q4



Graph depicts shock decomposition with respect to steady state. Supply shocks include potential growth and potential level.

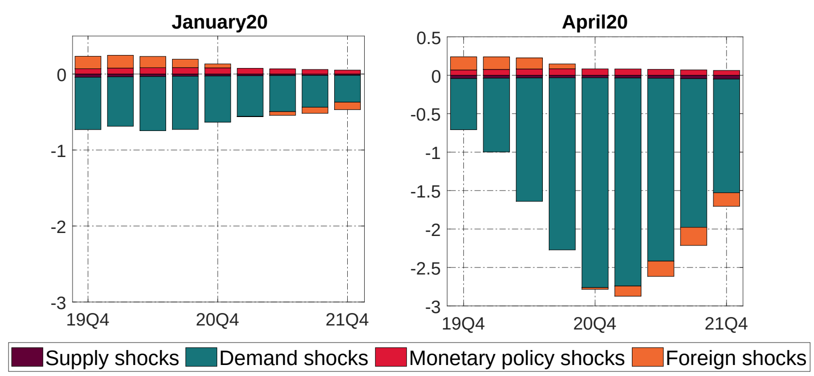
Furthermore, after filtering each analysts' set of forecasts through the model, macroeconomic stories emerge in terms of shocks. To initially grasp the general economic outlook on 2020 and 2021 implicit in the January20 release, these stories are averaged out and summarized in the mean shock decompositions depicted in Figure 3 and 4. First, the model interprets expected GDP growth would be underpinned by a dynamic local demand, despite potential output and foreign shocks might be slightly negative. Second, these shock decompositions also show that cost shocks might be pushing up inflation, while the real exchange rate appreciations generated by foreign shocks would constitute a disinflationary force. Mainly, a low Fed funds rate might be causing said appreciations and exerting further downward pressure on the monetary policy rate.

Figure 3: Variables' Mean Shock Decomposition



Graph depicts shock decomposition with respect to steady state. In the Real GDP growth shock decomposition, supply shocks include potential growth and potential level. In inflation, supply shocks are cost push shocks.

Figure 4: Output gap Mean Shock Decomposition

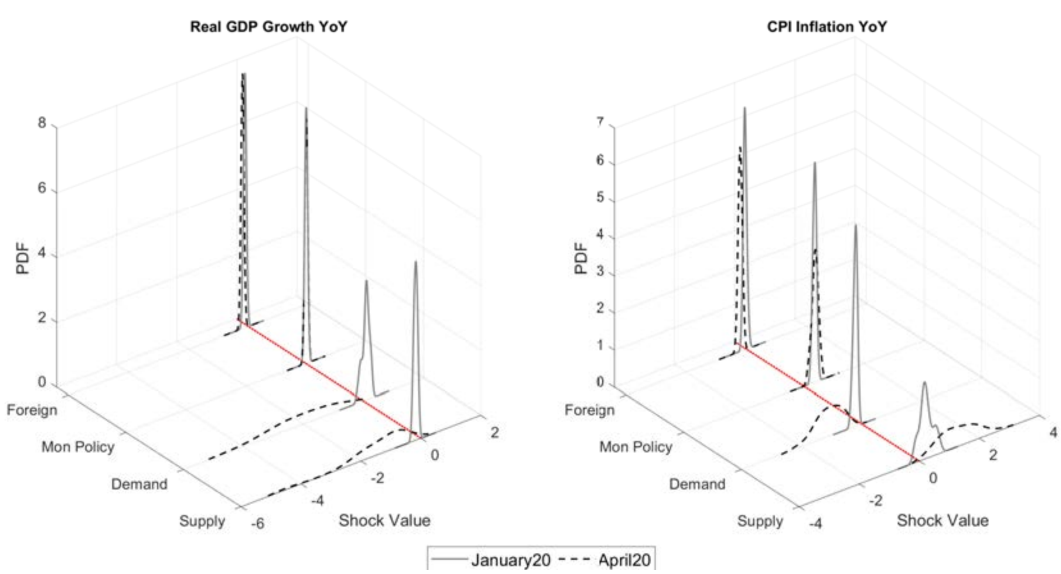


Graph depicts shock decomposition with respect to steady state where the output gap is zero.

Once the general outlook is retrieved, the next step is to ascertain if there is relative agreement among analysts about that story. Figure 5 contains the distributions for each group of shocks in the shock decompostion of GDP growth and inflation at 2020Q4. Previous to the pandemic, there was strong consensus about local demand playing a small positive role and aggregate supply a small negative one in GDP growth. After the pandemic started and lockdowns were imposed, all analysts agreed that demand was playing a negative role in GDP growth. There was also consensus about how this depressed local demand pushed inflation down, whilst cost shocks pushed it up. In spite the starting point matters to compute the output gap over the forecast horizon, the behavior of the shocks distributions for GDP growth is consistent with an average estimated output gap for 20T4 of -2.6% in April20, while it was projected to be -0,4% for the same period in the mean January20 projections.

