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Global Demand and Supply Sentiment: Evidence from Earnings 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. We use two alternate approaches to decompose economic shocks: text mining techniques on earning 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.

Topics: Business fluctuations and cycles; International topics; Inflation and prices; Econometric and statistical methods; Coronavirus disease (COVID-19)
JEL codes: G10, E32, C11, C32

Résumé

Dans cette étude, les auteurs quantifient les chocs de demande, d'offre et d'incertitude à l'échelle mondiale, et ils comparent deux grandes récessions mondiales : la Grande Récession de 2008-2009 et la pandémie de COVID-19. Ils utilisent deux méthodes pour analyser ces chocs économiques, soit 1) des techniques de traitement automatique du langage naturel appliquées à des transcriptions de présentations des résultats financiers et 2) un modèle vectoriel autorégressif structurel avec estimation bayésienne. Les résultats révèlent des contrastes marqués dans l'ampleur des chocs d'offre et de demande au fil du temps et selon les secteurs. Tandis que la Grande Récession s'est caractérisée par des chocs de demande, la pandémie de COVID-19 a engendré des perturbations considérables à la fois de la demande et de l'offre. Ces chocs ont été généralisés et d'importance variable selon les grands secteurs économiques. En outre, certains sous-secteurs se sont mieux tirés d'affaire que d'autres durant la pandémie, comme ceux des services professionnels et aux entreprises, de la vente au détail sur Internet, ou encore les épiceries et les grands magasins.

Sujets : Cycles et fluctuations économiques; Questions internationales; Inflation et prix; Méthodes économétriques et statistiques; Maladie a coronavirus (COVID-19)
Codes JEL : G10, E32, C11, C32

1 Introduction

The COVID-19 pandemic sparked a heated debate on the nature of economic shocks that could have substantial ramifications for the design of policies that address macroeconomic stability and other issues. This paper quantifies demand and supply shocks since 2008, allowing for a comparison of the two major global recessions: the 2009 Great Recession and the COVID-19 pandemic. Our approach to decompose economic shocks combines two alternative methods. First, we use recently popularized natural language processing (NLP) techniques to identify demand and supply sentiment in the transcripts of corporate earnings calls following the methods of Baker et al. (2016) and Hassan et al. (2020). Specifically, we measure sentiment (positive or negative) around demand and supply discussions and calculate the deviations from long-term trends at both aggregate and sectoral levels. This method allows us to perform a systematic quantitative analysis of global demand and supply using earnings calls transcripts of publicly listed firms on the US stock market and headquartered in 80 countries. Second, to corroborate the sentiment analysis, we use a structural Bayesian vector autoregressive (SBVAR) model to identify structural demand and supply shocks and quantify their impacts on output and inflation.

Our combined NLP and SBVAR analysis identified several key facts related to demand and supply during the COVID-19 pandemic and the Great Recession. First, a detailed evaluation of the COVID-19 pandemic timeline shows that the corporate sector was exposed to large disruptions in demand and supply of more than ten standard deviations larger than their long-term averages. During the COVID-19 pandemic, both demand and supply sentiment simultaneously collapsed with supply sentiment falling by more. Demand and supply sentiment levels rebounded to their long-term averages by the end of 2020. Supply sentiment then dropped significantly in 2021, in line with the disruptions to global supply chains. These demand and supply dynamics differ from those of the Great Recession. In 2009, demand sentiment collapsed but there was no material decline in supply sentiment.

Second, uncertainty rose dramatically, but more so during COVID-19 pandemic than during the Great Recession. However, current evidence suggests that uncertainty persisted much longer during the Great Recession than during the COVID-19 pandemic.

Third, we find substantial sectoral heterogeneity in demand and supply sentiment during the COVID-19 pandemic. Demand and supply disruptions were widespread 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 better than others during the pandemic, based on demand and supply sentiment scores. During the pandemic's collapse and recovery phases, the relative magnitudes of demand and supply varied dramatically across sectors. For instance, airlines and airport services were constrained by demand shifts and much smaller supply shifts throughout 2020, and this appears to have continued despite global economic activity rebounding in 2021. On the other hand, demand sentiment in the automobile sector has improved since the second half of 2020, despite the persistence of considerable supply restrictions during the pandemic.

The aggregated demand and supply sentiment are corroborated using a sign-restricted SBVAR model. We decompose the contribution of demand and supply shocks to output and inflation fluctuations and highlight the large demand and supply shocks present during the COVID-19 pandemic, the greater relative importance of demand during the Great Recession, the significant increase in uncertainty during both events, and the generally strong correlation between demand and, to a lesser extent, supply.

