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Aggregate demand and aggregate supply effects of Covid-19: A real-time analysis[1]

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We extract aggregate demand and supply shocks for the US economy from real-time survey data on inflation and real GDP growth using a novel identification scheme. Our approach exploits non-Gaussian features of macroeconomic forecast revisions and imposes minimal theoretical assumptions. After verifying that our results for US post-war business cycle fluctuations are largely in line with the prevailing consensus, we proceed to study output and price fluctuations during COVID-19. We attribute two thirds of the decline in 2020:Q1 GDP to a negative shock to aggregate demand. In contrast, regarding the staggeringly large decline in GDP in 2020:Q2, we estimate two thirds of this shock was due to a reduction in aggregate supply. Statistical analysis suggests a slow recovery due to persistent effects of the supply shock, but surveys suggest a somewhat faster rebound with a recovery in aggregate supply leading the way.

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Aggregate Demand and Aggregate Supply Effects of COVID-19: A Real-time Analysis

1 Introduction

Distinguishing supply shocks from demand shocks has long been a goal of empirical macroeconomics (e.g., Shapiro and Watson, 1988, Blanchard and Quah, 1989, or Gali, 1992), in part because the appropriate monetary and fiscal policy responses may be quite different for adverse demand versus supply shocks. We define aggregate supply shocks as shocks that move inflation and real activity in the opposite direction. Similarly, demand shocks are defined as innovations that move inflation and real activity in the same direction. This definition is motivated by Blanchard (1989), who finds empirically that the joint behavior of output, unemployment, prices, wages and nominal money in the U.S. is consistent with this structure.

The decomposition is of particular interest in the context of the COVID-19 pandemic. While it is intuitively clear that, for instance, oil crises in the 1970s constituted aggregate supply shocks and the Volcker experiment an aggregate demand shock, the economic fluctuations during COVID-19 combine a range of different effects. The massive lockdown of the economy represents a large negative demand shock. However, an accompanying increase in unemployment benefits has increased the income of some low- and middle-income households at least temporarily[1], which could helpfully support aggregate demand. At the same time, supply chains in a number of industries have been affected not only internationally, with international trade in general greatly reduced, but also domestically, resulting in price increases for many goods and services.[2] With increased unemployment benefits some workers may experience greater income staying at home

[1]For instance, *"Coronavirus Relief Often Pays Workers More Than Work"*, Wall Street Journal, April 28, 2020, by Eric Morath: `http://www.wsj.com/articles/coronavirus-relief-often-pays-workers-more-than-work-11588066200`

[2]Among others, *"Grocers Hunt for Meat as Coronavirus Hobbles Beef and Pork Plants"*, Wall Street Journal, April 23, 2020, by Jacob Bunge, Sarah Nassauer, and Jaewon Kang: `http://www.wsj.com/articles/grocers-hunt-meat-as-coronavirus-hobbles-beef-and-pork-plants-11587679833`.

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rather than returning to work.[3] This situation may have positive effects on public health by supporting social distancing, but it may also further complicate the process of business re-openings. Among others, Mulligan (2012) argues that this type of unemployment benefits has been one of the main reasons for the long and slow recovery following the Great Recession. Low energy prices could potentially offset some of the negative supply effects: oil prices have plummeted due to a combination of OPEC policies and weak fuel demand.[4]

In this article, we quantify the relative magnitudes of the aggregate demand and aggregate supply shocks during the first two quarters of COVID-19. Our identification of demand and supply shocks follows Bekaert, Engstrom, and Ermolov (2020) and differs from the extant literature. First, we extract aggregate supply and demand shocks for the US economy from survey data on inflation and real GDP growth. By using survey-based forecast revisions to measure shocks, there is no need to model the conditional means of inflation and output growth, and survey-based shocks are observed in real time. Second, we use a novel approach to resolve the identification problem for the structural aggregate supply and aggregate demand (AS/AD) shocks. We exploit unconditional higher-order moments in the data, which we show to be highly statistically significant in the post-war US data, even excluding the COVID-19 episode. Despite this economically agnostic approach, we show that the structural shocks that we identify exhibit some intuitive properties. For example, in a classic paper, Blanchard and Quah (1989) use a vector-autoregressive dynamic structure to identify "demand-like" shocks as shocks that affect output temporarily, whereas supply disturbances have a permanent effect on output. The shocks that we estimate also exhibit these dynamic properties, even though we do not impose them ex-ante.

We first examine the AS/AD classification of earlier recessions, finding that our clas-

[3]For example, *Paying Americans Not to Work*, Wall Street Journal, April 22, 2020, Editorial: `http://www.wsj.com/articles/paying-americans-not-to-work-11587597150`.

[4]For example, *Oil Prices Fall as Demand Concerns Outweigh Supply Cuts*, Wall Street Journal, May 11, 2020, by Amrith Ramkumar: `https://www.wsj.com/articles/oil-prices-swing-after-saudi-arabia-deepens-supply-cuts-11589205635`,

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sification of the recessions up to the eighties largely corroborates earlier work by Gali (1992). We find that negative demand shocks contributed more importantly to the Great Recession than supply shocks, in line with work by Mian and Sufi (2014), who conclude using micro data that lower aggregate demand was the main cause of the steep drop in employment during the Great Recession.

We next proceed to quantify the AS/AD decomposition of the COVID-19 event. We estimate that the real GDP growth shock during 2020:Q1 is -6.6 percent at an annual rate, and is largely due to an aggregate demand shock. In 2020:Q2 the real GDP growth shock is -34.3 percent at an annual rate. We find that roughly two thirds of it, -19.5 percent, is due to an aggregate supply shock and the rest, -14.8 percent, is due to an aggregate demand shock. Forecast revisions for 2020:Q3-2021:Q1 suggest that the recovery will be "check mark"-shaped and more aggregate supply driven, although the aggregate demand component contributes to the recovery as well. This somewhat contradicts a statistical analysis based on historical data which suggests a multi-year recovery, because of the permanent growth effect due to the large AS shock, a view some leading experts concur with.[5]

The rest of the paper is organized as follows. Section 2 describes our structural framework and identification. Section 3 focuses on the estimation and Section 4 on the COVID-19 analysis. Section 5 concludes.

2 Modeling Macro Shocks

2.1 A simple model of aggregate supply and demand shocks

Consider a bivariate system in real GDP Growth (g_t) and inflation (π_t):

$$\begin{aligned} g_t &= E_{t-1}[g_t] + u_t^g, \\ \pi_t &= E_{t-1}[\pi_t] + u_t^\pi, \end{aligned} \tag{1}$$

[5]For example, "Why Our Economy May Be Headed for a Decade of Depression", New York Magazine, May 22, by Eric Levitz: `http://nymag.com/intelligencer/2020/05/why-the-economy-is-headed-for-a-post-coronavirus-depression-nouriel-roubini.html`.

where E_{t-1} denotes the conditional expectation operator. We model the shocks to output growth and inflation as a function of two structural shocks, u_t^s and u_t^d:

$$\begin{aligned}
&u_t^\pi = -\sigma_{\pi s} u_t^s + \sigma_{\pi d} u_t^d,\\
&u_t^g = \sigma_{gs} u_t^s + \sigma_{gd} u_t^d,\\
&\sigma_{\pi s} > 0, \sigma_{\pi d} > 0, \sigma_{gs} > 0, \sigma_{gd} > 0,\\
&Cov(u_t^d, u_t^s) = 0, Var(u_t^d) = Var(u_t^s) = 1.
\end{aligned} \tag{2}$$

The first fundamental economic shock, u_t^s, is an aggregate supply shock, defined so that it moves GDP growth and inflation in opposite directions, as happens, for instance, in episodes of stagflation. The second fundamental shock, u_t^d , is an aggregate demand shock, defined so that it moves GDP growth and inflation in the same direction as would be the case in a typical economic boom or recession. Supply and demand shocks are assumed to be uncorrelated, and we also assume co-skewness moments to be zero ($E[(u_t^s)^2 u_t^d] = E[u_t^s (u_t^d)^2] = 0$).