Recall that, as mentioned in Section 3, monitoring the implicit output gap is a simple way of keeping track of the final balance between aggregate demand and aggregate supply forces. That is exceptionally relevant in the context of the pandemic since its unknown nature leads to questions about the relative importance of demand shortages and the destruction of productive capacity during the crisis. For instance, going back to Figure 2, it is possible to notice two ways in which the virus arrival drastically changed analysts' view about the economy's use of its productive capacity. First of all, in the April20 release, analysts seemed to broadly became more pessimistic about the implicit output gap, as the distribution shifted notoriously to the left. Secondly, there was a significant amplification of the distribution, reflecting more dissent among analysts about the size of the output gap. Albeit volatility surged, analysts implicitly agreed that output gap would be negative in 2020. It is worth highlighting that, even at the start of the crisis, this result indicates a general agreement among analysts on the COVID-19 shock being predominantly a negative demand shock.

Figure 5: Shocks Distributions for GDP and Inflation-2020Q4



Considering the variables observed by the model further elucidates the way it interprets April20 forecasts. According to Figure 2, most analysts became more pessimistic about GDP growth in 2020 but with similar inflation expectations, hence the negative shocks to potential output seen in Figure 5. Similarly, the negative shocks to domestic demand help explain the leftwards shift of the monetary policy rate distribution, despite inflation stability. Lastly, in the presence of wide and negative estimated output gaps, the model can only explain such stability through inflationary cost shocks. Potential explanations for these cost shocks are manifold and hard to pin down with this model and survey. Some plausible explanations are biosafety costs, capacity restrictions, goods scarcity, disruptions in global value chains, and lagged responses to weak demand.

As these decompositions illustrate, the entire macroeconomic landscape endured a profound revision, in which variables' paths changed course along with their drivers. It also exemplifies the unprecedented nature of the crisis, since analysts' implicit shocks for 2020 and 2021 were orders of magnitude larger than those of the January20 release. In fact, one striking narrative revealed by the shock decomposition for GDP growth is that domestic demand shocks are just as responsible for the recession in 2020 as they are for the recovery in 2021. Conversely, aggregate supply shocks that reduce potential output have an increasingly negative effect on GDP growth for 2021. On top of that, foreign shocks also hurt economic activity locally, which points out the global nature of the COVID-19 shock.

To a great extent, the stories of April20 were in sharp contrast with the general outlook implicit in the January20 release, therefore markedly symbolizing the sudden entrance of the virus. Nevertheless, the narratives stemming from the model's interpretation of April20 forecasts portrayed an early macroeconomic assessment on behalf of analysts while still at the dawn of an unknown shock. With most of the crisis yet unlived, analysts were likely to revisit in future MES releases their views of the Colombian economy during the next two years.

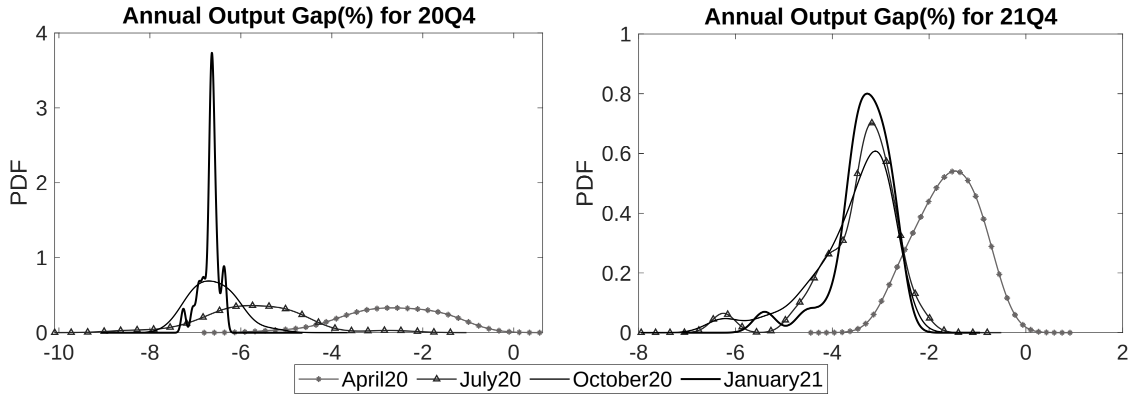
4.2 Evolution of the pandemic

In the April 20 release, analysts had already changed their outlooks in the face of the COVID-19 shock. From that point on, the pandemic saw many new domestic and global events unfold. We now analyze how analysts' macroeconomic perspectives changed as the pandemic and containment policies evolved and more information about the virus became available. For this purpose, the analysis carried out in this subsection will focus on an inter-temporal assessment of analysts' mean stories and their uncertainty across the following survey releases: April20, July20, October20 and January21[9]. Together these surveys cover the advent, peak and descent of the first wave of the pandemic in

[9]For the January21 survey GDP growth official data for the last quarter of 2020 were still not published. Therefore, data filtered for the end of 2020 are analysts 'nowcasts'.