Prior research

This paper connects with two major lines of research. First, our sentiment analysis builds on the literature about applying NLP methods to digital texts in economics and finance.[1] For example, Baker et al. (2016) and Hassan et al. (2019) study political uncertainty at the

[1] NLP is a branch of machine learning that focuses on textual data applications. See Gentzkow et al. (2019) for a recent survey.

aggregate and firm level using text-based measures. Baker et al. (2020) measure the role of COVID-19 developments in recent stock market behavior using automated and human readings of newspaper articles. Hassan et al. (2021) use earnings call transcripts to estimate the firm-level impact of Brexit in the United Kingdom and across the world. Hassan et al. (2020) document firm-level impacts of epidemiological diseases using earnings call transcripts. Gosselin and Taskin (2023) study earnings calls transcripts to draw insights on the Canadian output gap and inflationary pressures. We contribute to this strand of literature by using NLP methods to documenting the size of demand and supply disruptions at a global scale, and linking our results to global economic activity and inflation.

Understanding the demand and supply dynamics of the economic impact of the COVID-19 pandemic is vital for designing an effective policy response. If a supply shock dominates, a strong countercyclical response may create unnecessary demand and increase risks related to debt and financial and inflation stability. However, the delineation between demand and supply shocks is unclear, and the two are likely intertwined with what started as a supply shock–mobility restrictions, layoffs, and firm exits– that lead to a demand shock as losses in income or precautionary behavior reduced consumption (Guerrieri et al., 2022). If the policy response is inappropriate, demand and supply shocks can become reinforcing: the initial supply shock depresses aggregate demand, which in turn induces firms to reassess investment and damages productivity, which depresses demand further (Fornaro and Wolf, 2020). The expectations of consumers and businesses can play an important role in these dynamics (Lorenzoni, 2009).

A number of studies have focused on how demand and supply dynamics vary across sectors given the pandemic's disproportionate impact on industries that require face-to-face interaction. del Rio-Chanona et al. (2020) show that for the United States, the dominance of demand or supply depends on the sector. Demand likely dominates in transport, whereas supply dominates in manufacturing, mining and services. The entertainment, restaurant, and tourism sectors are likely dominated by both. Baqaee and Farhi (2022) use a disaggregated macroeconomic model to capture the different cyclical conditions faced by different sectors, and find that the decline in real US GDP is distributed equally between demand and supply shocks. They also warn that countercyclical policy is one-third less effective than in typical recessions, requiring more targeted interventions. Brinca et al. (2020) also investigate the sectoral impacts of the COVID-19 pandemic in the United States, finding that during the initial peak of the crisis in March and April of 2020, two-thirds of the contraction in hours worked was due to supply shocks. Balleer et al. (2022) study the price-setting behavior of firms in Germany during the COVID-19 pandemic and find that demand and supply responses are both present, but demand dominates in the short-term. Meyer et al. (2022) use the Federal Reserve Bank of Atlanta's Business Inflation Expectations Survey to determine that firms saw the COVID-19 pandemic mainly as a demand shock in the early part of the pandemic (August 2020). Dietrich et al. (2022) use a daily survey to show that uncertainty played an overwhelming role in the collapse of output during the pandemic.

As this sectoral work highlights, the responses of different economies to the pandemic depended on their economic structure, which in turn aggravated the size and duration of the shock. The response of output and employment depended on what proportion of workers were able to work from home (Gottlieb et al., 2021). In advanced economies, about half of total employment can work from home, whereas about one-third can in poorer countries. 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 to determine what new features are needed to understand the impact of the pandemic on economic activity. For example, Eichenbaum et al. (2021) extend a standard macroeconomic model to include epidemiological features and show that epidemics generate large and persistent recessions. The demand and supply outcomes are consequences of people reacting to the risk of infection by reducing labor supply and consumption, and increasing precautionary behavior. The COVID-19 shock also requires solutions to estimating and forecasting using macroeconomic models. Lenza and Primiceri (2022), 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 the COVID-19 pandemic.

The rest of the paper is organized as follows: section 2.1 provides details of our approach, section 3 presents data and descriptive statistics, section 4 discusses results, section 5 tests robustness of our results, and 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 transcripts of earnings calls. *Demand sentiment* on a given call is obtained by aggregating sentiment scores around each mention of demand. We compute *demand sentiment* 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:

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

where B_{it} denotes the entire set of words in the call of firm i at time t, and $\mathbf{1}^{\boldsymbol{DEM}}(\cdot)$ is an indicator function which takes a value of 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 that are before and after word b. Parameter r is set to 10 and the function $S(c)$ is defined as follows[2]:

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

in which S^+ and S^- represent the lists of positive- and negative-tone words, respectively. Supply sentiment is calculated using the same approach where we supply replaces demand.