Note that the sample covariance matrix of the shocks from the bivariate system in (1) only yields three unique moments (two variances and the covariance), but we need to identify four coefficients in equation (2) to extract the supply and demand shocks. Hence, absent additional assumptions, a system with Gaussian shocks would be underidentified. Fortunately, it has been well established that macroeconomic data exhibit substantial non-Gaussian features (see, e.g., Evans and Wachtel (1993) for inflation, and Hamilton (1989) for GDP growth). Thus, we exploit that the demand and supply shocks are potentially non-Gaussian in that they may have non-zero unconditional skewness and excess kurtosis. For example, there are four available univariate unconditional skewness and co-skewness moments for GDP growth and inflation. These four moments, in conjunction with the three available second moments, could in principle be used to identify the four $\sigma_{\pi/g,s/d}$ parameters (of course, we also have to estimate the unconditional skewness and kurtosis of the supply and demand shocks in this case, which we do).

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While econometrically it is clear that non-Gaussianity achieves identification (see Lanne, Meitz, and Saikkonen, 2017, for a theoretical paper on obtaining identification through higher-order moments in a VAR and Bekaert, Engstrom, and Ermolov, 2019, for an empirical application to the US term structure), it is useful to clarify the economic sources of identification. Consider, for example, co-skewness moments, that is, in unscaled form, the expectation of the inflation shock squared times the GDP growth shock or vice versa. Under our formulation, the coskewness of inflation and real activity shocks are as follows:

$$\begin{aligned} E[u_t^g(u_t^\pi)^2] &= \sigma_{gd}\sigma_{\pi d}^2 E[(u_t^d)^3] + \sigma_{gs}\sigma_{\pi s}^2 E[(u_t^s)^3], \\ E[(u_t^g)^2 u_t^\pi] &= \sigma_{gd}^2\sigma_{\pi d} E[(u_t^d)^3] - \sigma_{gs}^2\sigma_{\pi s} E[(u_t^s)^3]. \end{aligned} \tag{3}$$

Clearly, such moments only depend on the shock sensitivities and the third moments of supply and demand shocks and, thus, would be zero under Gaussianity. Suppose that demand and supply shocks are negatively skewed to a similar degree (if they are differentially skewed, that information also helps identification). In this case, the $E[u_t^g(u_t^\pi)^2)]$-moment has a negative contribution coming from both supply shocks (as the movements of inflation and GDP growth in opposite directions are cancelled) and demand shocks. However, the $E[(u_t^g)^2 u_t^\pi]$ moment retains its negative contribution from demand shocks but obtains a positive contribution from supply shocks (as the negative skewness is multiplied by shock exposures of opposite sign). Therefore, skewed structural shocks should result in different magnitudes of these two co-skewness moments, with the inflation squared moment much more negative than the GDP growth squared moment. The exact relative magnitude of these two moments then reveals information about the sensitivity of the macro shocks to the structural shocks.

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2.2 The Interpretation of the Macro Shocks

The main advantage of the definition of the supply and demand shocks above is that it carries minimal theoretical restrictions (only a sign restriction).[6] However, these supply and demand shocks definitions do not necessarily comport with demand and supply shocks in, say, a New Keynesian framework (see e.g. Woodford, 2003) or identified VARs in the Sims tradition (Sims, 1980).[7] The classic Blanchard and Quah (1989) paper famously identifies "demand-like" shocks as those that affect output only temporarily whereas supply disturbances have a permanent effect on output, with neither having a long run effect on unemployment rate. However, Blanchard (1989) notes that these short- and long-run effects of supply and demand shocks are consistent with responses to shocks in the context of standard Keynesian models. For instance, supply shocks include productivity shocks which tend to have a longer run effect on output. We reverse the identification strategy here, by first exploiting the sign restrictions to identify the shocks, and then verifying their long-run impact on inflation and real activity in subsequent analysis.

3 Identifying Macro Shocks in the US economy

The estimation consists of two steps. First, we use survey data to measure reduced-form shocks to the macroeconomic activity. Second, we filter the demand and supply shocks from the system in equation (2) by estimating a classical minimum distance system that includes higher-order unconditional moments of the macroeconomic variables. We begin by describing the data we use.

3.1 Data

As indicated above, we use survey data to identify reduced-form macroeconomic shocks. The survey data are from the Survey of Professional Forecasters (SPF). They are

[6]The idea to impose a minimal set of sign restrictions to achieve identification is reminiscent of Uhlig's (2005) identification scheme for monetary policy shocks. Gali (1992) uses sign restrictions similar to ours in a VAR setting but does not obtain identification through non-Gaussianity.

[7]Furthermore, in some models the "supply" shocks might move real activity and inflation in the same direction: see, for instance, news shocks in Cochrane (1994).

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available quarterly from 1968:Q4. We use data through 2019:Q2 for the estimation and then analyze the dynamics during 2020:Q1 and 2020:Q2 using the estimated parameters. In this way, our analysis of the COVID-19 event is an out-of-sample exercise, relying on identification using higher-order moments that exist in the in-sample period.

We show below that even prior to the COVID-19 recession, non-Gaussian features of our macroeconomic survey data are very statistically and economically significant in our sample. To identify inflation shocks we use revisions to survey forecasts:

$$u_t^\pi = E_t[\pi_t] - E_{t-1}[\pi_t], \tag{4}$$

where π_t is the percentage change in the GDP deflator and E_t refers to the mean survey-based expectation at time t. The SPF survey is usually published in the middle of the second month of each quarter.[8] As a concrete example, our measured revision to inflation for the period 2020:Q1 is equal to the SPF expectation as of early February 2020 for inflation for 2020:Q1 inflation minus the expectation for 2020:Q1 inflation that was measured in the previous SPF survey, taken in early November 2019. Our inflation data refers to the percentage change in the GDP price deflator over the first (calendar) quarter of 2020; this data is first published by the Bureau of Economic Analysis in April.