Colombia.

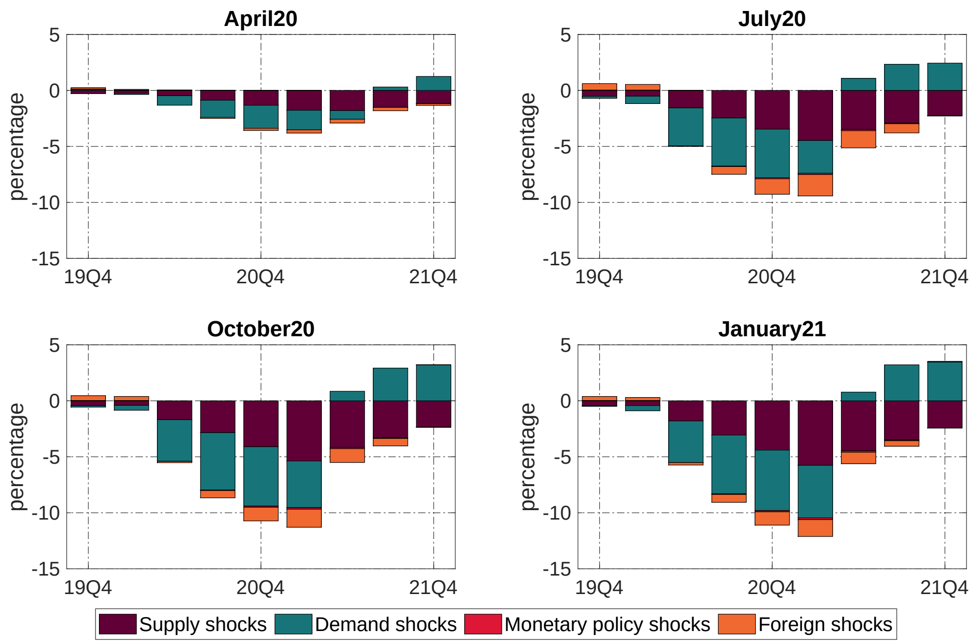
Figure 6: Output Gap Distribution



In this evolution, one thing that stood out was that from the start (April20), all analysts implicitly had a negative output gap for 2020 and 2021. As seen in Figure 6, this view qualitatively holds in every release, notwithstanding the high degree of disagreement about its exact value. Compared to April20, implicit output gaps for the end of 2020 moved downwards on July20, though the degree of disagreement about its magnitude remained almost the same. In the following releases, the output gap moved further down for 2020, while some analysts implicit output gap was marginally revised up for 2021 in each of the last two. Moreover, market's uncertainty about 2020 subsided significantly along survey releases, but not as much about 2021. Contrasting July20 with January21, analysts' implicit output gap went, on average, from -6.7% to -6.7% for 2020 and from -3.5% to -3.3% for 2021. Ultimately, this implies analysts seemed to be more certain that aggregate demand was hit harder in 2020 relative to aggregate supply due to COVID-19, but less so, about how much faster than aggregate supply it will recover in 2021.

The drivers of the output gaps implied in each MES release can be broadly seen in the mean shock decomposition for GDP growth depicted in Figure 7. These decompositions evidence that, on average, analysts considered domestic demand shocks to be the main driver of the recession caused by the COVID-19 pandemic in 2020 and the subsequent recovery in 2021. Importantly, they also estimated supply shocks would have lasting negative effects on GDP growth along the forecast horizon. This is also the case for foreign shocks, which analysts expected to slow down growth until the end of 2021, although to a lesser extent than supply shocks.