Finally, we calculate aggregate uncertainty in a given call by the ratio of the frequency of uncertainty-related words to the total number of words. More specifically, the uncertainty score of a given call is calculated as follows:

$$Uncertainty_{it} = \frac{1}{|B_{it}|} \sum_{b \in B_{it}} \mathbf{1}^{\boldsymbol{UNC}}(b), \tag{2}$$

where $\mathbf{1}^{\boldsymbol{UNC}}(\cdot)$ denotes an indicator function which takes a value of 1 if the input word is among the words related to uncertainty, and 0 otherwise.

The positive-tone, negative-tone, 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 transcripts of earnings calls.

Sector-specific indices are calculated using the same methods where we aggregate the scores of firms that operate in a given sector.

[2]We repeated the same exercise with $r = 20$ and $r = 30$, and the results remain similar.

2.2 A Structural Bayesian Vector autoregressive model

To decompose output and consumer price inflation growth into demand and supply, a SBVAR model in line with the identification assumptions of Blanchard (1989).[3] The model is specified as:

$$Y_t = BX_t + M_t, \tag{3}$$

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 price inflation, central bank policy rates, and oil prices. The model is estimated using quarterly data from 1991Q2 to 2021Q4 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 of 0.1, and cross-variable weighting of 0.5. A total of 25,000 iterations are run, with the first 5,000 iterations discarded and every 5^{th} draw retained.

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

$$\begin{bmatrix} \mu_t^Y \\ \mu_t^\pi \\ \mu_t^i \\ \mu_t^{Oil} \end{bmatrix} = \begin{bmatrix} + & + & - & * \\ + & - & - & * \\ * & * & + & * \\ + & + & * & * \end{bmatrix} \begin{bmatrix} \epsilon_t^Y \\ \epsilon_t^\pi \\ \epsilon_t^i \\ \epsilon_t^{Oil} \end{bmatrix}, \tag{4}$$

where a positive structural supply shock (ϵ) is defined as that which raises output, decreases inflation, and increases oil prices. A positive demand shock is defined as that which 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 im-

[3]The model is implemented using the BEAR toolbox of Dieppe et al. (2016). BEAR stands for the Bayesian Estimation, Analysis and Regression toolbox.

posed for the first two periods. The model is based on data for 14 economies and weighted using equity market capitalization in US dollars. In the robustness section (section 5), we look at the role of weighting strategy and alternative policy rates have on demand and supply.

The unprecedented nature and size of the COVID-19 shock presents possible challenges to the effective modeling of the pandemic. In order to deal with the significant change in volatility, the SBVAR model includes stochastic volatility in the error structure as in Jacquier et al. (1994) and a generic version of what is suggested in Lenza and Primiceri (2022) as a solution to the COVID-19 shock.