Survey-based measures have the advantage of being model-free, and also capture, in principle, the real time expectations of market participants. Ang, Bekaert and Wei (2007) show that inflation expectations from the SPF provide accurate forecasts of future inflation, compared to statistical forecasts. Similarly, we measure shocks to the outlook for real activity as:

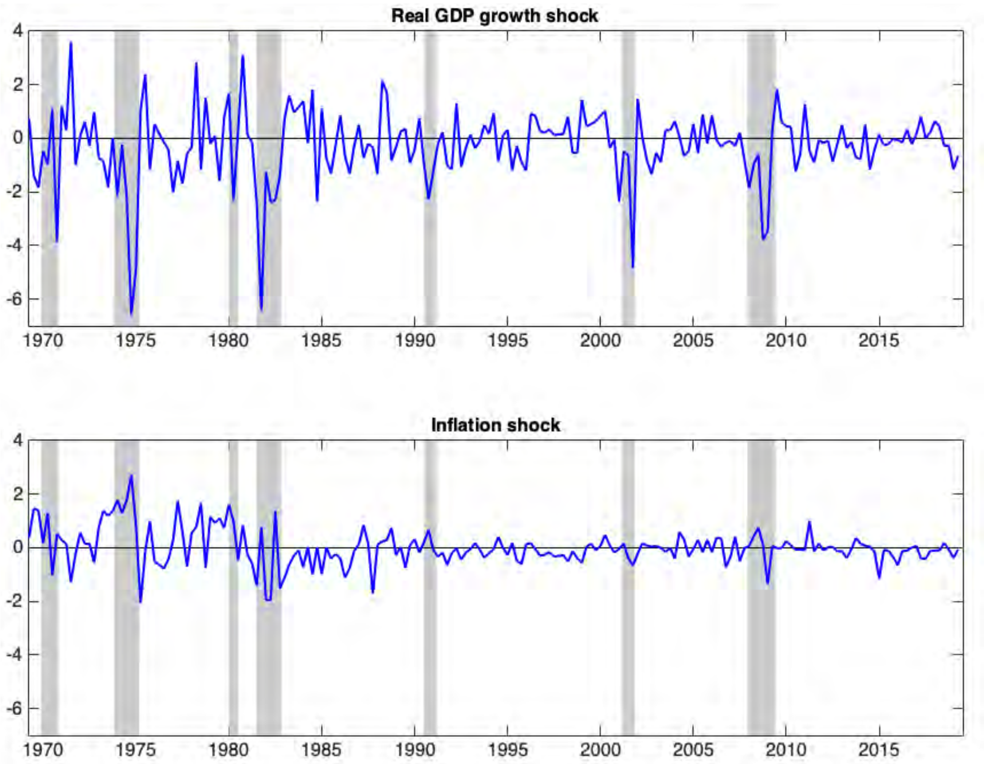
$$u_t^g = E_t[g_t] - E_{t-1}[g_t], \tag{5}$$

where g_t is the percentage change in real GDP growth.

[8] A few historical disruptions have caused the survey to be published later in the quarters. See `https://www.philadelphiafed.org/-/media/research-and-data/real-time-center/survey-of-professional-forecasters/spf-release-dates.txt?la=en`.

Using forecast revisions to measure shocks obviates the need to model GDP growth and inflation dynamics and conduct model selection. Figure 1 depicts the real GDP and inflation shocks that we use in the estimation, expressed at annual rates. Shocks to real GDP shocks are generally larger earlier in the sample, and deeply negative spikes occur during recessions throughout the sample. Similarly inflation variability is higher earlier in the sample and large positive and negative spikes are evident during recessions that occur early in the sample period. Later in the sample period, the overall variability of inflation decreases and the shocks during recessions are notably negative.

Figure 1 – Real GDP Growth and Inflation Shocks. The sample is quarterly 1968Q4-2019Q2. Shading corresponds to NBER Recessions.



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3.2 Identifying supply and demand shocks

To begin, note that if we can identify the σ coefficients in (2), we can infer the supply and demand shocks from the original macro shocks u_t^π and u_t^g.[9]

To estimate the σ coefficients, we use information in all available 2^{nd}, 3^{rd} and 4^{th} order unconditional moments of the reduced-form macroeconomic shocks in a classical minimum distance (CMD) estimation framework (see, e.g., Wooldridge, 2002, pp. 445-446). Specifically, we calculate 12 statistics based on the two series of shocks measured in the survey data. These are the unconditional standard deviations (2 statistics), the correlation (1 statistic), univariate (scaled) skewness and excess kurtosis (4 statistics), co-skewness (2 statistics), and co-excess kurtosis measures (3 statistics). The parameters we use to match these moments include the loadings of inflation and real activity onto supply and demand shocks (σ_π^d, σ_π^s, σ_g^d, σ_g^s), the unconditional skewness ($E[(u_t^d)^3]$ and $E[(u_t^s)^3]$) and excess kurtosis ($E[(u_t^d)^4] - 3$ and $E[(u_t^s)^4] - 3$) of supply and demand shocks, and the excess cross kurtosis of supply and demand shocks ($E[(u_t^d)^2(u_t^s)^2] - 1$). The final parameter, $E[(u_t^d)^2(u_t^s)^2] - 1$, captures that the volatility of supply and demand shocks may be correlated, even though the shocks themselves are assumed to be uncorrelated.

With 12 moments to match and 9 parameters to estimate, our system is overidentified, thus requiring a weighting matrix. To generate a weighting matrix, we use the inverse of the covariance matrix of the sampling error for the statistics, consistent with asymptotic theory suggesting that this choice leads to efficient estimates. We use a block bootstrapping routine to calculate the covariance matrix,. Specifically, we sample, with replacement, blocks of length 12 quarters of the two survey-based macroeconomic shocks, to build up a synthetic sample of length equal to that of our data. We calculate the same set of higher order statistics for each of 10,000 synthetic samples. We then calculate the covariance matrix of these statistics across bootstrap samples.

Table 1 reports the sample higher-order moments we use in the estimation, bearing

[9]The inverse of the 2×2 matrix $\begin{bmatrix} \sigma_{gs} & \sigma_{gd} \\ -\sigma_{\pi s} & \sigma_{\pi d} \end{bmatrix}$ multiplied by $\begin{bmatrix} u_t^g \\ u_t^\pi \end{bmatrix}$ yields $\begin{bmatrix} u_t^s \\ u_t^d \end{bmatrix}$.

in mind that these statistics are based on the in-sample period that ends in 2019:Q2. Not surprisingly, all volatility statistics are statistically significantly different from zero, but the unconditional correlation of inflation revisions and revisions to real growth is insignificantly different from zero at -0.13. Real growth shocks are significantly negatively skewed with a skewness of -1.23, and the co-skewness moment involving inflation revisions squared times real growth revisions is significantly negative. Together, these two moments suggest that that real growth is, on average, more negative when inflation volatility is high and when real growth volatility is high. The excess kurtosis of real growth is significantly positive with a value of 4.71, as is the fourth moment involving squared inflation revisions times squared growth revisions. The latter indicates that the volatilities of inflation and real growth tend move together. The p-value for the joint significance of all the 3^{rd} and 4^{th} order moments is 0.26 percent, strongly rejecting the hypothesis that the data are distributed unconditionally according to a multivariate Gaussian distribution and providing strong support for our identification assumption.

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Table 1 – Unconditional Moments of Macroeconomic Revisions: Classical Minimum Distance Fit. The sample is quarterly 1968Q4-2019Q2. *** corresponds to statistical significance at the 1 percent level.