Figure 7: GDP Shock Decompositions

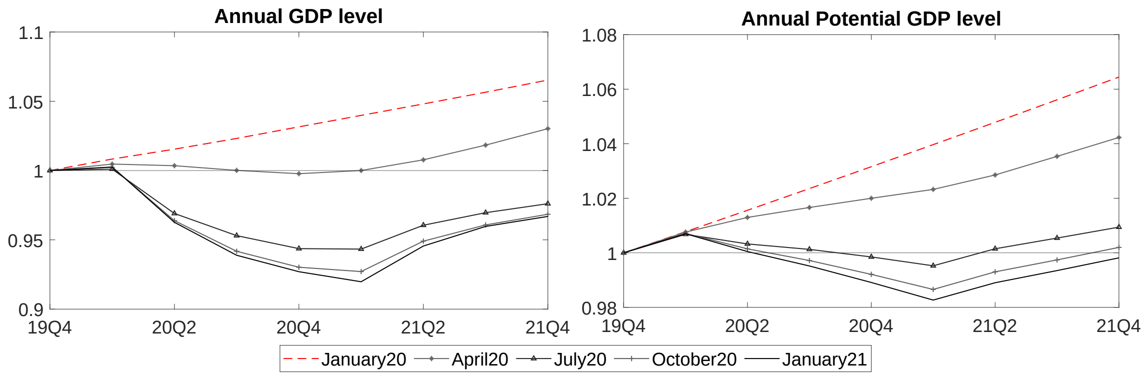


Graph depicts shock decomposition with respect to steady state. Supply shocks include potential growth and potential

Even though this macroeconomic narrative remains constant through all MES releases since the pandemic started, the quantitative assessment of the crisis and recovery did not. On the one hand, all shocks sizes were strongly revised between April20 and July20, witnessing the pessimism about the domestic economic consequences of the pandemic. Recall that when the July20 release was conducted, Colombia was at the peak of the pandemic and had endured almost four months of continuous lockdown. In the October20 and January21 releases, people already knew how bad was the 2020Q2 contraction, and consequently, analysts reassessed shock sizes more modestly. On the other hand, throughout the evolution of the pandemic, analysts seemed to be more optimistic about the recovery of domestic demand. For example, in the April20 release, analysts judged demand shocks would become positive in the last quarter of 2021. However, in the July20 release, this turning point moved two quarters ahead to 2021Q2. In the last two releases, these positive shocks subsequently increased despite the timing of the turning point did not change.

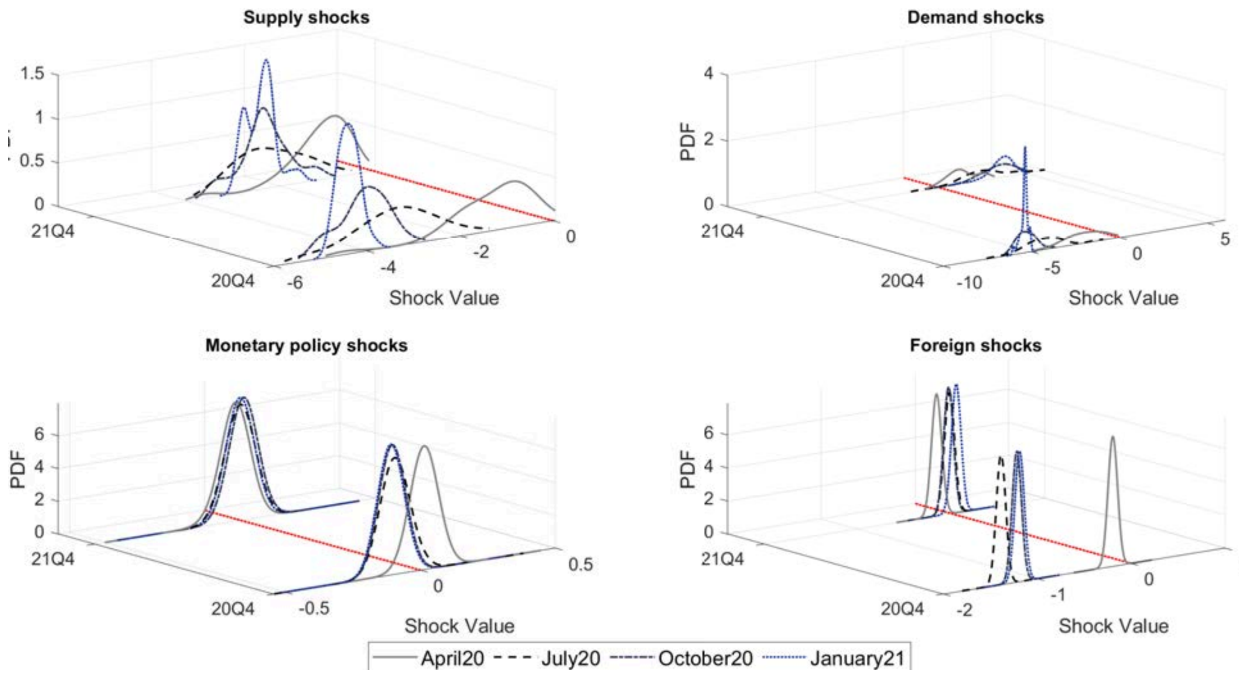
Analyzing the evolution of GDP and potential output levels throughout the releases provides additional insights to this story. Figure 8 depicts the mean forecasts of these levels in each survey release, normalized by their respective 2019 level. Notice the largest revisions for both variables were made in July20. Also these graphs show that analysts expected GDP level would not recover in the forecast horizon, while their implicit potential output level would do it in the second-half of 2021.