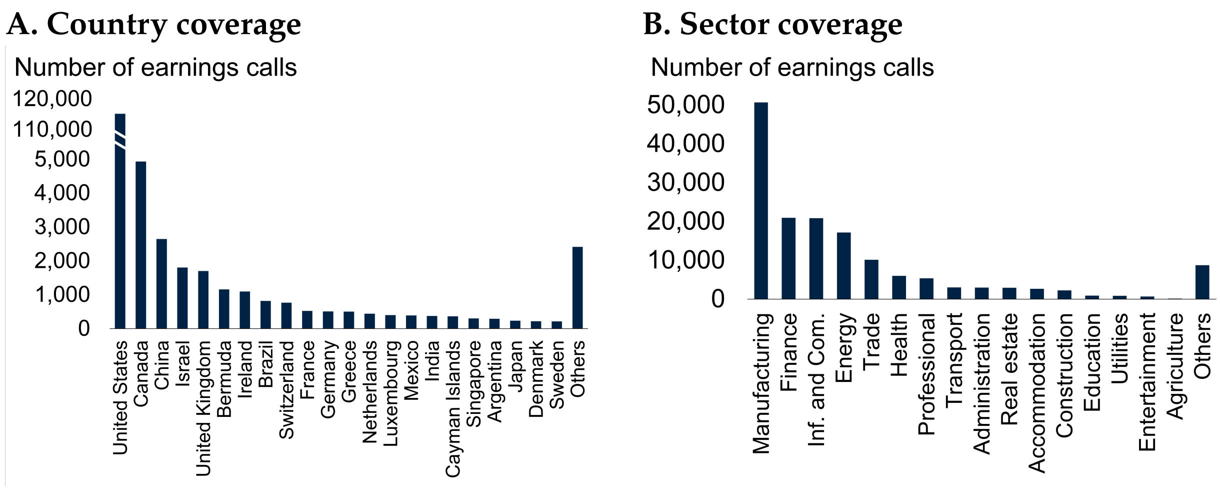
3 Data

3.1 Transcripts of earnings calls

The empirical analysis is based on two main data sets: the transcripts of earnings conference calls of publicly listed firms, and the lexicon dictionary of Loughran and McDonald (2011) for the identification of positive-tone, negative-tone, and uncertainty sentiment words.

Our primary dataset is composed of transcripts of quarterly earnings calls from publicly listed firms on the US stock market, which we obtained through Factiva's Fair Disclosure Wire. In these calls, senior management discuss the company's performance in the previous quarter and provide forward-looking guidance for future conditions. Market participants on the calls can ask questions and more widely debate key topics with management. We collected 181,562 transcripts of earnings calls between 2008Q1 and 2021Q4 for firms headquartered in 80 different countries, including both advanced economies and emerging markets. The dataset covers a large number of earnings calls from all major sectors and countries (figure 1). This equates to over 13,000 earnings calls per year, on average. The largest share of earnings calls are for firms headquartered in the United States, accounting for 77 percent of the total. The next largest is Canada, accounting for about about 7 percent of the earnings calls. The data cover all sectors with manufacturing representing the greatest share of earning calls, at about 33 percent, followed by finance and information and communication–each with about 13 percent.[4]

Figure 1: Data coverage



Sources: Factiva; World Bank.
Note: Not all earnings call transcripts provide country or sectoral information.
B. "Inf. and Com." stands for information and communication. "Others" includes administrative and support; waste management and remediation services; agriculture, forestry, fishing and hunting; arts, entertainment and recreation; educational services; management of companies and enterprises; public administration, utilities; and other services.

We clean the textual dataset using standard NLP techniques by removing stop words and applying tokenization (Gentzkow et al., 2019). Tokenization splits sentences into individual words, known as tokens, based on text delimiters like spaces and commas. This is an important step in preparing data for input into models because it converts text into a machine-readable format.

Stop words–which are common words such as prepositions (before, an, above) and determiners (the, a)–and names are removed from the tokenized text. Further, we remove words with fewer than three letters. These pre-processing steps ensure that the various sentimental and uncertainty variables (section 2.1) from the earnings calls transcripts can

[4]See Appendix A for examples of representative call transcripts.

be calculated accurately.

A possible limitation of this study's text-based approach is that the conversations in earnings calls may reflect corporate managers' subjective viewpoints, which may include error and bias. However, the public nature of earnings calls forces the content to be reliable and accurate because financial figures are disclosed, and call participants may immediately address possible biases. Furthermore, because the calls are conducted 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 2.2, which predicts shocks to demand and supply under structural assumptions without any reference to earnings calls, produces findings that are broadly consistent with the text-based sentiment series.

3.2 Macroeconomic data for the SBVAR model

The SBVAR model is estimated using real GDP, consumer price inflation, central bank policy rates, and oil prices (table 1). The variables are aggregated using fourteen economies, which are chosen based on the data from earnings calls, 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, and 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.

