

# Demand and Supply Shocks

## Evidence from Corporate Earning Calls

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## Abstract

This paper quantifies global demand, supply, and uncertainty shocks and compares two major global recessions: the 2008–09 Great Recession and the COVID-19 pandemic. Two alternative approaches are used to decompose economic shocks: text mining techniques on earnings call transcripts and a structural Bayesian vector autoregression model. The results highlight sharp contrast in the size of supply and demand shocks over time and across sectors. While the Great Recession was characterized by demand shocks, COVID-19 caused sizable disruptions to

both demand and supply. These shocks were broad-based with varying relative importance across major sectors. Furthermore, certain sub-sectors, such as professional and business services, internet retail, and grocery/department stores, fared better than others during the pandemic. The results imply that both targeted policies and conventional countercyclical fiscal and monetary policy can accelerate the economic recovery. Large demand shocks highlight an environment of deficient demand with countercyclical policy calibrated to the size of these shocks.

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# Demand and Supply Shocks: Evidence From Corporate Earning Calls\*

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# 1 Introduction

The COVID-19 pandemic sparked a heated debate on the nature of economic shocks, which can have substantial ramifications for the design of macroeconomic stabilization and other policies. This paper quantifies demand, supply, and uncertainty shocks since 2005, allowing for a comparison of the two major global recessions, the 2008-09 Great Recession and the COVID-19 pandemic.

Our approach to decompose economic shocks combines two alternative methods. First, we use the recently popularized natural language processing (NLP) techniques and corporate earning call transcripts to identify sentimental demand, supply, and uncertainty shocks, following the methods of [Baker et al. \(2016\)](#) and [Hassan et al. \(2020\)](#). More specifically, we measure (positive or negative) sentiment around demand and supply discussions and calculate their deviations from long-term trends at both aggregate and sectoral levels. This method enables a systematic quantitative analysis of global demand and supply shocks using earning call transcripts of firms listed in United States stock market and headquartered in 80 countries. We add to the existing literature by providing a perspective of supply and demand shocks over time, and comparing the evolution of these shocks during the COVID-19 pandemic and the Great Recession. We also link these sentiment shocks to global economic activity and inflation. Second, to corroborate the sentiment analysis, we use a structural Bayesian vector autoregression (SBVAR) model to identify structural supply and demand shocks and quantify their impact on output and inflation. The model is identified using sign restrictions: a demand (supply) shock is assumed to move prices and output in the same (opposite) directions.

We highlight the following results. First, a detailed evaluation of the COVID-19 pandemic timeline shows that the corporate sector was exposed to large demand and supply disruptions, 10 standard deviations larger than their longer-term averages. Demand and supply sentiment levels rebounded to their long-term averages by the first quarter of 2021. These supply and demand shocks differ from those of the Great Recession. Dur-

ing COVID-19, both demand and supply sentiment simultaneously collapsed with supply sentiment shocks dominating. During the Great Recession in 2008-09, demand sentiment collapsed but there was no material decline in supply sentiment.

Second, uncertainty in response to both events rose dramatically but more so during COVID-19 than during the Great Recession. While the level of uncertainty surrounding the Great Recession was slightly lower than that around the COVID-19 crisis, evidence so far suggests that it persisted much longer in the case of the Great Recession.

Third, we show that aggregated demand and supply sentiment shocks both have statistically significant impacts on real GDP growth and consumer inflation. Positive demand sentiment shocks lead to an increase in real GDP growth and inflation while supply shocks raise growth but lower inflation.

Fourth, there is substantial sectoral heterogeneity in demand and supply shocks during COVID-19. There were widespread demand and supply disruptions in all key sectors, including manufacturing, energy, and wholesale and retail trade. Some industries and sectors, such as professional and business services, internet retail, and grocery and department stores, fared relatively better than others during the pandemic, as measured by demand and supply sentiment scores. During the pandemic's collapse and recovery phases, the relative magnitudes of demand and supply shocks varied dramatically across sectors. For instance, airlines and airport services were constrained by demand shocks and much smaller supply shocks throughout 2020, and this appears to continue despite global economic activity rebounding as of the first quarter of 2021. On the other hand, demand sentiment in the automobile sector has improved since the second half of 2020, despite the persistence in considerable supply restrictions so far.

Fifth, the aggregated demand and supply sentiment shocks are corroborated using an SBVAR model. We decompose the contribution of demand and supply shocks to output and inflation fluctuations and highlight the large supply and demand shocks present during COVID-19, the greater relative importance of demand during the Great Recession, the

significant increase in uncertainty during both events, and the generally strong correlation between structural supply and demand shocks identified using the alternate approaches.

## Prior research

This paper adjoins two major lines of research. First, our sentiment analysis builds on the literature that uses NLP methods on digital text in economics and finance.<sup>1</sup> For example, [Baker et al. \(2016\)](#) and [Hassan et al. \(2019\)](#) study political uncertainty at the aggregate (former) and firm level (latter) using text-based measures. [Baker et al. \(2020\)](#) measure the role of COVID-19 developments in recent stock market behavior by using automated and human readings of newspaper articles. [Hassan et al. \(2021\)](#) employ earning call transcripts to estimate the impact of Brexit on publicly listed firms in the United Kingdom and across the world. [Hassan et al. \(2020\)](#) document the firm-level impact of epidemiological diseases using earning call transcripts. We contribute to this strand of literature by documenting the size of demand and supply disruptions using text-based methods and earning call transcripts at global scale and link it to aggregate economic activity.

Understanding the supply and demand dynamics of the economic impact of COVID-19 is vital for designing an effective policy response. If the pandemic is a demand shock, then countercyclical monetary and fiscal policy can mitigate its impact and prevent hysteresis. If, however, the shock is mainly related to supply, then the appropriate response would include loans, guarantees, and other insurance-like mechanisms. If the supply shock dominates a strong countercyclical response may create unnecessary demand and increase risks related to debt and financial stability. An easy delineation between supply and demand shocks is, however, not clearcut and the two are likely intertwined with what started as a supply shock—mobility restrictions, layoffs, and firm exit—leading to a demand shock as losses in income or precautionary behavior lead to a reduction in consumption ([Guerra-](#)

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<sup>1</sup>NLP is a branch in machine learning literature and focuses on textual data applications. See [Gentzkow et al. \(2019\)](#) for a recent survey.

eri et al., 2020). If the policy response is ineffective or inappropriate, then demand and supply shocks can become reinforcing where the initial supply shock depresses aggregate demand, which in turn induces firms to reassess investment and damages productivity, which further depresses demand (Fornaro and Wolf, 2020). Expectations of consumers and businesses can play an important role in these dynamics (Lorenzoni, 2009).

The supply and demand dynamics vary across sectors given the pandemic's disproportionate impact on industries that require face-to-face interaction. A number of studies have focused on the sectoral impact. del Rio-Chanona et al. (2020) show that for the United States the dominance of supply and demand depend on the sector. In transport, demand likely dominates; in manufacturing, mining and services supply dominates; and in entertainment, restaurants and tourism it is likely both. Farhi and Baqaee (2020) use a disaggregate macroeconomic model to capture the different cyclical conditions faced by different sectors. They find that in the United States the decline in real GDP is due to both demand and supply shocks and about equally distributed between them. They also warn that countercyclical policy is less effective than in typical recessions (at a third) with more targeted interventions required. Brinca et al. (2020) also look at the sectoral impacts of COVID-19 in the United States finding that during the initial peak of the crisis, in March and April, two-thirds of the contraction in hours worked was due to supply shocks. Balleer et al. (2020) study price setting behavior of firms in Germany during the COVID-19 recession and find that supply and demand responses are both present, but demand dominates in the short-run.

As this sectoral work highlights, the response of economies to the outbreak depend on their economic structure which in turn can aggravate the size and duration of the COVID-19 shock. The response of output and employment depend on the ability to work from home (Gottlieb et al., 2020). In advanced economies about half of total employment can work from home whereas in poorer countries it is around one-third. Similarly, an economy's dependence on trade and location in global value chains may affect the relative

importance of supply or demand shocks (Kirby and Maliszewska, 2020). Supply shocks would likely dominate in economies that have greater backward linkages, i.e. those whose exports embody imported value-added. Demand shocks, however, would likely dominate in economies with greater forward linkages.

The COVID-19 pandemic has also required the reevaluation of macroeconomic models with new features needed to understand the impact of pandemic on economic activity. Eichenbaum et al. (2020), for example, extend a standard macroeconomic model to include epidemiological features and show that epidemics generate large and persistent recessions. The supply and demand outcomes are consequences of people reacting to the risk of infection by reducing labor supply, reducing consumption, and increasing precautionary behavior. The COVID-19 shock also requires solutions to estimating and forecasting using macroeconomic models. Lenza and Primiceri (2020), for example, highlight the need to introduce stochastic volatility into a vector autoregressive model to account for the significant increase in shock uncertainty that occurred during COVID-19.

The rest of the paper is organized as follows. The next section provides details of our approach, section 3 presents data and descriptive statistics, section 4 discusses results, section 5 provides robustness checks, and finally section 6 concludes.