Figure 8: Annual GDP and Potential GDP Levels



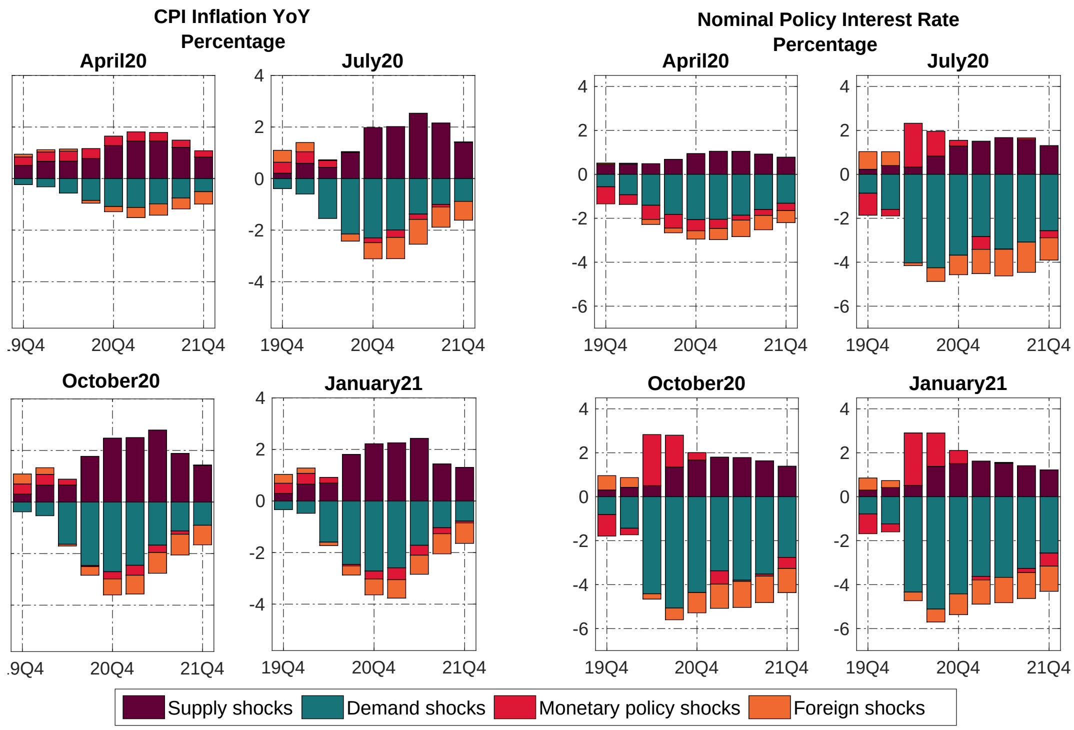
The story for GDP growth and output gap was true for all survey respondents, admitting there is high and time-variant dispersion across them. Figure 9 illustrates that for 2020 domestic demand shocks were always and growingly perceived negative by analysts, and that with each new survey, more analysts expected larger positive demand shocks for 2021. Particularly, demand shocks in 2020 were considered worst in each release, and analysts gradually centered more around the same negative value. Regarding 2021, analysts collectively moved towards more positive ground as the pandemic evolved. The graph also presents a similar pattern for supply shocks in 2020, yet uncertainty did not cave as quickly and markedly. As for 2021, contrary to demand shocks, supply shocks were consistently revised downwards (more negative) as the pandemic unfolded. Whereas monetary policy and foreign shocks were not a significant source of disagreement among analysts, they were a relevant source of inter-temporal variation throughout MES releases. Notably, foreign shocks had a negative revision for 2020 and 2021 in July20, but from that point on were consecutively adjusted upwards. This behavior might signal the fact that advanced economies such as the US bounced back faster than Colombia because they had their epidemic peak earlier and relaxed containment measures sooner.

Figure 9: GDP Shocks Distributions



To round up this macroeconomic story is important to take a look at prices and depreciation. Figure 10 shows the mean shock decompositions for inflation and the monetary policy rate. In the case of inflation, these graphs suggest that from the analysts' perspective, demand shocks, both domestic and foreign, were pushing prices down, while cost shocks put positive pressure on inflation. Of course, as said in the outbreak analysis, another substantial disinflationary force was the exchange rate appreciation caused by an extremely low Fed funds rate. On the whole, the stories for inflation and the implicit output gap jointly determine that of the monetary policy rate. From the model's perspective, the weak aggregate demand implied by analysts' forecasts for 2020 and foreign shocks explained the reductions and subsequent stability of the monetary policy rate. Similarly, these reductions were not larger because inflation was being held up by positive cost shocks. Unlike the macroeconomic story for GDP growth and the output gap, the shocks for inflation and monetary policy rate do not feature very important revisions after the July20 release.