Table 1: Data for the SBVAR model

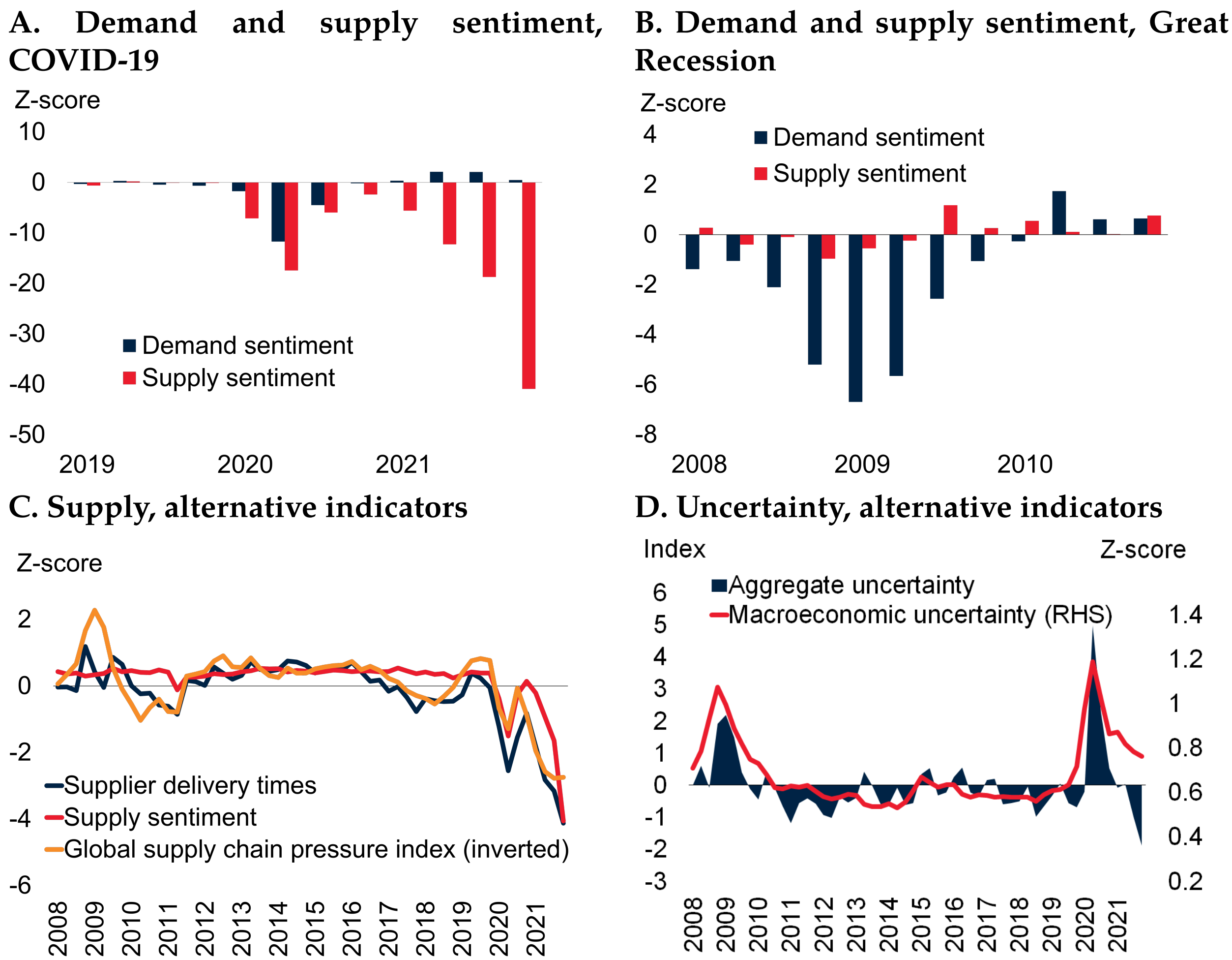
Variable	Definition	Transformation	Source
Y_t	Real GDP, seasonally adjusted	Log first difference, annualized	Haver Analytics
π_t	Consumer price index, seasonally adjusted	Log first difference, annualized	Haver Analytics
i_t	Central bank policy rate	Level	Haver Analytics
Oil_t	Average of Brent, West Texas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

4 Results

4.1 Demand and supply sentiment in earnings calls

In this section, we provide time series of demand and supply sentiment indices that cover both the COVID-19 pandemic and the 2009 Great Recession. Significant demand and supply disruptions occurred during the COVID-19 pandemic (figure 2). Supply sentiment dropped more than ten standard deviations from its long-term average during the first half of 2020, in line with the collapse of global supply chains at the onset of the pandemic.. Demand sentiment, on the other hand, dropped only slightly in 2020Q1 before plummeting in 2020Q2 as a result of widespread lockdowns and increased precautionary behavior. In contrast, demand during the Great Recession was broadly identical to that of 2020, with a mild decline in supply sentiment.

Figure 2: Demand and supply sentiment and aggregate uncertainty



Sources: Factiva; Federal Reserve Bank of New York; Jurado et al. (2015); IHS Markit; World Bank.
Note: The sentiment series reflect z-scores within the sample period.
A.B. Demand and supply sentiment from earnings calls are calculated using equation (1).
C. Supplier delivery times represent global manufacturing PMI series, with lower values reflecting longer delivery times. Global supply chain pressure index: lower values reflect higher pressure. Supply sentiment from earnings calls is calculated using equation (1).
D. Aggregate uncertainty index from earnings calls is calculated using equation (2). Raw series are linearly detrended and z-scores are calculated using the sample period. "Macroeconomic uncertainty" is based on Jurado et al. (2015).