## 2 Methodology

### 2.1 Measuring demand and supply sentiment in earning calls

We follow Hassan et al. (2020) to measure sentimental variables in the pre-processed earning call transcripts. *Demand sentiment* on a given call is obtained by aggregating sentiment scores around each mention of “demand”. *Demand sentiment* is computed by the frequency of positive-tone terms minus negative-tone terms within the  $r$ -words range of the mention, divided by the total number of words on the given call. More specifically, the score is calculated as follows:



$$Sentiment_{it}^D = \frac{1}{|B_{it}|} \sum_{b \in B_{it}} \left\{ \mathbf{1}^{DEM}(b) \times \left( \sum_{c \in C^r(b)} S(c) \right) \right\}, \quad (1)$$

where  $B_{it}$  denotes the entire set of words in the call of firm  $i$  at time  $t$ , and  $\mathbf{1}^{DEM}(\cdot)$  is an indicator function which takes value 1 if the input word is in the “demand” word list, and 0 otherwise.  $C^r(b)$  denotes the set of words in the  $r$ -terms range of word  $b$  (before and after), and the function  $S(c)$  is defined as follows:

$$S(c) = \begin{cases} +1 & \text{if } c \in S^+ \\ -1 & \text{if } c \in S^- \\ 0 & \text{otherwise,} \end{cases}$$

in which  $S^+$  and  $S^-$  represent the lists of positive and negative tone words, respectively.

Finally, demand uncertainty on a given call is measured by aggregating uncertainty scores around each discussion of “demand”. The score is computed by the frequency of uncertainty-related words within the  $r$ -words range of mentions, divided by the total number of words on a given call. More specifically, the uncertainty score of a given call is calculated as follows:

$$Uncertainty_{it}^D = \frac{1}{|B_{it}|} \sum_{b \in B_{it}} \left\{ \mathbf{1}^{DEM}(b) \times \left( \sum_{c \in C^r(b)} \mathbf{1}^{UNC}(c) \right) \right\}, \quad (2)$$

where,  $\mathbf{1}^{UNC}(\cdot)$  denotes an indicator function which takes value 1 if the input word is in the words related to uncertainty, 0 otherwise. We set  $r$  to 10.

The positive, negative, and uncertainty keywords are identified using the [Loughran and McDonald \(2011\)](#) sentiment word lists. These word lists contain finance related sentiment text which allows us to correctly identify the most relevant words in the earnings call reports.

The same method is used to calculate sentiment and uncertainty scores around supply

discussions. For sector-specific outcomes, only firms that operate in a specific sector are used.

## 2.2 Local projection model

To link the supply and demand sentiment shocks generated from earning call transcripts to economic activity, a local projection model is used. This method is preferred to a vector autoregressive model since it does not require dynamic restrictions on the behavior of underlying variables and uses shocks defined in the textual analysis. The model, following [Jordà \(2005\)](#), identifies impulse response functions through consecutive regression models at different horizons ( $h$ ):

$$y_{t+h} = \alpha_h + \Gamma_h(L)x_{t-1} + \beta_h shock_t + \mu_{t+h} \quad (3)$$

where  $y_{t+h}$  is the variable of interest, in this case real GDP,  $x_{t-1}$  are lagged control variables, and  $shock_t$  is the supply and demand sentiment shocks. Control variables include consumer inflation, central bank policy rates, nominal exchange rates, oil prices, and the alternate sentiment measure. The models are estimated from 2006Q1 to 2021Q1. Four lags are included for real GDP, inflation and shock variable of interest and 1 lag for all other control variables.

## 2.3 Vector autoregressive model

To decompose output growth into supply and demand, we use a Bayesian structural vector autoregressive model in line with the identification assumptions of [Blanchard \(1989\)](#). The model is specified as:

$$Y_t = BX_t + M_t, \quad (4)$$

where  $Y_t$  is an  $N \times 1$  vector of endogenous variables,  $X_t$  is an  $N \times p + 1$  vector of

lagged dependent variables and an intercept term and where  $p$  is the lag length,  $B$  is a matrix of coefficients, and  $M$  is a  $N \times 1$  vector of residuals. The model includes real GDP, consumer inflation, central bank policy rates, nominal effective exchange rates, and oil prices. The model is estimated on quarterly data from 1991Q2 to 2021Q1 and includes a constant. We estimate the model using Bayesian techniques and the Minnesota prior with hyperparameters on the first lag coefficients at 0.8, on overall tightness at 0.1, and cross-variable weighting at 0.5. A total of 12,000 iterations are run, with the first 2,000 discarded.

To identify demand and supply shocks, the following sign restrictions are imposed:

$$\begin{bmatrix} \mu_t^Y \\ \mu_t^\pi \\ \mu_t^i \\ \mu_t^{ER} \\ \mu_t^{Oil} \end{bmatrix} = \begin{bmatrix} + & + & - & * & * \\ + & - & - & * & * \\ * & * & + & * & * \\ * & + & + & * & * \\ + & + & * & * & * \end{bmatrix} \begin{bmatrix} \epsilon_t^Y \\ \epsilon_t^\pi \\ \epsilon_t^i \\ \epsilon_t^{ER} \\ \epsilon_t^{Oil} \end{bmatrix} \quad (5)$$

where a positive structural supply shock ( $\epsilon$ ) is defined as that which raises output, decreases inflation, increases oil prices and appreciates the exchange rate. A positive demand shock raises economic growth, inflation, and oil prices. A positive monetary policy shock is defined as that which decreases economic growth and inflation. Sign restrictions are imposed for the first two periods. The model is based on data for 14 economies weighted using equity market capitalization in US dollars. In the robustness section we look at the role of weighting strategy and alternate policy rates have on supply and demand decompositions.

The unprecedented nature and size of the COVID-19 shock presents possible challenges to the effective modeling of the pandemic, especially for the historical decomposition used in this paper. However, in order to deal with the significant change in volatility, the VAR model includes stochastic volatility in the error structure as in [Cogley and Sar-](#)

gent (2005) and a generic version of what is suggested in [Lenza and Primiceri \(2020\)](#) as a solution to the COVID-19 shock.

## 3 Data

### 3.1 Earning call transcripts

The empirical analysis is based on two main data sets. These are the earning conference call transcripts of publicly listed firms, and the lexicon dictionary of [Loughran and McDonald \(2011\)](#) for the identification of positive, negative, and uncertainty sentiment words.

Our primary dataset is composed of transcripts of quarterly earning calls from publicly listed firms in the United States stock market, obtained through Factiva’s Fair Disclosure Wire. In these calls, senior management discuss the company’s performance in the previous quarters as well as provide forward-looking guidance for the future conditions. Market participants can ask questions and more widely debate key topics with management on the calls, which are held in conjunction with earnings announcements.

We collect 169,891 available earning call transcripts from 2006Q1 to 2021Q2, of 5,901 firms headquartered in 80 different countries including both advanced economies and emerging markets. The dataset covers a large number of earning calls from all major sectors and countries (figure 1). This equates to over 11,000 earning calls per year for about 3,100 firms on average. The earning calls are mostly from firms headquartered in the United States, accounting for 77 percent of the total. The next largest is Canada accounting for about 7 percent of the earning calls. The data covers all sectors with the most earning calls, about one-third, from manufacturing followed by finance and ITC—about 13 percent each.

We clean the textual dataset using standard NLP techniques by removing stop words, and apply tokenization and stemming ([Gentzkow et al., 2019](#)). Tokenization splits sen-

tences into tokens or individual words based on text delimiters like spaces and commas. Tokenization is an important step in preparing data to be input into models because it converts text into a machine readable format. Stemming is the process of reducing a word to its base version. During the stemming process, for example, “talking”, “talks”, and “talked” will be reduced to “talk”. Stemming ensures the accurate count for words within each document.

Stop words—which are common words such as prepositions (before, an, above) and determiners (the, a)—and names were removed from the tokenized text using a custom lexicon made up of words from earnings call reports. Further, we removed words with fewer than three letters. These pre-processing steps ensure that various sentimental and uncertainty variables (section 2.1) from the earning call transcripts can be accurately calculated.

It is worth noting a key issue about the text-based approach employed in this study. The conversations in earnings calls may reflect corporate managers’ viewpoints which may include error and bias. However, the nature of earning calls forces its content to be reliable and accurate because financial figures are disclosed at the time of the call, and possible biases may be addressed immediately by other participants in the earning calls. Furthermore, because they are repeated every quarter, consistency in reporting is critical for the company’s credibility, encouraging an unbiased conversation about the company’s performance and broader economic developments in these calls. Finally, the SBVAR model in section 2.3, which predicts shocks to demand and supply under structural assumptions without any reference to earning calls, produces findings that are broadly consistent with the text-based sentiment series.

### **3.2 Macroeconomic data for SBVAR and LPM models**

The SBVAR model is estimated using real GDP, consumer price inflation, central bank policy rates, nominal effective exchange rates, and oil prices (table 1). The variables are

aggregated for 14 economies, chosen based on the earning call data, and include nine advanced economies (Australia, Canada, Germany, Israel, Japan, Switzerland, Sweden, the United Kingdom, and the United States) and five emerging market economies (Brazil, China, India, Mexico, South Africa). Weights are based on 2018-20 equity market capitalization in US dollars with the United States (46 percent), Japan (13 percent), and the United Kingdom (9 percent) accounting for the majority.

## 4 Results

### 4.1 Demand and supply sentiment in earning calls

In this section, we provide a time series of demand and supply sentiment indices, covering both COVID-19 and the Great Recession. As documented before, there were significant supply and demand disruptions during the COVID-19 pandemic (figure 2). Supply sentiment dropped more than ten standard deviations from its long-term average during the first and second quarter of 2020, in line with the collapse of global supply chains amid the virus outbreak. Demand sentiment, on the other hand, dropped only slightly in the first quarter before plummeting in the second quarter as a result of widespread lockdowns and increased precautionary behavior. During the Great Recession of 2008-09, in contrast, demand sentiment was broadly identical to that of 2020, with a mild decline in supply sentiment.