	Standard deviation		Correlation		
	u_t^π	u_t^g	$u_t^\pi u_t^g$		
Data	0.6361	1.1885	-0.1344		
Standard error	(0.0913)	(0.1448)	(0.1555)		
Fitted value	[0.7083]	[1.3295]	[-0.2776]		
	Skewness		Coskewness		
	u_t^π	u_t^g	$(u_t^\pi)^2 u_t^g$	$u_t^\pi (u_t^g)^2$	
Data	0.2005	-1.2343	-0.7873	0.4309	
Standard error	(0.3712)	(0.3890)	(0.2674)	(0.4884)	
Fitted value	[0.3663]	[-1.4465]	[-0.9808]	[0.4874]	
	Excess kurtosis		Excess cokurtosis		
	u_t^π	u_t^g	$(u_t^\pi)^2 (u_t^g)^2$	$(u_t^\pi)^3 u_t^g$	$u_t^\pi (u_t^g)^3$
Data	1.7280	4.7138	1.9239	-0.5464	-1.6186
Standard error	(0.9813)	(1.3877)	(0.8979)	(1.1467)	(1.5647)
Fitted value	[1.7502]	[4.3216]	[2.6462]	[-1.7761]	[-3.2401]
Test for joint significance of 3^{rd} and 4^{th} order moments					
J-stat	25.3618				
p-value	0.26%***				
Overidentification test					
J-stat	2.9781				
p-value	38.74%				

In Table 2, Panel A, we report the supply and demand loadings for GDP growth and inflation. These are generally quite precisely estimated. Our estimates suggest that supply and demand shocks contribute roughly equally to the unconditional variance of inflation shocks over this sample period: the inflation supply and demand loadings are -0.48 and 0.51, respectively. For real growth, supply shocks, unconditionally, contribute somewhat more than demand shocks to the overall variance: the real GDP growth supply and demand loadings are 1.18 and 0.60 respectively.

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Table 2 – CMD Parameter Estimates. Asymptotic standard errors are in parentheses.

Panel A: Loadings of Reduced-form Shocks onto Supply and Demand Shocks		
	u_t^π	u_t^g
u_t^s	-0.4829	1.1802
	(0.0566)	(0.1129)
u_t^d	0.5141	0.6035
	(0.0685)	(0.1064)
Panel B: Higher-order Moments of Supply and Demand Shocks		
	Skewness	Excess kurtosis
u_t^s	-1.9563	6.8535
	(0.3873)	(1.5692)
u_t^d	-0.6896	1.0062
	(0.5413)	(1.6825)
Co-excess kurtosis	-0.0095	
	(0.2843)	

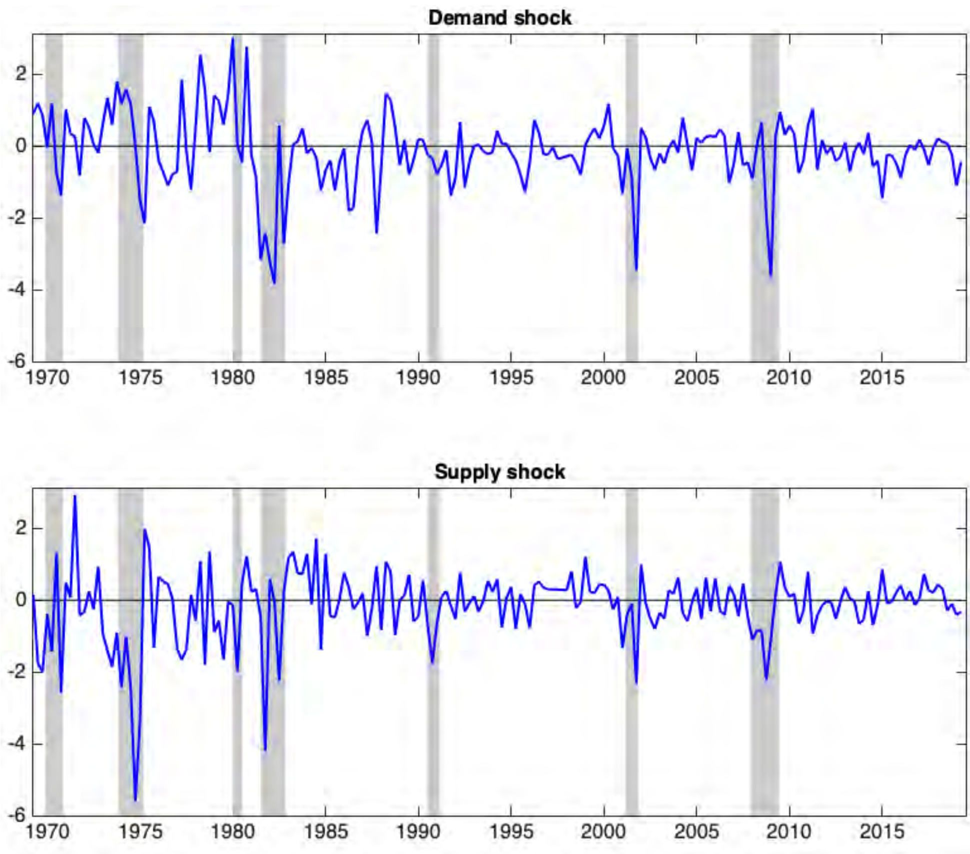
Returning to Table 1, in square brackets we report the fitted values for all statistics. Recall that because the system is overidentified by 3 degrees of freedom, not all moments can be fit perfectly. Nonetheless the overall fit is quite good. All second and third-order moments are within a one standard error band of the point estimate, and all the fourth order moments are within a two standard error band. We also report a standard overidentification test for the CMD model fit. The corresponding p-value is 38.74 percent implying that the model is not rejected.

3.3 Properties of Demand and Supply Shocks

In Panel B of Table 2, we report the estimated skewness and kurtosis of the supply and demand shocks. Both shocks are negatively skewed and leptokurtic (though only for supply shocks are these estimates statistically significant). Interestingly, we find little evidence for excess co-kurtosis, meaning that the variances of supply and demand shocks do not covary strongly on an unconditional basis.

Figure 2 depicts the supply and demand shocks that we recover from this exercise. Both sets of shocks exhibit greater overall variability early in the sample period, followed by a secular decline that perhaps reflects the so-called "Great Moderation", although deeply negative shocks occur during recessions throughout the entire sample.

Figure 2 – Aggregate Demand and Aggregate Supply Shocks. The sample is quarterly 1968Q4-2019Q2. Shading corresponds to NBER Recessions.



Our identification of supply and demand shocks utilizes a set of minimal linear sign restrictions and information in higher order moments. These sign restrictions are present in other classic papers as well, such as Gali (1992), but are accompanied by a set of additional economic restrictions (e.g., that demand shocks have no long run effect on the level of GDP as in the classic Blanchard and Quah (1989) paper) which we do not need.[10]

[10]Shapiro and Watson (1988) show that key results may depend on assumptions regarding differencing and cointegration of the data.

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We now characterize the long run effects of the structural shocks using standard impulse response analysis.