Figure 10: Shock Decomposition



Graph depicts shock decomposition with respect to steady state. Supply shocks are cost push shocks.

All in all, since the pandemic outbreak in Colombia, the model interprets that economic analysts agreed the shock weakened aggregate demand more than potential output and that this view lasted throughout the pandemic. What is more, it construes there seemed to be consensus about the role of supply and demand in the macroeconomic adjustment to the pandemic, but not about the shocks' magnitudes. The market's uncertainty about what happened in 2020 shrank as analysts obtained more information about the pandemic and economic outcomes. Nonetheless, even in the last survey release, there was still much dissension on the size of the demand and supply shocks featuring the recovery in 2021. For that year, comparable disagreement about cost shocks affecting inflation and the monetary policy rate was observed. Such market's uncertainty about 2021 denotes that for analysts, the pandemic did not end in 2020 and withal draws attention to the usefulness of this methodology: in forthcoming MES releases, there are still many stories to be interpreted.

5 Concluding Remarks

Behind any economic expectation, there is an economic story. Modern macroeconomics focuses on the identification of the primitive exogenous forces generating business cycles to construct such stories. But macroeconomic forecasts collected through surveys are about endogenous variables. This paper uses a general equilibrium model as an interpreter to infer the shocks behind market analysts' forecasts and thus, unravel their implicit macroeconomic stories. As a case study, this methodology is applied to Colombia's MES releases during the COVID-19 pandemic, using the Kalman Smoother and IMF's canonical semi-structural New Keynesian model in Carabenciov et al. (2008a) for a small-open economy to filter analysts forecasts.

The results obtained show that filtering analysts' forecasts through this interpreter to obtain the implicit shocks can yield sound macroeconomic narratives that enrich survey expectations assessment by treating forecasts as *foredictions*. Although the stories thus obtained might not be the actual shocks analysts expected, they are those consistent with a rigorous framework built upon an economic theory one considers credible. Moreover, using such interpreter to analyze surveys enables comparisons between analysts and sheds light on why they might change their macroeconomic forecasts through time. It might also be used as a nontraditional device to measure the market's uncertainty about its general macroeconomic outlook and, more notably, to understand its sources in terms of shocks.

In the particular case of Colombia during the pandemic, the latter is illustrated by gathering, in light of the interpreter, a broad landscape of how analysts foresaw the unfolding of the COVID-19 crisis. From the advent of the virus, economic analysts agreed the shock weakened aggregate demand more than potential output in 2020. Conversely, in 2021 demand would boost the recovery while supply and foreign demand would continue to weigh down output growth. This view lasted throughout the pandemic. More dissent was observed about these shocks' magnitudes, despite the apparent qualitative consensus. The market's uncertainty about future domestic demand shocks on GDP's growth was larger than about aggregate supply shocks. For both shocks, this disagreement about their size in 2020 waned as the pandemic unfolded, but remained relatively high for 2021.

The latter exemplifies that the approach here proposed yields valuable results for different types of users, provided each believes in the interpreter employed. For instance, other analysts that want to understand why they differ (or not) from others could benefit from this methodology. Similarly, researchers interested in studying the possible stories behind surveys forecasts, the drivers of their changes through time and the sources of market's uncertainty about the future might find it useful. Lastly, policymakers might be prompted to use it on a regular basis. It would be especially helpful for central banks, who constantly monitor market expectations and communicate their own macroeconomic outlooks to the public, and thus, might want to compare analysts' foredictions with theirs and understand the sources of discrepancy through the lenses of the same framework.