The supply sentiment scores calculated from earnings calls move fairly consistently with other indicators of global supply conditions. Panel C in figure 2 plots our supply sentiment index against two commonly used global supply indices: the Purchasing Managers' Index of suppliers' delivery times and the Federal Reserve Bank of New York's Global Supply Chain Pressure Index. The deterioration during the COVID-19 pandemic, as well as the Great Recession is common to all indices, with variation in magnitude across indicators.[5]

Given the central role of uncertainty in investment decisions as well as broader economic activity (see Bernanke, 1983; Pindyck, 1988; Bloom et al., 2007), we calculate uncertainty scores using the full transcripts of earnings calls. Aggregate uncertainty–measured by applying equation (2) to the full transcripts of earnings calls–spiked by roughly seven standard deviations during the Great Recession and by more than ten standard deviations during the COVID-19 pandemic, but recovered faster during the pandemic. Aggregate uncertainty from transcripts of earnings calls compare favorably with macroeconomic uncertainty as defined by Jurado et al. (2015). The two measures have a correlation of 0.69. Both measures of uncertainty have peaks during the 2009 Great Recession and the COVID-19 pandemic. While uncertainty during the Great Recession recedes at about the same pace across the two measures, uncertainty based on earnings calls shifts lower significantly faster than observed by Jurado et al. (2015).

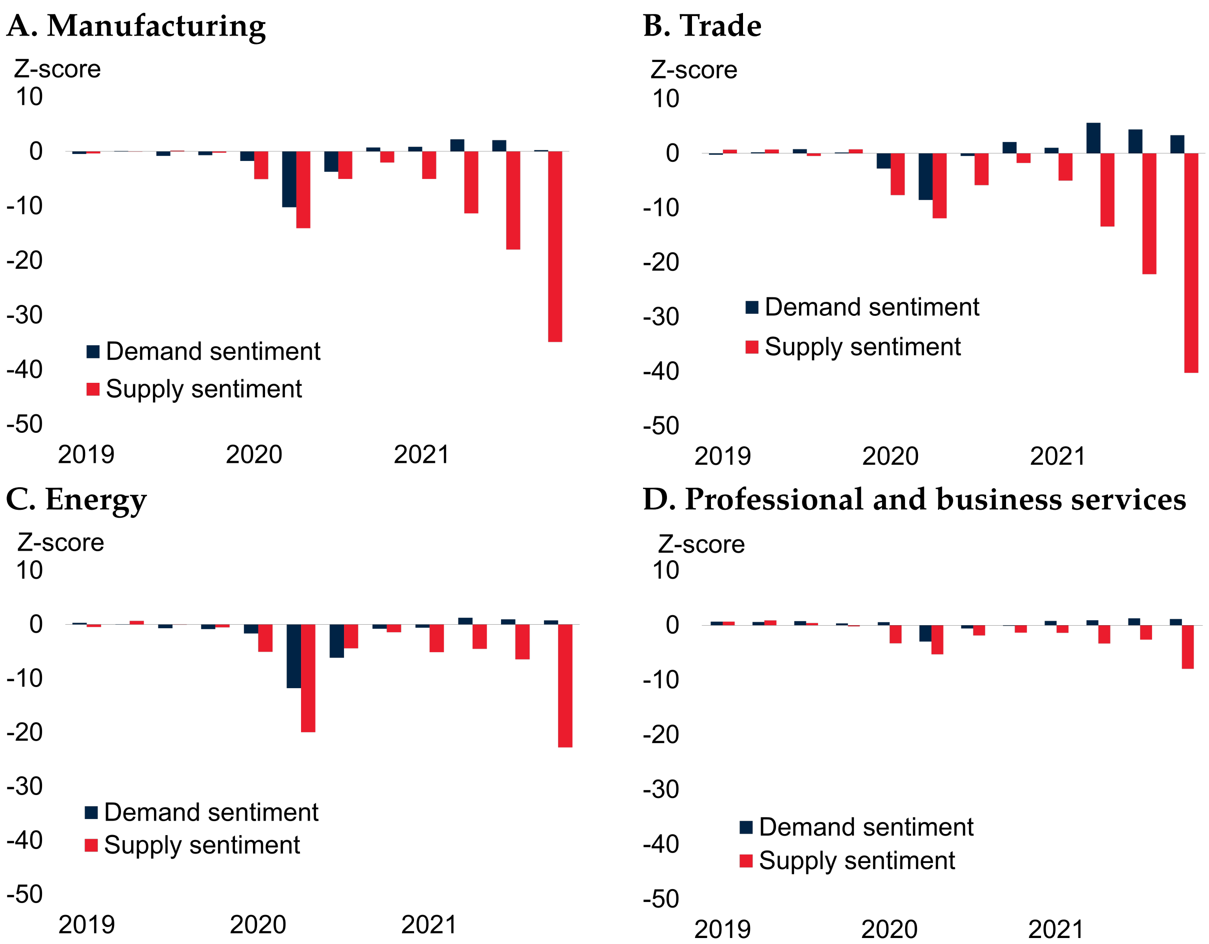
4.2 Sector-level demand and supply sentiment from earnings calls