Given the central role of uncertainty in investment decisions as well as broader economic activity (e.g., [Bernanke, 1983](#); [Pindyck, 1988](#); [Bloom et al., 2007](#)), we calculate uncertainty scores around demand and supply discussions, as well as in the entire earning calls. Uncertainty around supply and demand discussions were approximately mirrored by the corresponding sentiment levels. Both demand and supply uncertainty peaked in the second quarter of 2020, roughly ten standard deviations higher than the long-term average, when the number of cases reached their first peak and divergences within countries

became increasingly visible.

Aggregate uncertainty—measured by applying equation (2) to the full transcripts of earning calls—spiked roughly seven standard deviations during the Great Recession and more than ten standard deviation during COVID-19, with a faster recovery during the pandemic.

## 4.2 Sector-level demand and supply sentiment from earning calls

Demand and supply shocks were widespread across sectors, but there was significant sector-level variability. Figure 3 compares four sectors: manufacturing, wholesale and retail trade, energy, and professional and business services. Several important observations are noted in both the collapse and recovery periods during the pandemic. First, during the first half of 2020, major sectors such as manufacturing, trade, and energy were subjected to both demand and supply shocks at sizable magnitudes, reflected as large deviations from their long-term averages.

Second, relative to other sectors, the professional and business services sector had far smaller demand and supply shocks over the course of 2020. This is in line with the fact that professional and business services require fewer face-to-face interactions, and the sector's availability of home-based employment arrangements ([Bick et al., 2020](#); [Papanikolaou and Schmidt, 2020](#)).

Third, demand and supply sentiment in the manufacturing and energy sectors correlated strongly during the pandemic. However, while supply sentiment in the energy sector has returned to pre-pandemic levels, in the manufacturing sector it has remained negative as of the first quarter of 2021, likely due to supply issues that extend beyond energy inputs.

Fourth, the size of supply sentiment shocks are comparable between trade and the other two major sectors (energy and manufacturing): during the second quarter of 2020, supply sentiment dropped roughly ten standard deviation below its long-term average in these sectors. Demand in the trade sector, however, diverged: demand sentiment in the

trade sector fell just one-third as much as it did in the manufacturing and energy sectors during the second quarter. These findings are consistent with the widely reported supply chain disruptions during the pandemic (based on current data).

Fifth, since the second half of 2020, demand sentiment has improved significantly across the board. However, supply challenges in the manufacturing and trade sectors look to be persisting.<sup>2</sup>

We present results for select sub-sectors to shed further light on how demand and supply shocks differed across the nature of business (figure 4). The findings demonstrate remarkable disparity in demand and supply shocks in some sub-sectors.

Airlines and airport services, for example, saw large demand shocks as a result of international travel restrictions, with little interruption in supply conditions. In the second quarter of 2020, demand sentiment fell by more than 5 standard deviations, and this trend continued into the first quarter of 2021. Deficient demand conditions persist reflecting the slow recovery in the airline sector. In the automotive sector, negative supply shocks remained large throughout 2020 and intensified in the first quarter of 2021 with a shortage in semiconductors and shipping delays. Demand, on the other hand, has rebounded strongly since the second half of 2020.

In sharp contrast with the case of airlines and automotive sectors, supply shocks dominated disruptions in the internet retail and grocery/department stores, roughly at similar magnitudes. In these two sectors, however, demand shocks were minor, and shifted quickly to positive shocks. In sectors such as internet retail and grocery/department stores, both demand and supply sentiments converged to their long-term norms.

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<sup>2</sup>See the recent discussions on “chip shortage”, for instance: <https://www.cnbc.com/2021/05/14/chip-shortage-expected-to-cost-auto-industry-110-billion-in-2021.html>



### 4.3 Linking sentiment to economic activity

While the supply and demand sentiment measures provide the relative size of supply and demand shocks over time and their sectoral differences, their impacts on economic activity are not observed. We use a local projection model to trace out the impact of sentiment as measured in the earning call transcripts. The benefit of such approach is we do not need to place onerous restrictions as in the case of VAR models. The model controls for the alternate sentiment measure, consumer inflation, exchange rates, oil prices, and policy interest rates.

Figure 5 plots the impulse response functions from demand and supply sentiment shocks. Both supply and demand sentiment shocks are statistically significant drivers of output. On average, the impact from a 1 unit positive shock to demand is larger than the equivalent supply shock—by about three-quarters—and leads to a 1.25 percent increase in output. One possible reason for why supply sentiment has a weaker impact in comparison to the demand shock is that the worsening sentiment might be transmitted at different degrees to the real economic activity. For example, supply chain difficulties might be addressed by existing inventories and/or alternate supply channels for some firms. Even if the initial disruption is a shock to supply, intersectoral linkages might exacerbate the impact of demand shocks, resulting in significant reductions in aggregate demand (Guerreri, Lorenzoni, Straub, and Werning, 2020). While the larger impact of demand on output may be contrary to the perspective of real business cycle models (see, for example, Kydland and Prescott, 1982) of the importance of supply shocks, it fits into models of hysteresis and other possible sources of demand shocks (see, for example, Cerra et al., 2020).

A demand sentiment shock does not lead to a statistically significant increase in inflation beyond the first period, with the increase in inflation small (0.1 percentage point) relative to the shift in output. This implies a contemporaneous Phillips curve slope of 0.075; a 1.0 percent increase in growth increases inflation by 0.075 percent. This result is consistent with less sensitivity of inflation to economic activity over time (see, for ex-

ample, [Matheson and Stavrev \(2013\)](#) for advanced economies, and [Szafranek \(2017\)](#) and [Kabundi et al. \(2019\)](#) for emerging markets). In the case of supply sentiment shocks, inflation decreases significantly—in line with prior expectations—after about eight quarters and by a peak of 0.3 percentage point.

#### **4.4 Decomposing supply and demand factors in output and inflation fluctuations**

We use an SBVAR model to determine the relative size of supply and demand shocks on output and inflation to corroborate the findings in our sentiment analysis. Many studies in empirical macroeconomics have emphasized the importance of decomposing the supply and demand shocks in output and inflation fluctuations, since the optimal monetary and fiscal policy responses are different for adverse demand versus supply shocks.<sup>3</sup> In the case of COVID-19, this is of particular importance, as the nature of the shock has evolved considerably, owing to differing sectoral impacts, despite the fact that the initial shock was caused by policy-induced lockdowns and precautionary behavior.

Figure 6 plots the historical decomposition of output and inflation fluctuations during COVID-19 and the Great Recession of 2009, using the model and identification strategy described in section 2.3. It indicates that demand and supply shocks were large with demand accounting for 64 percent, on average, of the (relative) decline in annual output growth.<sup>4</sup> On a cumulative basis from 2020Q1-21Q1, supply shocks accounted for 53 percent of the moves in output. The share of demand grew as the pandemic evolved accounting for 56 percent in 2020Q2 and over 70 percent in 2021Q1. On a quarterly basis, the decline in growth from the fourth quarter of 2019 to the first quarter of 2020 was about two-thirds demand-related. This switched into the second quarter to 51 percent supply-related. The

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<sup>3</sup>[Blanchard and Quah \(1988\)](#), [Blanchard \(1989\)](#), [Gali \(1992\)](#), [Ha et al. \(2019\)](#), and [Bekaert et al. \(2020\)](#) are only a few examples.

<sup>4</sup>The model includes other shocks that explain movements in output and inflation. Supply and demand alone account for about half of the change in output growth from 2020Q1 to 2021Q1.

recovery into the third quarter was again mainly supply accounting for about two-thirds, reflecting evolving lockdown restrictions, countercyclical policy responses, and a rebound in production.

In comparison to the Great Recession in 2009, the supply and demand shocks were larger during COVID-19. The shocks following the Great Recession were also more staggered with supply reacting first in late 2008 and the demand shock coming through strongly by the middle of 2009. Demand shocks dominated and accounted for about 80 percent, on average, of the decline in output in 2009 and for the four quarters starting in 2008Q4. While a direct accounting of aggregate supply and demand shocks during the Great Recession in the literature are scarce, related literature can provide some insight. [Benguria and Taylor \(2020\)](#) who study the impact of financial crises on international trade flows find that financial crises are mainly demand shocks. [Mian and Sufi \(2009\)](#) reject the finding that productivity-driven growth was an important driver of the rapid build-up and subsequent collapse of credit during the Great Recession but rather from the role of securitization. This suggests that aggregate demand shocks are a more likely explanation for shifts in GDP during the Great Recession.

The historical decompositions from the VAR model generally corroborate the findings of the earnings calls that both supply and demand sentiment shifted quickly into negative territory and were large during 2020. While the relative importance of supply tends to dominate in the case of earnings calls, the local projection model indicates that demand sentiment shocks are associated with larger shifts in output. In the case of the Great Recession, the shifts in supply and demand sentiment agree with the greater importance of demand. The earlier supply shift, however, is not clear from earnings calls.

In the case of inflation, the historical decomposition shows that demand and supply shocks countered each other during COVID-19 dampening the decline in inflation, similar to the finding by [Ha et al. \(2021\)](#). The relatively larger role of demand also occurs in the case of inflation and, as a consequence, annual inflation fell from 2 percent on an annual

basis in the first quarter of 2020 to 0.7 percent in the second quarter and rebounded quickly. In the case of the Great Recession, the decline in inflation was more protracted falling from 2.5 percent in the fourth quarter of 2008 to -0.3 percent in the third quarter of 2009, with supply and demand both contributing to the decline.