To do so, we estimate a VAR on real GDP growth and aggregate inflation, using final, revised quarterly data from the St. Louis Federal Reserve "Fred". Our demand and supply shocks computed from forecast revisions serve as the structural shocks to the VAR and we retrieve the contemporaneous loadings of real GDP growth and inflation on these shocks by simple regression analysis. We then compute impulse responses of real GDP growth and inflation to one standard deviation demand and supply shocks, with confidence intervals determined via block-bootstrap. In particular, our VAR model is:

$$Y_t = A_0 + A_1 Y_{t-1} + S \begin{bmatrix} u_t^s \\ u_t^d \end{bmatrix} + \epsilon_t, \tag{6}$$

where Y_t is the vector of final, revised real GDP growth and inflation, $\begin{bmatrix} u_t^s \\ u_t^d \end{bmatrix}$ are pre-estimated structural shocks from the SPF, and ϵ_t is a residual noise vector.

Table 3 contains the results, with the contemporaneous (long-term) effects of demand and supply shocks on the left (right). The effects are consistent with the standard Keynesian interpretation. Demand shocks have positive short run effects on real GDP growth (with the contemporaneous response being 0.19 percent and highly statistically significant) but their cumulative effect on output is 0.00 percent out to two decimal places. Supply shocks generate larger short run GDP growth effects (0.32 percent and highly statistically significant) and their cumulative effect at 0.66 percent is economically large and strongly statistically significantly different from zero.

As expected, demand and supply shocks have very different effects on the price level. The contemporaneous demand shock increases the price level by 0.33 percent and the contemporaneous supply shock decreases it by 0.18 percent, with both values highly statistically significant. While the cumulative effect of the demand shock is 1.17 percent and statistically significant, the supply shock effect peters out to zero. In sum, our identification scheme yields shocks whose long-run effects are consistent with a well-established macroeconomic literature.

Table 3 – VAR Impulse Responses of Real GDP and Aggregate Price Level to One Standard Deviation Demand and Supply Shocks. The data are 1968:Q4-2019:Q2 quarterly. The VAR model is: $Y_t = A_0 + A_1 Y_{t-1} + S[u_t^s, u_t^d]' + \epsilon_t$, where Y_t is the vector of final, revised real GDP growth and inflation, $[u_t^s, u_t^d]'$ are pre-estimated structural shocks from the SPF, and ϵ_t is a residual noise vector. The cumulative impulse responses include the quarter 0 (where the shocks happened) responses. Numbers in parentheses are probabilities that the impulse response is less than 0 obtained from 10,000 block-bootstrap samples of historical length with the block size of 8 quarters. The asterisks, ***, correspond to statistical significance at the 1 percent level.

	Contemporaneous (quarter 0) responses		Cumulative (20 quarters) responses	
Shock	Real GDP level	Price level	Real GDP level	Price level
Demand	0.19%***	0.33%***	0.00%	1.17%***
	(0.22%)	(0.00%)	(52.25%)	(0.00%)
Supply	0.32%***	-0.18%***	0.66%***	-0.45%
	(0.00%)	(99.98%)	(0.00%)	(93.95%)

3.4 Characterizing NBER Recessions Using Aggregate Demand and Supply Shocks

Our identification of supply and demand shocks allows us to characterize recessions as either supply or demand driven (or a combination of both). Table 4 quantifies this by simply adding up the (net) demand and supply shocks over the recession period (that is, positive and negative shocks can cancel each other out). The 1980 recession did not feature negative cumulative demand shocks but all the other recessions did, with the 1981-82 recession and the Great Recession featuring the largest negative demand shocks. All recessions except the 1981-1982 one featured negative supply shocks, with the largest negative shocks occurring in the 1969-1970 and 1973-1975 recessions. On a relative basis, the first three recessions were predominantly supply driven whereas three of the last four were more demand driven (the exception being the 1990-91 recession). Figure 2 visualizes this analysis.

For the first five recessions, these results are broadly consistent with Gali's (1992)

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results, who also characterizes the 1973-75 recession as mostly supply driven and the 1981-82 recession as mostly demand driven. There is a debate on the origins of the Great Recession of 2008-2009, with some researchers arguing for the predominance of a large negative aggregate demand shock (see, e.g., Mian and Sufi, 2014), others stressing the importance of supply shocks (see, e.g., Ireland, 2011, or Mulligan, 2012). We also find that negative demand shocks contributed more importantly to the Great Recession than supply shocks did.

Table 4 – Decomposition of Real GDP Growth during NBER Recessions into Demand and Supply Components. The aggregate demand component of the GDP growth is computed as σ_{gd} multiplied by the sum of aggregate demand shocks over the period of the recession. The aggregate supply component of the GDP growth is computed as σ_{gs} multiplied by the sum of aggregate supply shocks over the period of the recession.

NBER Recession	GDP shock: demand component	GDP shock: supply component
1969Q4-1970Q4	-0.34%	-2.11%
1973Q4-1975Q1	-0.08%	-2.33%
1980Q1-1980Q2	0.72%	-0.51%
1981Q3-1982Q4	-3.63%	0.12%
1990Q4-1991Q1	-0.20%	-0.32%
2001Q1-2001Q4	-1.55%	-0.37%
2008Q1-2009Q2	-1.92%	-0.18%

4 The COVID-19 Episode

4.1 The Shock

We start by analyzing 2020:Q1, the first quarter in which the COVID-19 pandemic affected U.S. economic activity. All GDP growth and inflation values below are changes from the previous quarter expressed at an annual rate. An important caveat about this analysis is that 2020:Q1 SPF was conducted in February, well before the devastating effects on the U.S. economy became apparent in the last three weeks of March. Thus, COVID 19 effects are not reflected at all in the SPF survey published in 2020:Q1. For this reason, we analyze 2020:Q1 dynamics using the actual macroeconomic data. In particular, for inflation we use the Bureau of Labor Statistics release on April 10^{th}, 2020,

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which indicates 2020:Q1 inflation of -0.80 percent. For real GDP growth we use the U.S. Department of Commerce release on April 29th, 2020, which estimates 2020:Q1 real GDP growth of -4.80 percent. We subtract off the survey-based expectations for these variables as measured from the previous SPF survey in November; this procedure implies a GDP growth shock of -6.60 percent and an inflation shock of -2.73 percent. These are very large negative shocks: the leftmost two columns of Table 5 indicate that the 2020:Q1 shocks were the strongest negative shocks for both real GDP growth and inflation in our sample. Both were about twice the size of the shocks seen in 2008:Q4 during the financial crisis. As shown in the middle two columns of Table 5, we estimate that the magnitude of the demand shock was -7.1 in 2020:Q1 and the aggregate supply shock was -1.9. While the demand shock in 2020:Q1 was unprecedented in magnitude, stronger supply shocks hav been observed in the sample period. The rightmost columns in Table 5 show that out of a total of -6.6 percent real GDP growth shock in 2020:Q1, we estimate that -4.3 percent is due to an aggregate demand shock and -2.3 percent is due to an aggregate supply shock. Intuitively, we find that the demand shock was more important, because real GDP growth and inflation shocks were both strongly negative. Table 5 also provides standard errors derived from standard errors of inversion coefficients (σ:s) in Table 2, which are quite tight.