Demand and supply shifts identified in the earnings calls were found to be widespread across sectors, but with significant sector-level variability. Figure 3 compares four sectors: manufacturing, wholesale and retail trade, energy, and professional and business services. We highlight three important observations about 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 large swings in both demand and supply sentiment, 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 shifts over the course of 2020 and 2021. This is in line with the fact that profes-

[5]The correlation coefficients between our indicator and the Global Supply Chain Pressure Index is 0.86, and 0.68 with the Purchasing Managers' Index of suppliers' delivery times.

sional and business services require fewer face-to-face interactions and the sector's ability to shift to home-based remote work (see, for example, Bick et al., 2020, and Papanikolaou and Schmidt, 2022). Third, supply sentiment fell across all sectors in 2021, but to a much larger extent than during the early stages of the pandemic, especially in the manufacturing and trade sectors.

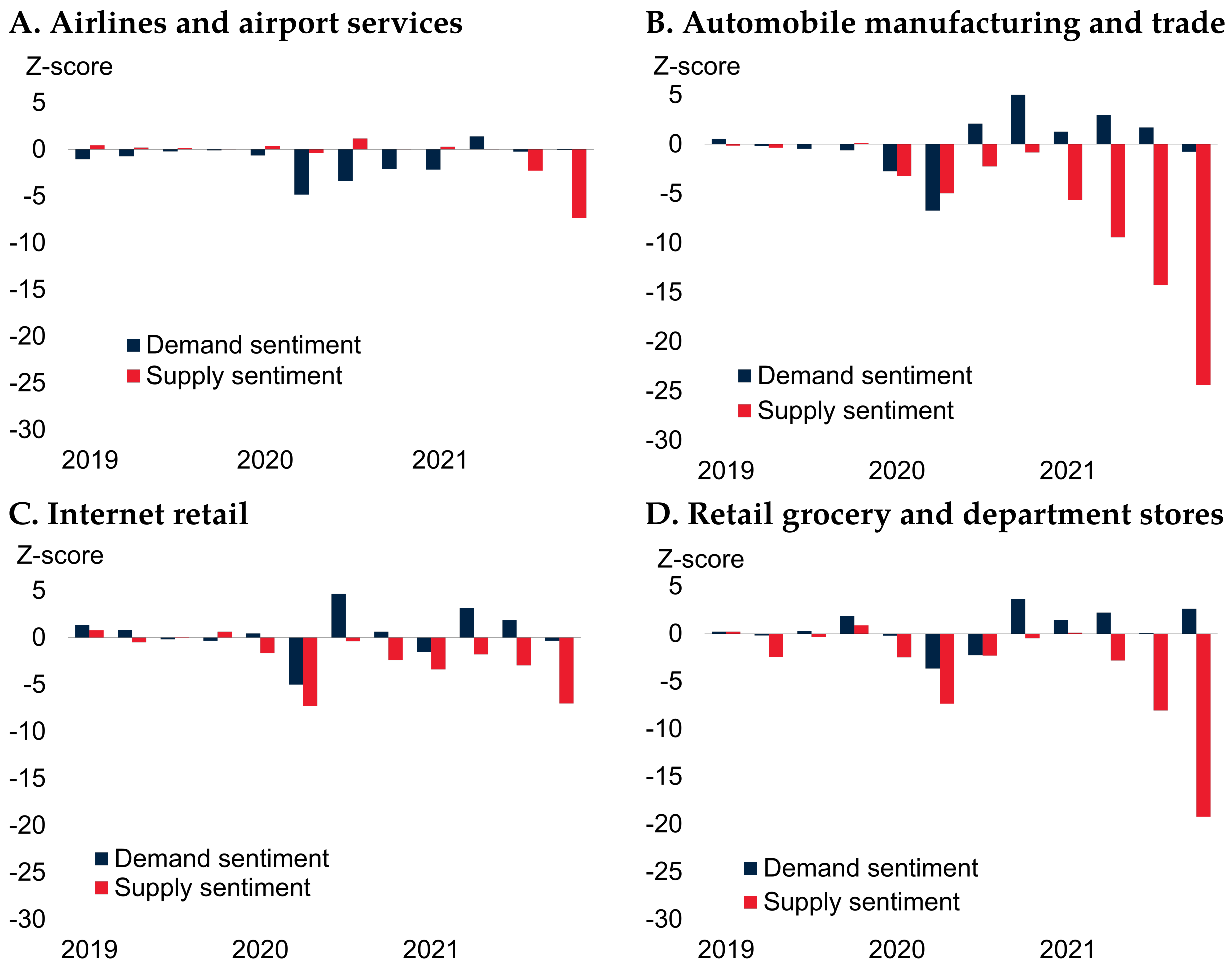
Figure 3: Demand and supply sentiment, sector level