The impulse response functions show the median response of growth and inflation to supply and demand shocks (figure 7). A positive demand shock leads to a statistically significant increase in GDP growth and consumer inflation. The effects remain significant for 4 quarters. The impact of a demand shock on inflation suggests a larger response from inflation than the local projection model outcome. A positive supply shock leads to a statistically significant increase in GDP growth and a decrease in consumer inflation.

The VAR model also provides a perspective on uncertainty given the inclusion of stochastic volatility (figure 8). During the COVID-19 shock, output (and equally true of inflation) volatility was 17 times larger than during normal times (average of 1992 to 2021 excluding the Great Recession and COVID-19) and five times larger than seen during the Great Recession. In normal times output volatility is about 1.2 percent. Compared to uncertainty generated from earning call transcripts, output uncertainty is seen to be much larger, about twice the relative size during COVID-19.

Lastly, the structural shocks from the VAR model can be compared to those generated from the sentiment measures (figure 9). In the case of demand, there is a strong positive correlation, of 0.76, between the sentiment demand measure and structural demand shocks from the VAR. While absolute magnitudes differ, both methods can clearly distinguish demand shocks. The measures do show some divergence on the timing of the demand shock following the Great Recession and the events surrounding the European debt crisis in 2011-12. The supply shocks are less well correlated, at 0.37, suggesting differences in the nature of the supply shock around both COVID-19 and the Great Recession.

## 5 Robustness

### 5.1 Sentiment measures

The sentiment measures are partly functions of choices in how to collate textual information. This section looks at the sensitivity of supply and demand sentiment to the size of the neighborhood of words used to determine positive or negative sentiment and words used to identify demand and supply.

First, we set  $r$ —the range around mentions of supply and demand to determine sentiment—to 20 instead of the benchmark value of 10. Figure 10 shows that the sentiment measure is robust to choices of neighborhood words to determine sentiment. The demand and supply sentiment measures constructed using differing values of  $r$  are effectively identical with a correlation coefficient of 0.99 over the whole sample period.

Next, instead of using only mentions of “supply” and “demand”, we expand the identifying words to {demand, exports} mentions to identify demand shocks, and {supply, imports} mentions to identify supply shocks. The series are plotted as the red-dashed lines in figure 10. This alternative demand sentiment series has a correlation coefficient of 0.99 with the benchmark series, whereas the supply sentiment series has a correlation coefficient of 0.89.

### 5.2 VAR model

To test the robustness of the supply and demand decomposition, in this section we use an alternative weighting structure and attempt to control for unconventional monetary policy. In the case of the weighting structure it may be that value added in production is a better reflection of the contribution of economies to overall activity and more appropriately linked to the economic performance of publicly listed firms. In the case of monetary policy, the zero lower bound has constrained conventional monetary policy responses and using nominal policy rates may under-represent the role of monetary policy in stimulat-

ing the economy in the years since the Great Recession in 2008 and hence the contribution of policy to the historical decomposition. To address this we use shadow interest rate estimates, where available, instead of policy rates (see [Wu and Xia, 2016](#)).

The historical decompositions are generally robust to using GDP weights instead of market capitalization with the relative share of demand and supply remaining similar—64 percent demand-related on average during COVID-19 in the case of market capitalization and 63 percent in the case of GDP weights (figure 11). The results from the Great Recession are also similar with about 89 percent (instead of about 80 percent) of the shock demand-related. In the case of inflation, the GDP-weighted model shows a similar offsetting role for supply and demand during COVID-19 with a larger demand shock driving down inflation overall. The historical decompositions are also generally robust to using the shadow policy rate instead of nominal policy rates with the relative share of demand accounting for 60 percent of the shock in the case of shadow policy rates.

## 6 Policy implications and conclusions

This study examines demand, supply, and uncertainty shocks over time, including during the Great Recession of 2008-09 and the COVID-19 pandemic. Our method for decomposing economic shocks combines two different approaches. First, we identify demand, supply, and uncertainty shocks at the global level using earning call transcripts and recently popularized text mining techniques as in [Baker et al. \(2016\)](#) and [Hassan et al. \(2020\)](#). We find that both demand and supply played an important role in driving output losses during the pandemic. Also, in contrast to the Great Recession, supply shocks were large, with significant variance across sectors. We link these supply and demand sentiment shocks to economic activity using a local projection model and show that both sentiment shocks have a statistically significant association with global real GDP growth.

Second, we provide estimates using a structural Bayesian VAR model with stochastic

volatility and standard macroeconomic data to cross-check the sentiment and uncertainty measures, and link these to output and inflation movements. The model results corroborate the findings of the textual analysis and find that both supply and demand played an important role in driving growth and inflation outcomes. On uncertainty, while both reflect significant increases in uncertainty during COVID-19, the SBVAR suggests that this uncertainty was significantly larger during COVID-19.

The recent debate over the nature of economic shocks has important implications for optimal design of macroeconomic policies. If the impact of the pandemic was mainly supply-related linked to mitigation measures that will end, then a strong countercyclical response may not be warranted but rather an insurance-type mechanism including through unemployment benefits and loans. If, however, the pandemic caused a large demand shock, then a strong countercyclical monetary and fiscal policy response is needed. Our results show that both demand and supply played an important role in the output collapse caused by COVID-19. To appropriately respond, therefore, a blend of measures are required including traditional fiscal and monetary policy stimulus calibrated to the size of the demand shock. Our results also reveal important heterogeneity across sectors and can be used by policy makers to design targeted relief to those firms most impacted by current conditions while limiting possible side effects such as lowering productivity through misallocation of capital and labor.

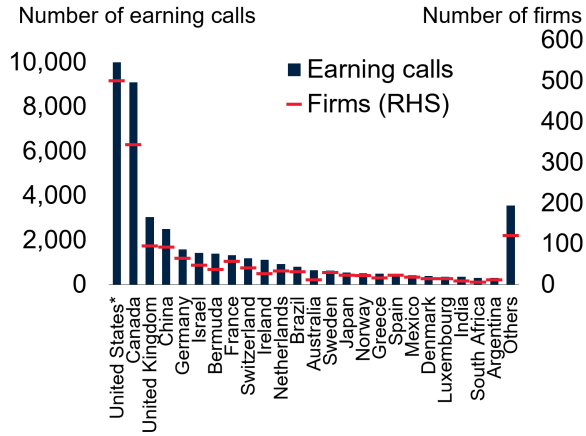
Table 1: Data for the VAR model

Variable	Definition	Transformation	Source
$Y_t$	Real GDP , seasonally adjusted	Log first difference, annualized	Haver Analytics
$\pi_t$	Consumer price index, seasonally adjusted	Log first difference, annualized	Haver Analytics
$i_t$	Central bank policy rate	Level	Haver Analytics
$ER_t$	Nominal broad effective exchange rate	Log first difference, annualized	Haver Analytics
$Oil_t$	Average of Brent, West Texas Intermediate, and Dubai	Log first difference, annualized	Haver Analytics
$Equity_t$	Equity market capitalization, USD	Share of 2018-21 total	Haver Analytics

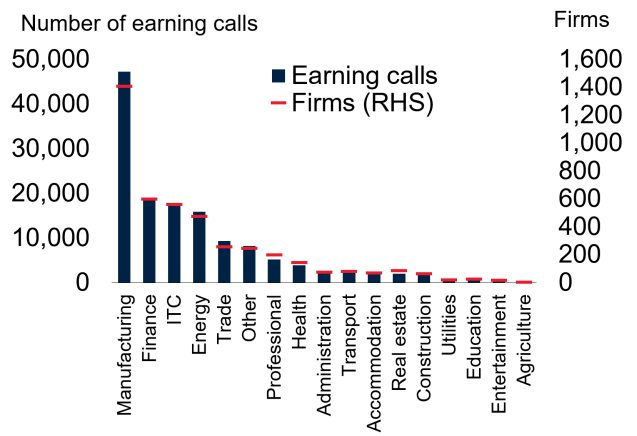


Figure 1: Data coverage

**A. Country coverage**



**B. Sector coverage**



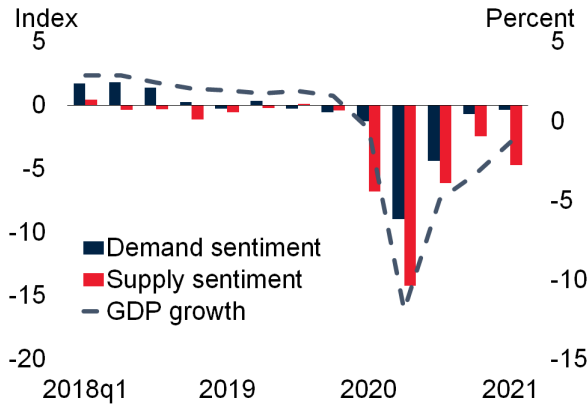
Sources: Factiva; World Bank.

A. The number of calls held by companies that have headquarter in United States is equal to 101,875 but it is set to 10,000 in the chart for visual purposes.

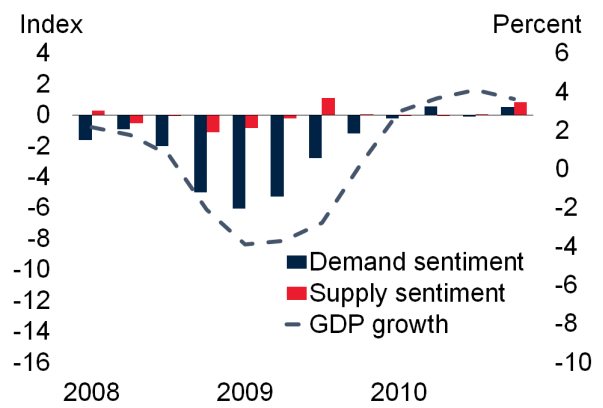
B. "ITC" stands for information technology and communication.