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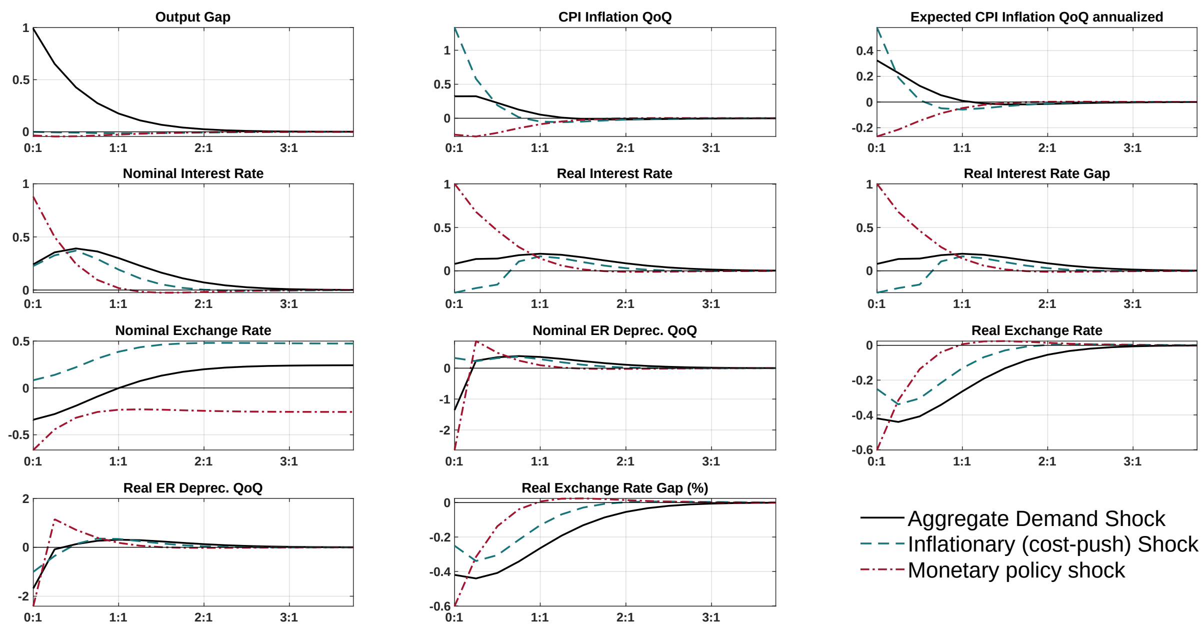
A Appendix Transmission Channels and IRF

Transmission Mechanisms and Model Historic Stories.

This section presents the impulse-response functions(IRF) and historical shock decompositions of the model's main variables. The latter depicts the macroeconomic story found by filtering historic Colombian data[10] through the interpreter used for the analysis.

First, we will describe the transmission channels of an aggregate demand shock, monetary policy shock, and an inflationary cost-push shock. For this, the IRF are a response to a positive, transitory, and equal to 1 standard deviation of the mentioned shocks. Then the historical shock decompositions are show and analyzed for the main variables: quarterly GDP growth, quarterly output gap, quarterly inflation, and the nominal interest rate, from 2007Q1 to 2019Q4.

Figure A.1: Impulse Response Functions



An aggregate demand shock creates a positive output gap that generates upward pressure on inflation and rises inflation expectations. In response to a positive GDP gap and inflation expectations, the monetary authority rise the nominal rate of interest inducing a contractionary policy stand (positive real interest rate gap); the latter leads to a negative nominal and real appreciation. This two effects, a higher real interest rate

[10]See calibration and estimation data in section 3.

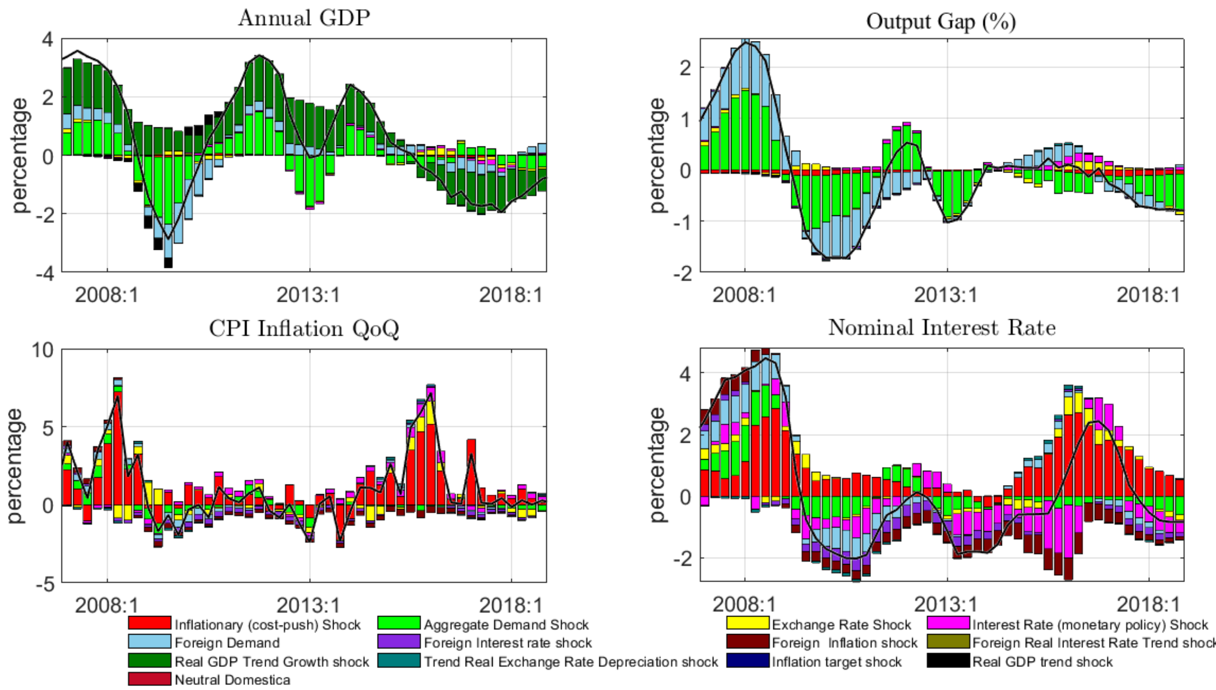
and a negative real exchange rate gap, induce a reduction of the aggregate demand and close the output gap, bringing the inflation and its expectations to the target.