We now proceed to analyze 2020:Q2, for which we can return to using our standard survey-based measure of shocks. The leftmost column of Table 5 indicates that the real GDP growth shock is an astounding 34.3 percent at an annual rate (reflecting an expected growth rate of -32.2 percent for the quarter versus an expectation of 2.1 percent from the previous survey) and the inflation shock is -4.6 percent (reflecting an expectation of -2.6 percent in the Q2 survey versus a previous expectation of 2 percent). The comparison to historical extremes in Table 5 indicates that the real GDP growth shock is truly extraordinary. While the inflation shock is also the largest in the sample, it does not stand out as much, because strong deflationary shocks have occurred before, for example, during the 1981-1983 recession. Together these translate into an estimated demand shock of -24.5 and a supply shock of -16.5, both being clearly the largest negative demand and

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supply shocks, respectively, in our sample, as can be seen in the middle columns of Table 5. Keeping in mind that both supply and demand shocks were defined to have an unconditional standard deviation of one in the in-sample period, it is clear that shocks of these magnitudes are astonishingly large. Given that a very large real GDP growth shock is accompanied by a relatively much smaller inflation shock, both aggregate demand and aggregate supply components must be large under our estimated coefficients in Table 2: both shocks will contribute negatively to real GDP growth but their effects on inflation are offsetting. This decomposition implies that out of a -34.3 percent real GDP growth shock -14.8 percent is due to aggregate demand and -19.5 percent due to aggregate supply.

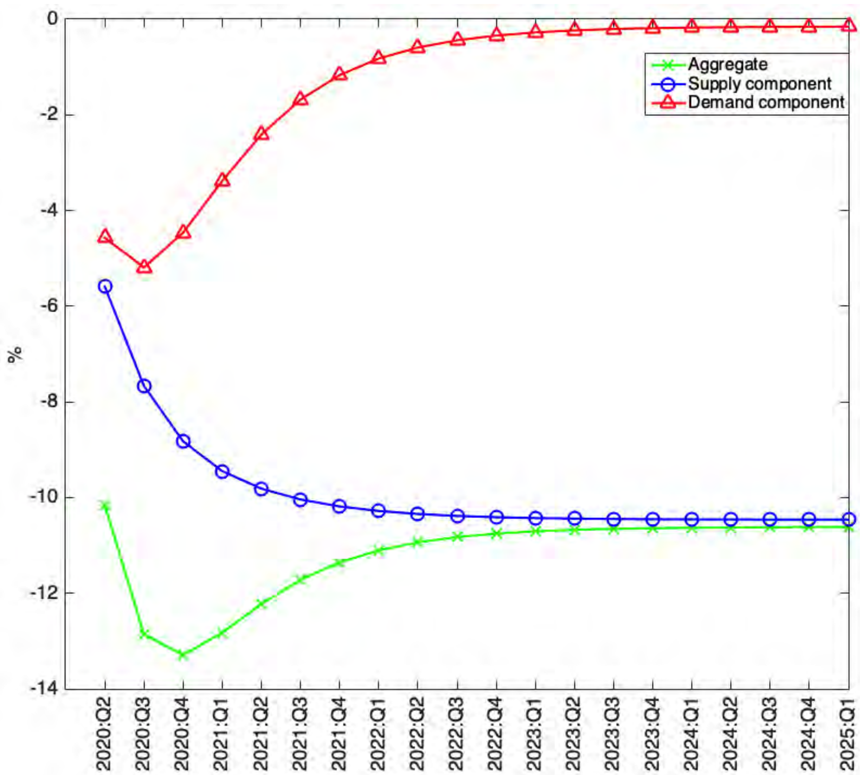
4.2 The Shape of the Recovery

With the COVID shock in the first half of 2020 showing a strong aggregate supply component, a standard new-Keynesian or Blanchard-Quah (1989)-type model would suggest that the recovery could unfortunately be relatively slow and incomplete. This is because negative supply shocks are usually associated with hits to productivity growth, increases in the natural rate of employment, and other reduction in the productive capacity of the economy from which some time may be required to recover. Indeed, anecdotal reports that some business models may no longer be economically viable, for instance, in sectors such as tourism, hospitality, and entertainment, are examples suggesting that a period of difficult adjustment may lay ahead, denting the potential output of the economy. We can illustrate the expected pattern of recovery using our previously estimated VAR for Table 3. Figure 3 shows the predicted responses of GDP growth due to 2020:Q2 shock. While the demand component of the negative hit to GDP recovers fairly quickly over the next several quarters, the supply component remains deeply negative for many years.

Table 5 – COVID-19 Shocks. Shocks are quarterly expressed at an annualized rate. The aggregate demand component of the GDP growth is computed as σ_{gd} multiplied by the sum of aggregate demand shocks over the period of the recession. The aggregate supply component of the GDP growth is computed as σ_{gs} multiplied by the sum of aggregate supply shocks over the period of the recession. CMD-implied standard errors are in parentheses.

	Real GDP growth shock	Inflation shock	Demand shock	Supply shock	Real GDP growth demand component	Real GDP growth supply component
2020:Q1	-6.6%	-2.7%	-7.1	-1.9	-4.3%	-2.3%
					(0.8%)	(0.2%)
2020:Q2	-34.3%	-4.6%	-24.5	-16.5	-14.8%	-19.5%
					(2.6%)	(1.9%)
Max(1968Q4-2019:Q2)	3.6%	2.7%	3	2.9	1.8%	3.5%
Min(1968Q4-2019:Q2)	-6.6%	-2.1%	-3.8	-5.6	-2.3%	-6.6%
2008:Q4	-3.5%	-1.4%	-3.7	-1.1	-2.2%	-1.3%
					(0.4%)	(0.1%)

Figure 3 – VAR Cumulative Real GDP Growth Response to 2020:Q2 Demand and Supply Shocks. The VAR model is: $Y_t = AY_{t-1} + S[u_t^s, u_t^d]' + \Sigma\epsilon_t$, where Y_t is the vector of final, revised real GDP growth and inflation, $[u_t^s, u_t^d]'$ are pre-estimated structural shocks from the SPF, and $\epsilon_{t+1} \sim \mathcal{N}(\mathbb{0}_{2\times1}, \mathcal{I}_{2\times2})$. The model is estimated using quarterly data 1968:Q4-2019:Q2.



That said, the negative supply shock associated with the COVID episode could prove to be unusual in that the productive capacity of the economy could recover more quickly, for instance, if a vaccine becomes available relatively soon, or if businesses find creative ways to restore operations even in the presence of continued social distancing. Indeed, with SPF forecasts available for future quarters, the survey is consistent with a faster recovery. To demonstrate this, we compute the forecast revisions to future real GDP growth and inflation as $E_t[g_{t+n}] - E_{t-1}[g_{t+n}]$ and $E_t[\pi_{t+n}] - E_{t-1}[\pi_{t+n}]$, respectively, where

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t=2020:Q2 and the data are available for n =1, 2, and 3 quarters. These revisions to the multi-period-ahead expectations are a natural extension of our definition of shocks to current quarter activity, and we interpret them as the expected reversal pattern following the 2020 COVID shock.

The top panel of Figure 4 illustrates the SPF-implied cumulative expected GDP growth until 2021:Q1 based on the 2020:Q1 (February) and 2020:Q2 (May) SPF's. The February survey predicted a steady growth of around 2 percent at an annual rate. The May survey suggests a strong drop in 2020:Q2 and a slow recovery: real GDP is not expected to catch up its pre-COVID-19 trend at least before 2021:Q1. The middle panel explicitly plots the forecast revisions that occurred between the February (2020:Q1) and May (2020:Q2) surveys suggesting that the recovery is expected to be "check mark"-shaped. The bottom panel of Figure 4 illustrates that both aggregate demand and aggregate supply components of cumulative GDP growth exhibit a "check mark"-trend as well. The AS component falls deeper but is also expected to recover faster. The relatively rapid recovery in the AS shock suggests that survey respondents anticipate that the supply-side of the economy may recover more quickly than average.