Figure 2: Supply and demand sentiment

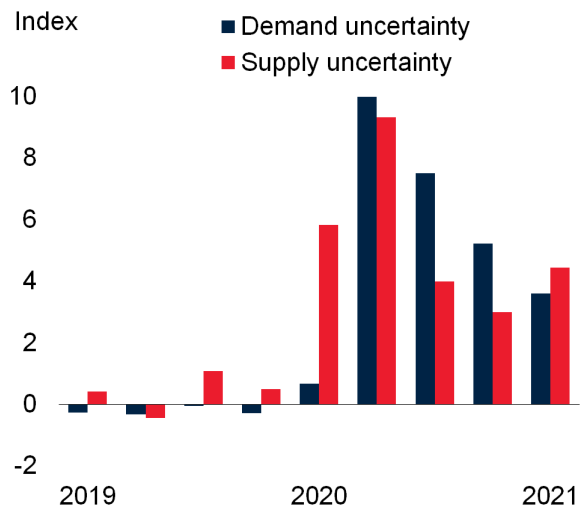
A. Demand and supply sentiment, COVID-19



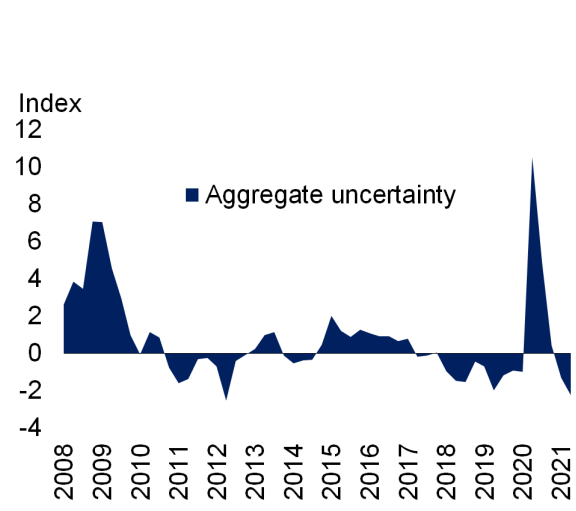
B. Demand and supply sentiment, Great Recession



C. Demand and supply uncertainty, COVID-19



D. Aggregate sentiment and uncertainty



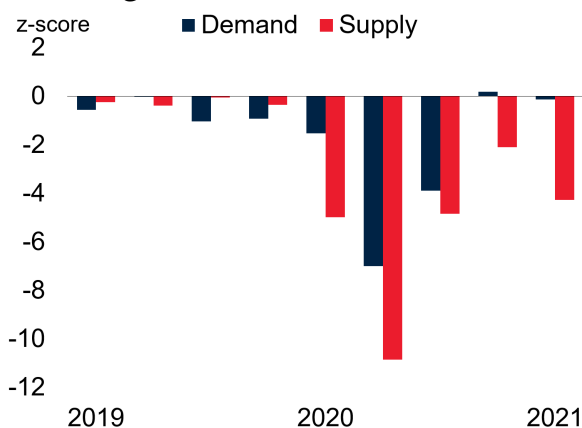
Sources: Factiva; World Bank.

Note: The sentiment series reflect z-scores. Long-term average and standard deviation is calculated using the period between 2010Q1 and 2018Q4.

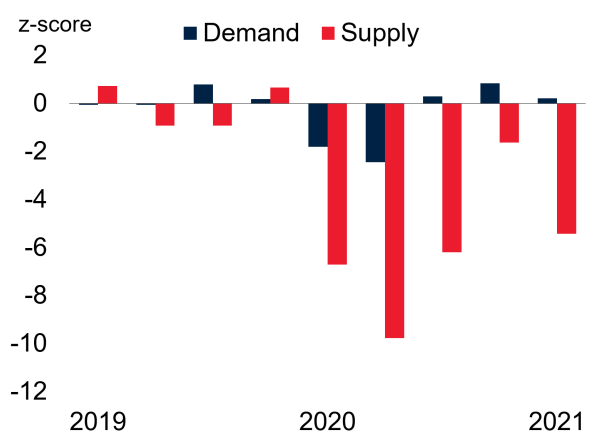
A.B. "GDP growth" is a weighted average of year-on-year growth of 14 countries based on 2018-20 equity market capitalization.

Figure 3: Demand and supply sentiment, sector level

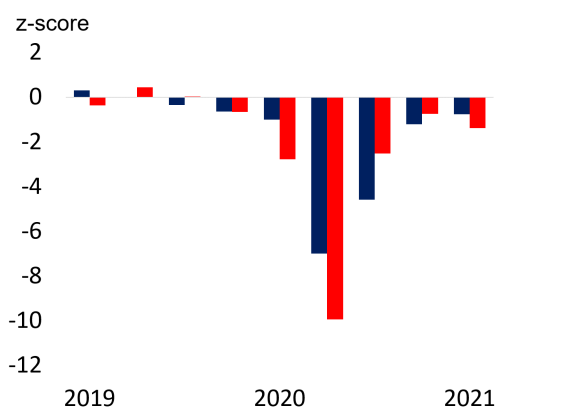
**A. Supply and demand sentiment, manufacturing**



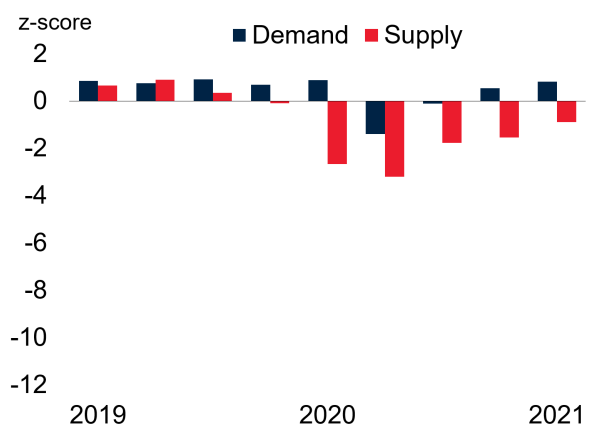
**B. Supply and demand sentiment, trade**



**C. Supply and demand sentiment, energy**



**D. Supply and demand sentiment, professional and business services**

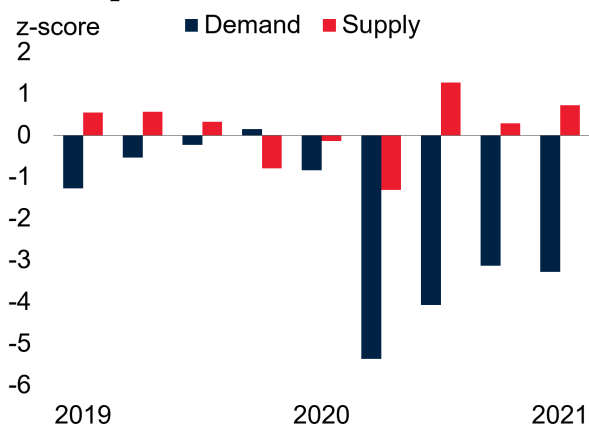


Sources: Factiva; World Bank.

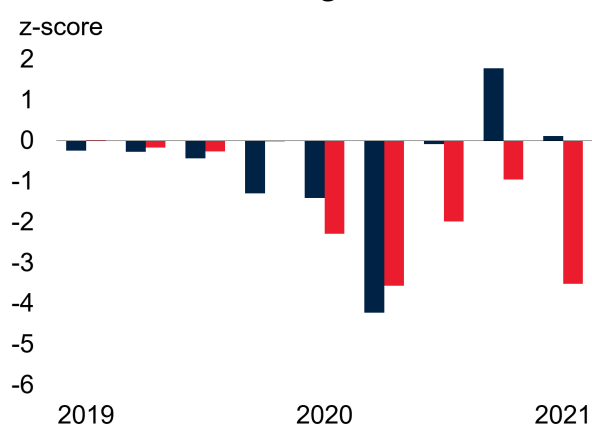
Note: The sentiment series reflect z-scores. Long-term average and standard deviation is calculated using the period between 2010Q1 and 2018Q4. Sector specific results are based on earning call transcripts for companies classified within each sector.