The inflationary cost-push shock directly increases inflation and therefore, its expectations. Due to this, the monetary authority reacts by raising the nominal interest rate; this produce a depreciation in nominal terms. Nevertheless, inflation expectations one quarter ahead increase more than the nominal interest rate and induce a fall of the real interest rate, implying a negative interest rate gap. For the same reason, there is appreciation in real terms, opening a negative exchange rate gap. The response of the monetary policy rate in the depicted horizon increases over the first periods, while inflation expectations decrease, which makes that eventually the real interest rate gap is positive. Finally, a positive and real interest rate gap generates downward pressures on inflation and its expectations impliying a monetary contractionary policy stance that lead to the steady state.

Lastly, a monetary policy shock directly rises the nominal interest rate, inducing a fall of inflation expectations and, therefore, in inflation. As followed by Fisher equation, a higher nominal interest rate, together with the fall in expectations, increase the real interest rate. The contractionary monetary policy results in a contemporary appreciation of the nominal and real rate of exchange, that generates a negative RER gap. The latter, along with the contractionary monetary policy stance, reduce the aggregate demand, inducing a slightly negative output gap. In the depicted horizon, the dilution of the shock lead to a moderation of inflation expectations and inflation itself.

Figure A.2 depicts the historical shock decomposition of the main variables: quarterly GDP growth, quarterly output gap, quarterly inflation, and the nominal interest rate, from 2007Q1 to 2019Q4.

Figure A.2: Historical shock decompositions- deviation form the steady state



The shock decomposition shows how fluctuations around steady state are caused by positive and negative forces, implied by some identified shocks, according to the model and its given mechanisms presented above in the IRFs. We summarize some important events depicted in those shock decompositions to tell the story obtained by the model by filtering Colombian historic data.

For instance, the 2008-2009 financial crisis generated a decrease in GDP growth, explained by a foreign and local demand contraction (i.e. negative demand shocks). That debilitated demand opened the output gap. However, there were still positive supply shocks restraining the economic slowdown. Afterwards, when domestic demand began to recover, external growth (USA GDP) kept generating downward pressures on the aggregate demand. By analyzing headline inflation in this period, the negative local and foreign demand shocks were also pushing inflation downwards. On the other side, the exchange rate shocks, caused by the movements of the nominal exchange rate, were generating positive pressures on inflation. Nonetheless, Colombian economy was experiencing negative cost-push shocks that explain why inflation was bellow the target.Finally, the interest rate fall in response to lower inflation and to a harmed global and local demand.

Other important episode displayed in figue A.2 is the 2014 fall in commodity prices, specially in the oil price that is an improtant component of Colombian production and revenues. This shock is therefore captured mainly by a decrease in real activity by supply shocks, as seen in the yearly growth of real GDP for the 2015 and posterior years. Note that the model also identify some negative local demand shocks that push downward the output gap. The inflation and nominal interest rate shock decompositions show that, in addition to big inflationary cost push shocks due to local strikes and climate effects, the fall in oil prices induced depreciation that pushed inflation and the interest rate upward. The latter is captured by the exchange rate shock but also in the real exchange rate depreciation trend shock.

B Appendix Estimation Data Sources and Details

The observable data were taken from:

- **Colombian GDP**: National Administrative Department of Statistics (DANE). Constant prices(2015) and seasonally adjusted.
- **Colombian inflation**: National Administrative Department of Statistics (DANE). Quarterly Consumer price Index variation. We do the seasonally adjustment using an ARIMA-X12.
- **Exchange rate**: Central Bank of Colombia. "Tasa Representativa del Mercado (TRM)" Colombian peso/USD.
- **Monetary policy rate**: Central Bank of Colombia. Quarterly average interest rate.
- **USA GDP**: Bureau of Economics Analysis. Seasonally adjusted, constant prices (2012) quarterly GDP growth at annual rates.
- **USA monetary policy rate**: USA Federal Reserve. Nominal FED's funds rate, quarterly average.
- **USA inflation rate**:US Bureau of labor statistics. Seasonally adjusted quarterly USA Consumer price Index variation.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