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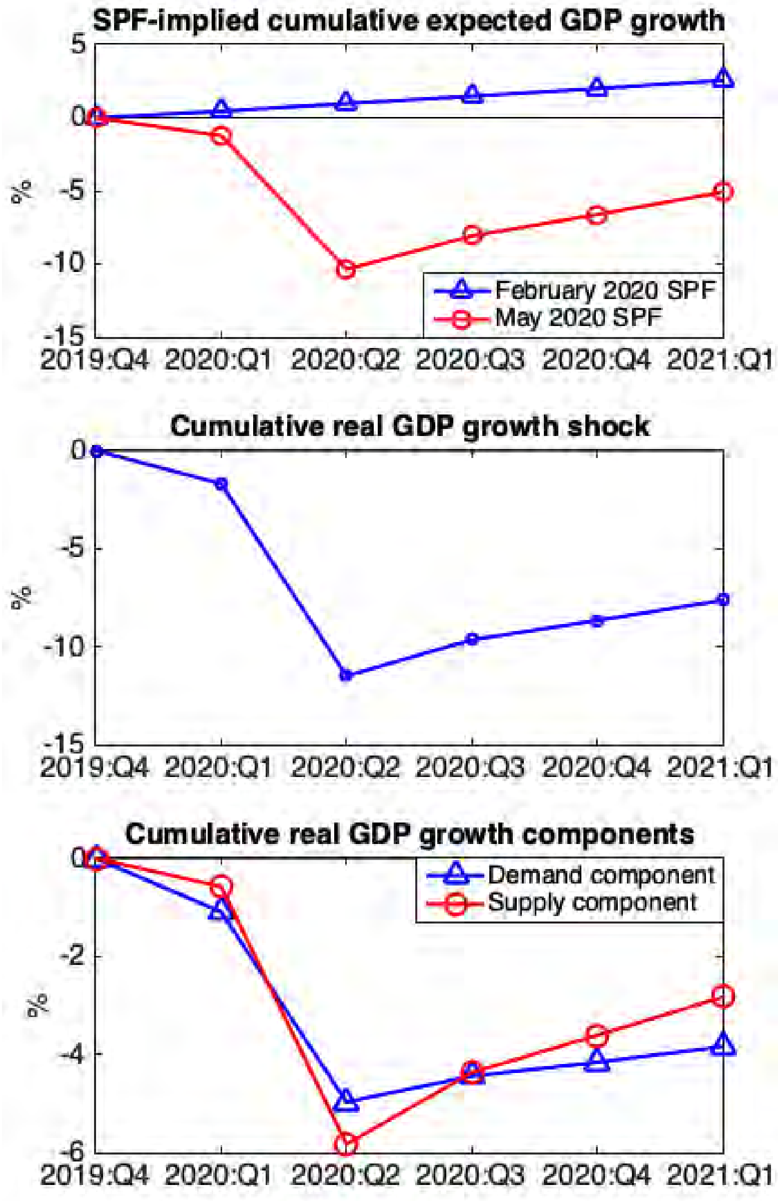
Figure 4 – Cumulative Real GDP Growth Shocks during COVID-19. The data is quarterly and not annualized. The starting point is the end of 2019:Q4. The aggregate demand component of the GDP growth is computed as σ_{gd} multiplied by the aggregate demand shock. The aggregate supply component of the GDP growth is computed as σ_{gs} multiplied by the aggregate supply shock.



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The results in Figure 4 average survey responses across respondents, and, given the unprecedented nature of the situation, could mask important differences in the cross-section of responses. Figure 5 shows the full cross-sectional distribution of the expected recovery pattern from the SPF. For each quarter on the horizontal axis, the horizontal red line shows the median estimate. The blue bar shows the interquartile range for the cross-section, and the "+" symbols show the individual forecasts that fall outside of the interquartile range. Except for a couple of outliers, the cross-sectional distributions are generally rather tight. Every respondent continues to estimate that GDP growth fell 1.2 percent at a quarterly rate in 2020:Q1, consistent with the advance release from the BEA. The expected cumulative depth of the contraction in 2020:Q2 varies from -7 percent to -20 percent at a quarterly rate. All respondents expect that the level of real GDP will remain lower than the level achieved in 2019:Q4, with the most pessimistic forecasters projecting that real GDP will be at least 10 percentage points lower than the 2019:Q4 level.

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Figure 5 – Cumulative Real GDP Growth: Individual SPF Forecasts. The data is quarterly and not annualized. The starting point is the end of 2019:Q4. For each quarter on the horizontal axis, the horizontal red line shows the median estimate. The blue bar shows the interquartile range for the cross-section, and the "+" symbols show the individual forecasts that fall outside of the interquartile range.

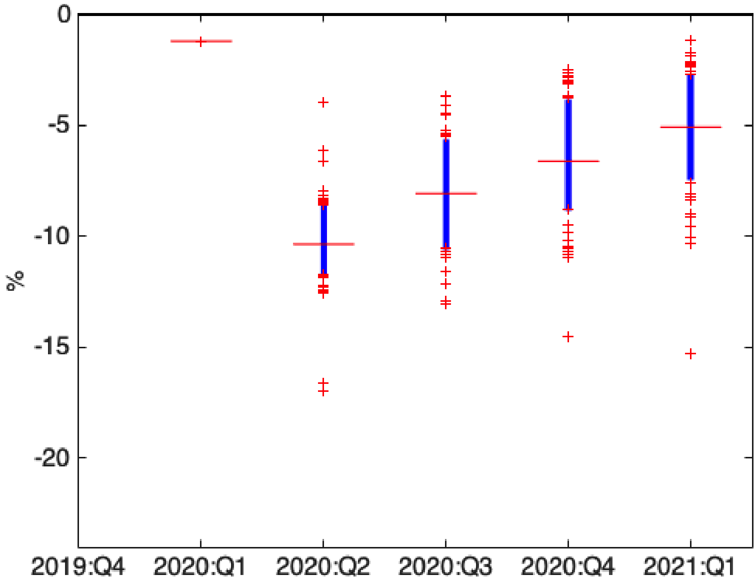

Figure 6 repeats the analysis of Figure 4 for inflation. The top panel suggests that the February 2020 SPF predicts a steady inflation of 2 percent annually while the May 2020 SPF expectation is 0 cumulative inflation over 2020 with the deflationary first half of the year. The middle panel plots our inflation forecast revision shock illustrating that the COVID-19 shock may have a permanent effect on the price level. The bottom panel indicates that the effect is mainly driven by the demand component.