Figure 4: Demand and supply sentiment, sector level

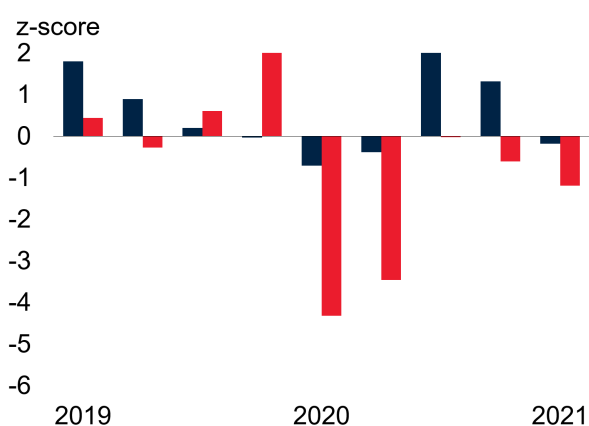
**A. Supply and demand sentiment, airlines and airport services**



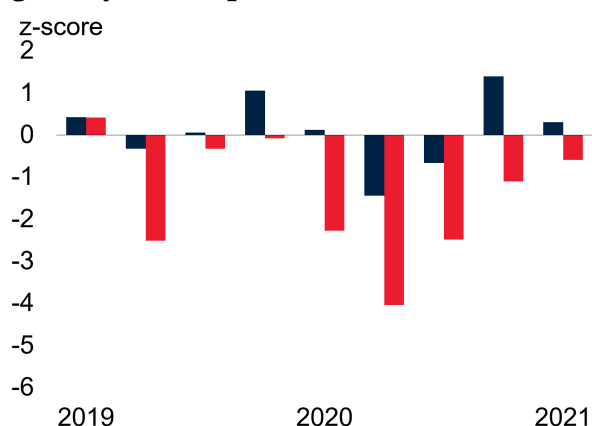
**B. Supply and demand sentiment, automobile manufacturing and trade**



**C. Supply and demand sentiment, internet retail**



**D. Supply and demand sentiment, retail grocery and department stores**

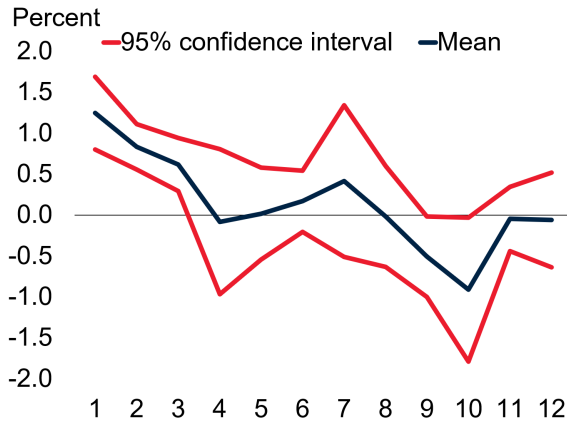


Sources: Author' calculations.

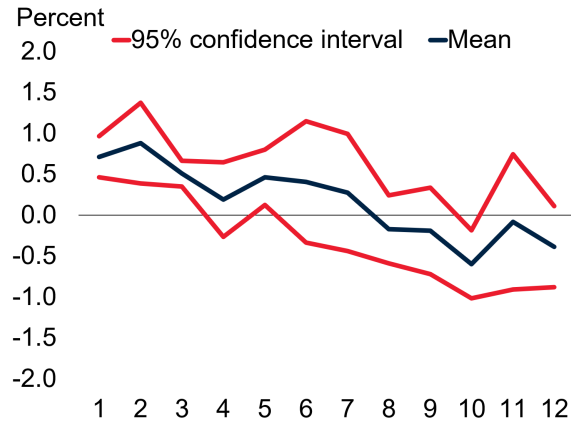
Note: The sentiment series reflect z-scores. Long-term average and standard deviation is calculated using the period between 2010Q1 and 2018Q4. Sector specific results are based on earning call transcripts for companies classified within each sector.

Figure 5: Impulse response functions

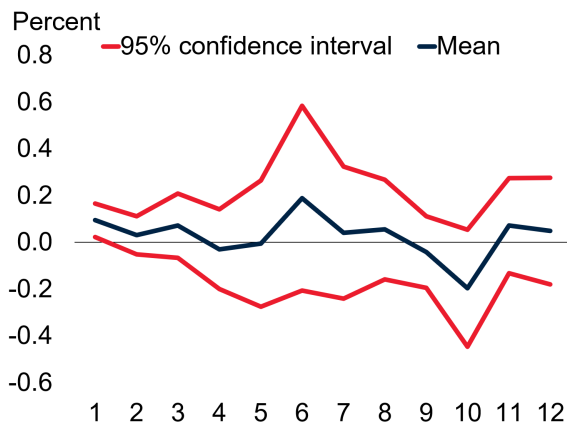
**A. Impact of a 1 unit shock to demand on output**



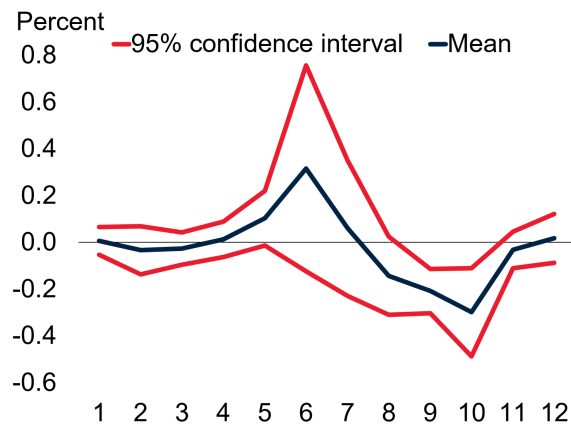
**B. Impact of a 1 unit shock to supply on output**



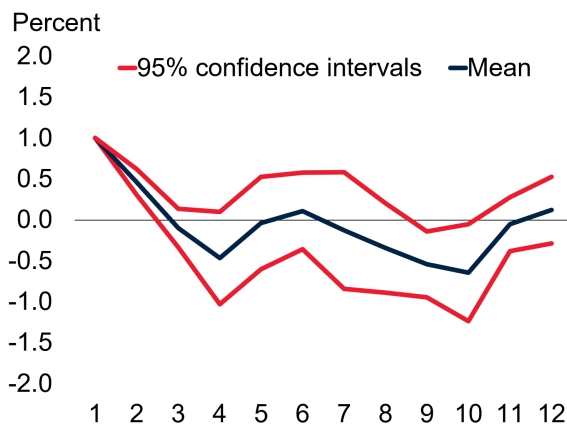
**C. Impact of a 1 unit shock to demand on inflation**



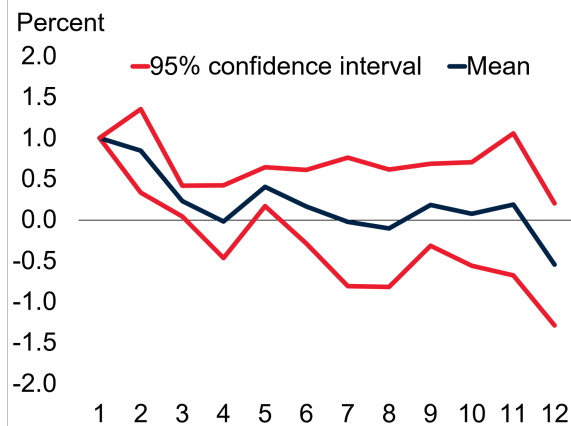
**D. Impact of a 1 unit shock to supply on inflation**



**E. Impact of a 1 unit shock to demand on demand**



**F. Impact of a 1 unit shock to supply on supply**

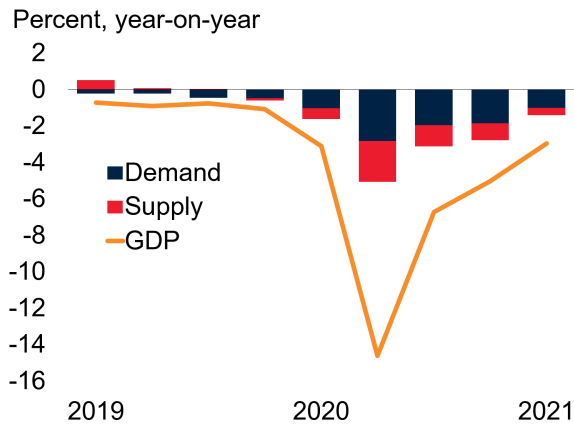


Source: Authors' calculations.

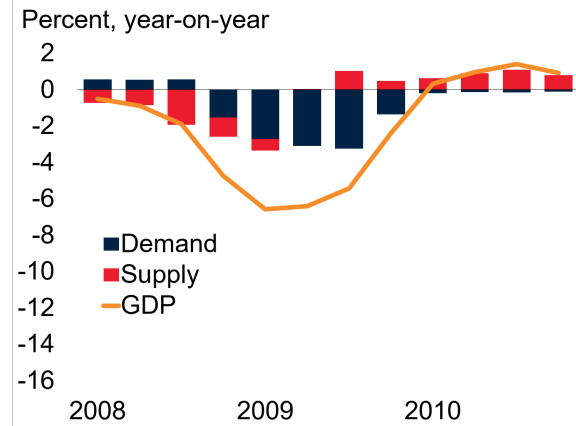
A.-F. Based on local projection model of Jordà (2005) where the shocks are demand and supply sentiment.

Figure 6: Supply and demand from VAR

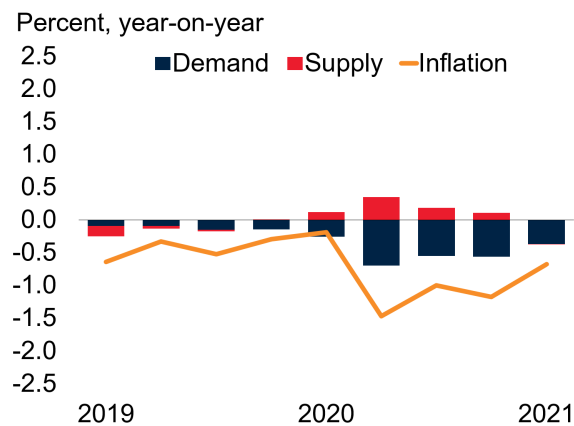
**A. Supply and demand decomposition of GDP growth, COVID-19**



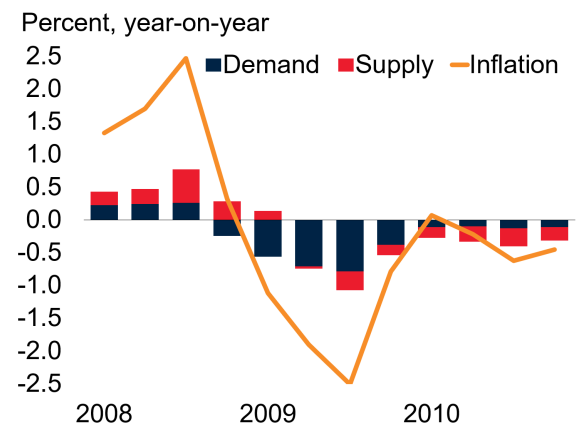
**B. Supply and demand decomposition of GDP growth, Great Recession**



**A. Supply and demand decomposition of inflation, COVID-19**



**B. Supply and demand decomposition of inflation, Great Recession**

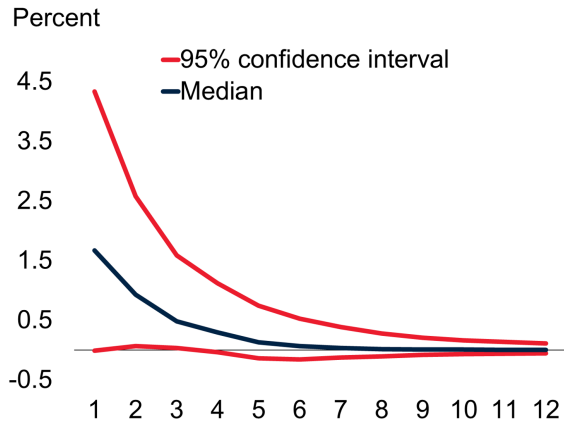


Sources: Authors' calculations.

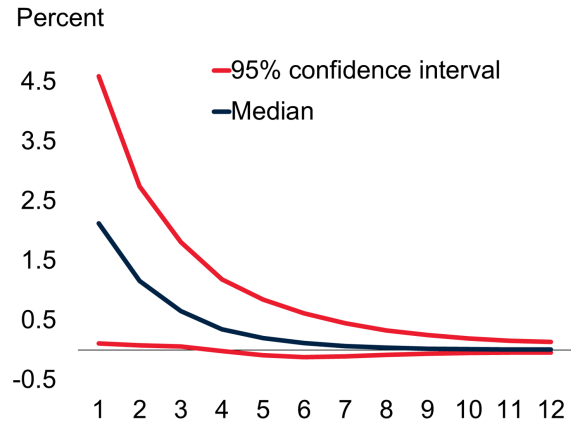
Note: Historical decomposition of real GDP growth and consumer inflation based on a sign-restricted Bayesian VAR with stochastic volatility. Quarter-on-quarter log changes are aggregated to year-on-year using a four-quarter moving average. Figures exclude all other shocks that account for growth and inflation movements. "GDP" and "Inflation" are as deviation from a model-determined constant.

Figure 7: Impulse response functions, SBVAR

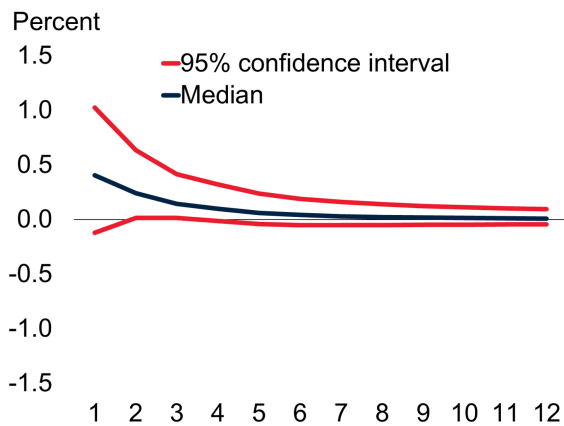
**A. Impact of a shock to demand on output**



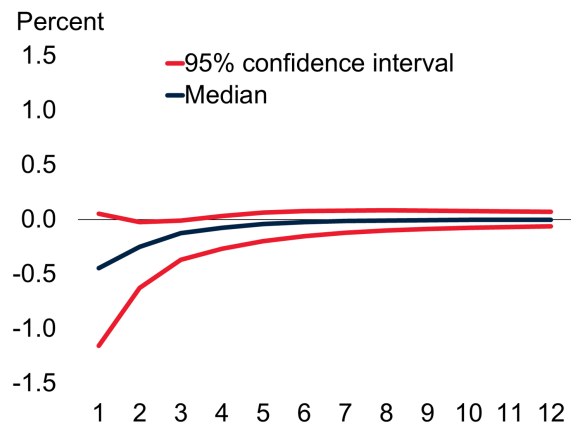
**B. Impact of a shock to supply on output**



**A. Impact of a shock to demand on inflation**

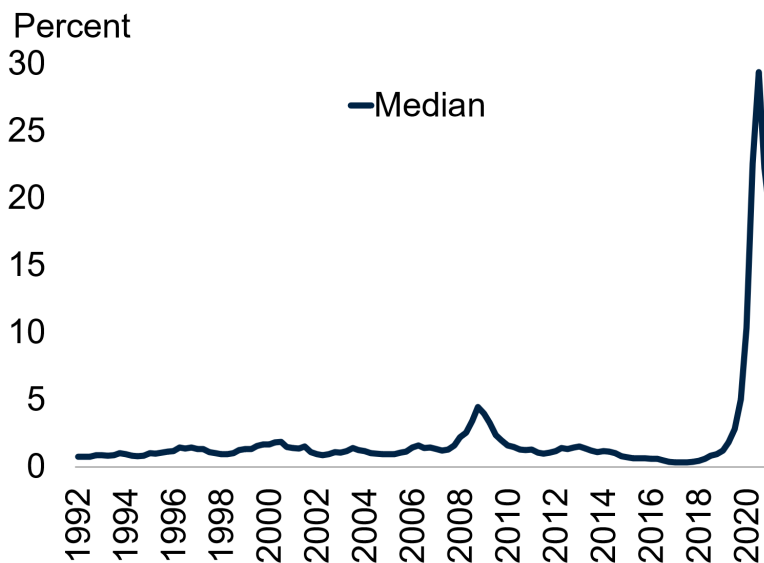


**B. Impact of a shock to supply on inflation**



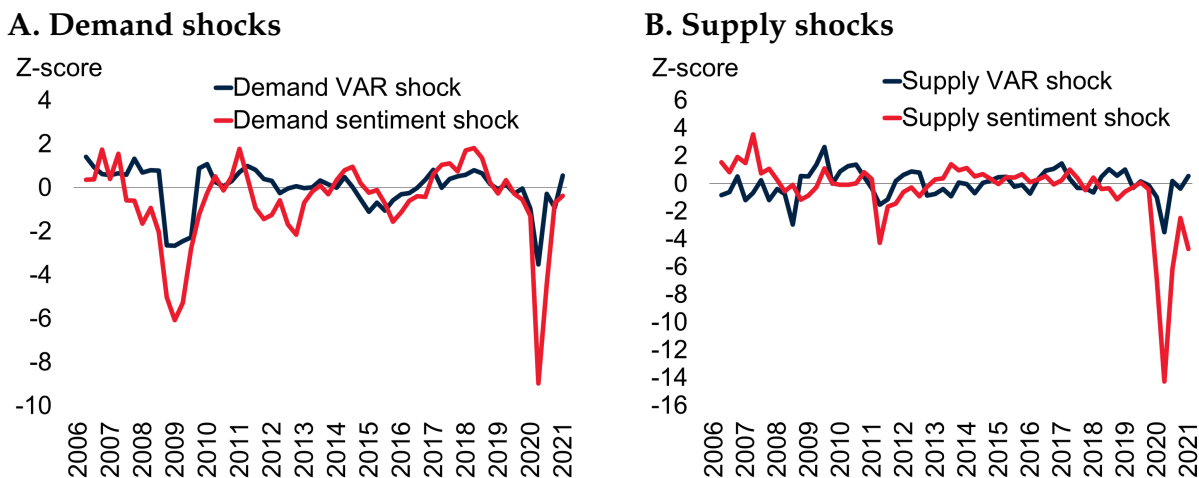
Source: Authors' calculations.

Figure 8: Output uncertainty



Source: Authors' calculations.

Figure 9: Shocks

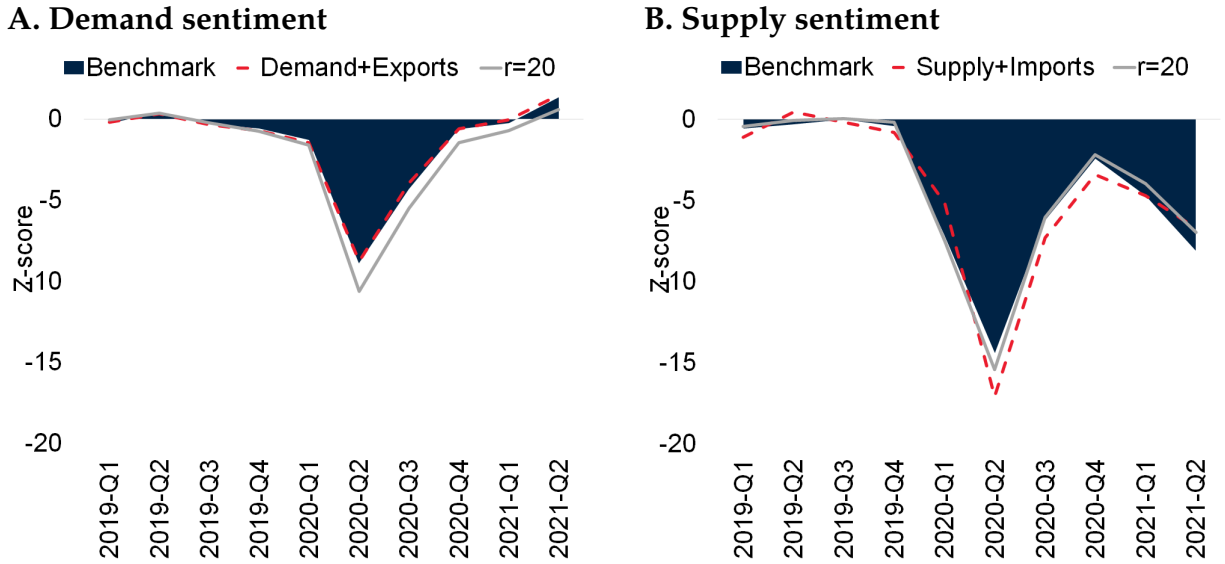


Source: Authors' calculations.