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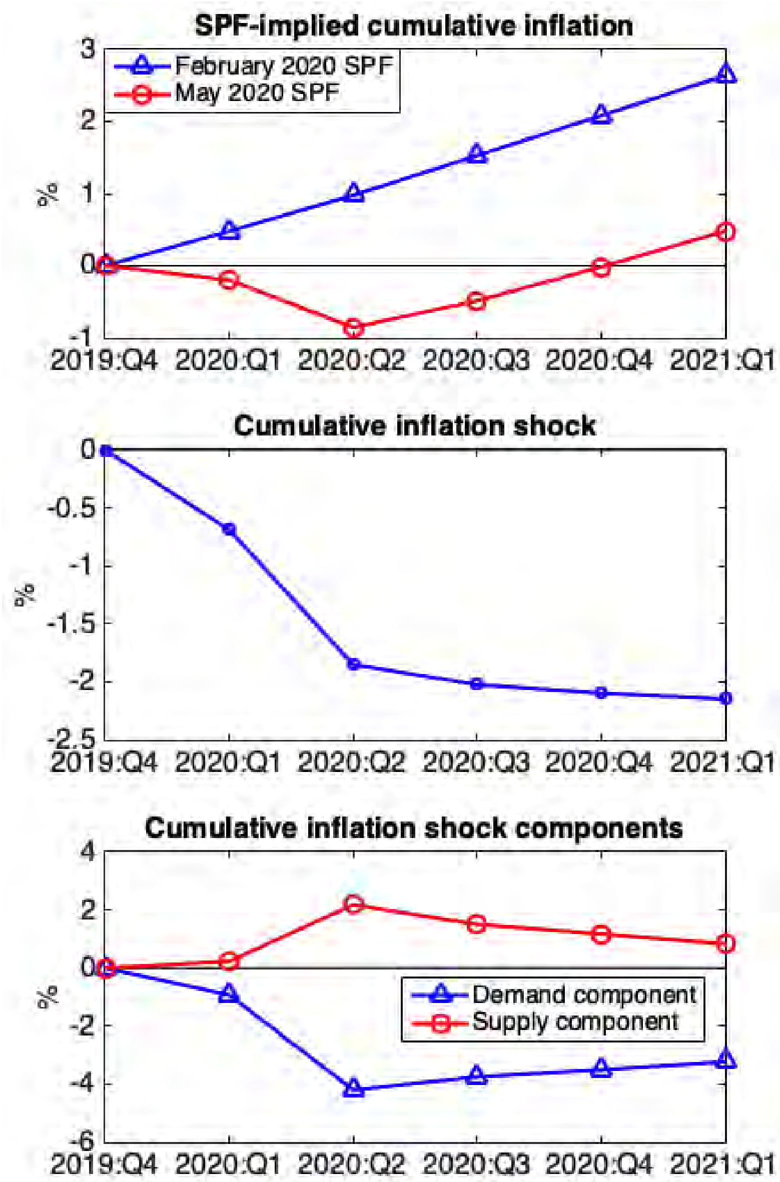
Figure 6 – Cumulative Inflation Shocks during COVID-19. The data is quarterly and not annualized. The starting point is the end of 2019:Q4. The aggregate demand component of the inflation is computed as $\sigma_{\pi d}$ multiplied by the aggregate demand shock. The aggregate supply component of the GDP growth is computed as $\sigma_{\pi s}$ multiplied by the aggregate supply shock.



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5 Conclusion

We provide real-time estimates of aggregate demand and aggregate supply components of the COVID-19 recession. Our methodology requires minimal theoretical assumptions and relies only on non-Gaussian features of macroeconomic data which we show to be pronounced in our sample, even excluding the COVD-19 observations. Our calculations show that the 2020:Q1 real GDP growth shock is largely due to an aggregate demand shock, while the staggeringly large shock in 2020:Q2 was due to both aggregate demand and aggregate supply shock, but with the latter contributing somewhat more to the decline. A VAR analysis suggests a very slow recovery path of multiple years whereas surveys indicate a checkmark recovery, with the AS component actually recovering faster than the AD component.

Of course, as better macroeconomic data and more microeconomic data becomes available, these estimates might be substantially revised. An important goal of future empirical research is to study the propagation and interplay of aggregate demand and supply shocks (see, e.g., Guerrieri et al., 2020, or Caballero and Simsek, 2020, for a theoretical framework).

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References

Ang, Andrew, Geert Bekaert, and Min Wei, 2007, Do Macro Variables, Asset Markets, or Surveys Forecast Inflation Better?, *Journal of Monetary Economics*, 4, 2007, pp. 1163-1212.

Bekaert, Geert, Engstrom, Eric, and Andrey Ermolov, 2019, Macro Risks and the Term Structure of Interest Rates, Working paper.

Bekaert, Geert, Engstrom, Eric, and Andrey Ermolov, 2020, Aggregate Demand and Aggregate Supply Macro Risks, Working paper.

Blanchard, Olivier, and Danny Quah, 1989, The Dynamic Effects of Aggregate Demand and Supply Disturbances, *American Economic Review*, 79, pp. 655-673.

Blanchard, Olivier, 1989, A Traditional Interpretation of Macroeconomic Fluctuations, *American Economic Review*, 79, pp. 1146-1164.

Caballero, R., and A. Simsek, 2020, A Model of Asset Price Spirals and Aggregate Demand Amplification of a "Covid-19" Shock, Working paper.

Cochrane, John, 1994, Shocks, *Journal of Monetary Economics*, 41, pp. 295-364.

Evans, Martin, and Paul Wachtel, 1993, Were Price Changes during the Great Depression Anticipated?: Evidence from Nominal Interest Rates, *Journal of Monetary Economics*, 32, pp. 3-34.

Gali, Jordi, 1992, How Well Does the IS-LM Model Fit Postwar U.S. Data?, *Quarterly Journal of Economics*, 107, pp. 709-738.

Guerrieri, Veronica, Lorenzoni Guido, Straub Ludwig, and Iv'an Werning, 2020, Macroeconomic Implications of COVID-19: Can Negative Supply Shocks Cause Demand Shortages?, Working paper.

Hamilton, James, 1989, A New Approach to the Economic Analysis of Nonstationary Time Series and the Business Cycle, *Econometrica*, 57, pp. 357-384.

Ireland, Peter, 2011, A New Keynesian Perspective on the Great Recession, *Journal of Money, Credit and Banking*, 43, pp. 31-54.

Lanne, Markku, Meitz, Miika, and Pentti Saikkonen, 2017, Identification and Estimation of Non-Gaussian Structural Vector Autoregressions, *Journal of Econometrics*, 196, pp. 288-304.

Mian, Atif, and Amir Sufi, 2014, What Explains the 2007-2009 Drop in Employment?, *Econometrica*, 82, pp. 2197-2223.

Mulligan, Casey, 2012, The Redistribution Recession: How Labor Market Distortions Contracted the Economy, Oxford University Press.

Shapiro, Matthew, and Mark Watson, 1988, Sources of Business Cylcle Fluctuations, *NBER Macroeconomics Annual*, 3, pp. 111-156.

Sims, Christopher, 1980, Macroeconomics and Reality, *Econometrica*, 48, pp. 1-48.

Uhlig, Harald, 2005, What Are the Effects of Monetary Policy on Output? Results from an Agnostic Identification Procedure, *Journal of Monetary Economics*, 52, pp. 381-419.

Woodford, Michael, 2003, Interest and Prices: Foundations of a Theory of Monetary Policy, Princeton University Press.

Wooldridge, Jeffrey, 2002, Econometric Analysis of Cross Section and Panel Data, MIT Press.