A.B. Structural demand and supply shocks from the SBVAR model are 4-quarter moving averages and standardized for ease of comparison to sentiment shocks. The sentiment series reflect z-scores.



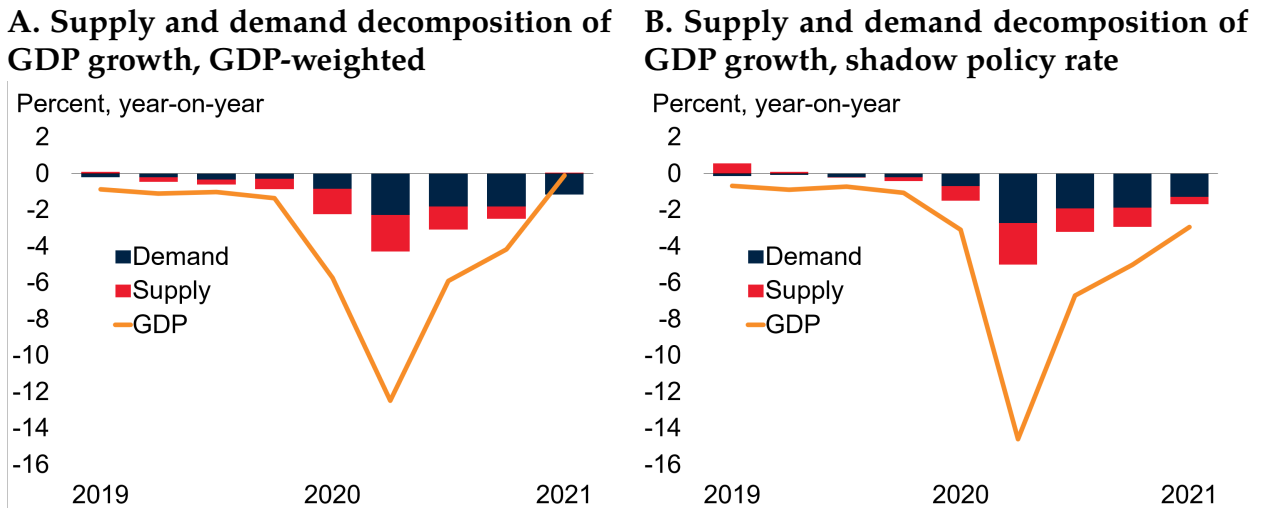
Figure 10: Robustness: Supply and demand sentiment measures



Sources: Authors' calculations.

A.B. The figure illustrates the demand and supply sentiment series based on alternative measurement methods. Shaded area shows the benchmark measure, red-dashed line shows the series using an alternative keyword list for demand and supply, and the silver line shows the series constructed by an extended range of words surrounding each mention of keywords. See section 2.1 for details of construction of benchmark series.

Figure 11: Robustness: Supply and demand from VAR



Sources: Authors' calculations.

A.B. Historical decomposition of growth based on a sign-restricted Bayesian VAR with stochastic volatility. Quarter-on-quarter changes are aggregated to year-on-year using a four-quarter moving average. Figures exclude all other shocks that account for growth and inflation movements. "GDP" is as deviation of growth from a time-varying intercept term.

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## Appendix A. Sample excerpts from selected earning calls

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FORD, 29-Oct-20

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Looking at North America, despite the difficult backdrop of **COVID**, the Ford team executed well operationally. We optimize incentives for lower dealer stock levels, we maximize production and skillfully manage **supply** chains to meet stronger-than-expected customer **demand**.

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Now that margin was driven largely by higher-than-expected vehicle **demand**, positive net pricing and favorable mix as inventories were limited because of the **virus**-related shutdowns in the first half of the year. North America and China benefited from growth in both wholesales and revenue, while Europe, South America and our international's market group were still affected by **COVID**-related industry declines.

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In South America, mitigating the ongoing pressure from inflation, currency and the industry structural challenges. And in IMG, IMG delivered a profit despite **COVID**-related industry declines in wholesale, which adversely affected the revenue. S-series gained share and our share with the Ranger pickup in Australia increased 6 points to 27%. Profitability in IMG also benefited from the work the team has done to lower structural cost. And finally, Ford Mobility, which is building fourth-generation autonomous test vehicles with the latest self driving technology, generated its first AV-related revenue from a fleet operations pilot in Austin, Texas, and at the same time, we are strategically expanding our spin scooter business in the US, the UK and Germany in generating strong revenue growth.

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Maybe to follow-up on that, how much of that you think is somewhat transitory for market factors, can you argue right now that the industry volume is pretty – is relatively strong relative to the peers, but is not really in absolute terms quite and quite that amazing. So it seems like there is an underlying **demand** for stronger mix than we all may have thought since 12, 18, 24 months ago.

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Throughout 2020, even during the industrywide shutdown of **COVID** and as we prioritize the safety of our team, we've been disciplined in preparing for high-quality fourth-quarter launch, first of the 2021 F 150 to live in, you work in it, you can sleep in it.

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**ZOOM, 3-Jun-20**

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Let me share some metrics that illustrate the **demand** we experienced in this past quarter. Customers with more than 10 employees grew 354% year-over-year, as we deployed millions of licenses for new customers in the quarter.

As our **demand** increased and we had limited visibility into the growth, AWS was able to respond quickly by provisioning the majority of the new servers we needed, so sometimes adding several thousands a day for several days in a row.

We are grateful for the incredible increase in **demand** as millions of doctors and patients, teachers and students, businesses and consumers chose Zoom to deliver critical communication and connection in a time of need. It speaks greatly of their trust and the quality and ease-of-use of our technology platform. We are also proud of our efforts to support our customers, employees and the global community during the **COVID-19** pandemic.

The **COVID-19** pandemic added unprecedented new variable to our business model, where historical knowledge may no longer apply. Today, as we present our current best estimate of future quarters based on new assumptions of the dramatic shift in our business, we caution that the impact and extent of the crisis and its associated economic concerns remain largely unknown.

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**NCLH, 20-Feb-20**

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Please note that given the unknown duration and severity of the outbreak, there may be additional direct impacts that are not yet quantifiable as well as material indirect impact affecting the broader global consumer **demand** environment, which extend to our global deployments outside of Asia, which cannot be quantified at this time. Based on the known direct impact of \$0.75 per share and the yet unknown and unquantifiable potential additional direct and/or indirect financial impacts from the **virus**, we no longer anticipate achieving our full speed ahead 2020 targets by year end.

The **virus** situation is extremely fluid and while we expect additional direct and indirect impacts, it is simply too early to quantify potential broader headwinds to the business resulting from softer global **demand** for travel and tourism. We were very explicit to say that this does not take into account any sort of indirect potential impacts on future **demand**. So as we said in our prepared remarks, we had over – we had 40 sailings, which were somehow impacted, 21 of those have been redeployed out of Asia to Eastern Europe, Eastern Med with a very short condensed booking window.

The **viruses** initial impact of the cruise industry began with the cancellation of a number of sailings by operators who had ships dedicated to the Chinese market and which sales from Chinese ports. With zero capacity dedicated to the Chinese source market and with only approximately 10 basis points of our global sourcing coming from China. The impact on our brands was deemed to be minimal at the time. Concerns then extended very quickly to include Pan-Asian voyages that originated outside of China but that called on Chinese ports. While these itineraries were quickly modified to avoid or bypass Chinese ports and were replaced with Asian ports of call outside of China. Trepidation by American and other Western consumers resulted in increased cancellations and a slowdown down in new bookings for sailings in the region.

As the **outbreak** intensified into February and countries throughout Southeast Asia refused to allow the docking of cruise ships on their shores, more drastic itinerary modifications were necessary, including the cancellation of certain sailings.

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**AMD, 29-Apr-20**

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Although there are some near-term uncertainties in the **demand** environment, we are well-positioned to navigate through this situation. We have a solid financial foundation and our product portfolio is very well positioned across the PC, gaming and data center markets.

While **demand** indicators across commercial, education and data center infrastructure markets are strong, we expect some softness in consumer **demand** in the second-half of the year depending on how overall macroeconomic conditions evolve.

I'm pleased with our execution in the quarter, as we quickly adopted our global operations to navigate pockets of **supply** chain disruption and addressed geographic and market **demand** shifts caused by **COVID-19**. We saw some softness based on the **COVID-19** situation in China that impacted PC-related sales in the first quarter.

We performed well in the first quarter as we navigated a challenging environment as a result of the ongoing impact of **COVID-19**. For the full-year 2020, despite expectations of weaker **COVID-19**-related consumer **demand** in the second-half of the year, we expect annual revenue growth of approximately 25%, plus or minus 5 percentage points. While the market environment has become more challenging given the impact of **COVID-19**, our first quarter results demonstrate the strength of our business model.

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