Sources: Factiva; World Bank.
Note: The sentiment series reflect z-scores within the sample period. Sector-specific results are based on transcripts of earnings calls for companies classified within each sector.

We present results for select sub-sectors to shed more light on how demand and supply conditions differed across different types of businesses (figure 4). The findings demonstrate remarkable disparity in demand and supply sentiment in some sub-sectors. For example, airlines and airport services experienced large drops in demand sentiment as a result of international travel restrictions, with little interruption in supply conditions. In 2020Q2, demand sentiment fell by more than five standard deviations, and this trend continued into 2021Q1. In the automotive sector, negative supply sentiment remained large throughout 2020 and intensified in 2021 due to a shortage of semiconductors and shipping delays. Demand, on the other hand, has rebounded strongly since the second half of 2020. In sharp contrast with the airlines and automotive sectors, supply disruptions dominated demand at roughly similar magnitudes in internet retail, and grocery and department stores. However, demand in these two sectors dropped moderately and then quickly recovered to positive levels. The global supply chain disruptions were reflected in all sub-sectors, with much larger drops in supply sentiment in automobile manufacturing and trade, and retail grocery and department stores.

Figure 4: Demand and supply sentiment, sector level



Source: Authors' calculations.
Note: The sentiment series reflect z-scores within the sample period. Sector specific results are based on transcripts of earnings calls for companies classified within each sector.

4.3 Decomposing demand and supply factors in output and inflation fluctuations

We use a sign-restricted structural Bayesian VAR model to determine the relative size of demand and supply 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 demand and supply shocks in output and inflation fluctuations, since the optimal monetary and fiscal policy responses are different for adverse demand shocks versus supply shocks.[6] This is of particular importance in the case of the COVID-19 pandemic. The nature of the shock has evolved considerably due to different sectoral impacts, even though policy-induced lockdowns and precautionary behaviour caused the initial shock.

Figure 5 plots the the historical decomposition of output and consumer price inflation fluctuations during the COVID-19 pandemic and the 2009 Great Recession using the model and identification strategy described in section 2.2. The results indicate that demand and supply shocks were large during the pandemic-induced collapse of 2020 with demand accounting for 55 percent, on average, of the (relative) decline in annual output growth.[7] On a cumulative basis from 2020Q1-2021Q4, supply shocks accounted for 54 percent of the moves in output. The contribution of demand to year-on-year growth increased as the pandemic evolved, accounting for 45 percent in 2020Q1 to almost all of the decline in 2021Q1. On a quarterly basis, more than half of the decline in growth from 2019Q4 to 2020Q1 was supply-related. This switched in 2020Q2 with 54 percent of the decline in growth demand-related. Supply accounted for about two-thirds of the rebound in growth in 2020Q3, reflecting evolving lockdown restrictions, countercyclical policy responses, and a rebound in production.

Compared with the 2009 Great Recession, the demand and supply shocks were larger during the COVID-19 pandemic. 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 87 percent of the annual decline in output in 2009, and 80 percent for the period between 2008Q4 and 2009Q3. While a direct accounting of aggregate demand and supply shocks during the Great Recession in the literature is scarce, related literature can provide some insight. A study on the impact of financial crises on international trade flows by Ben-

[6] Blanchard and Quah (1989), Blanchard (1989), Gali (1992), and Bekaert et al. (2020) are only a few examples.

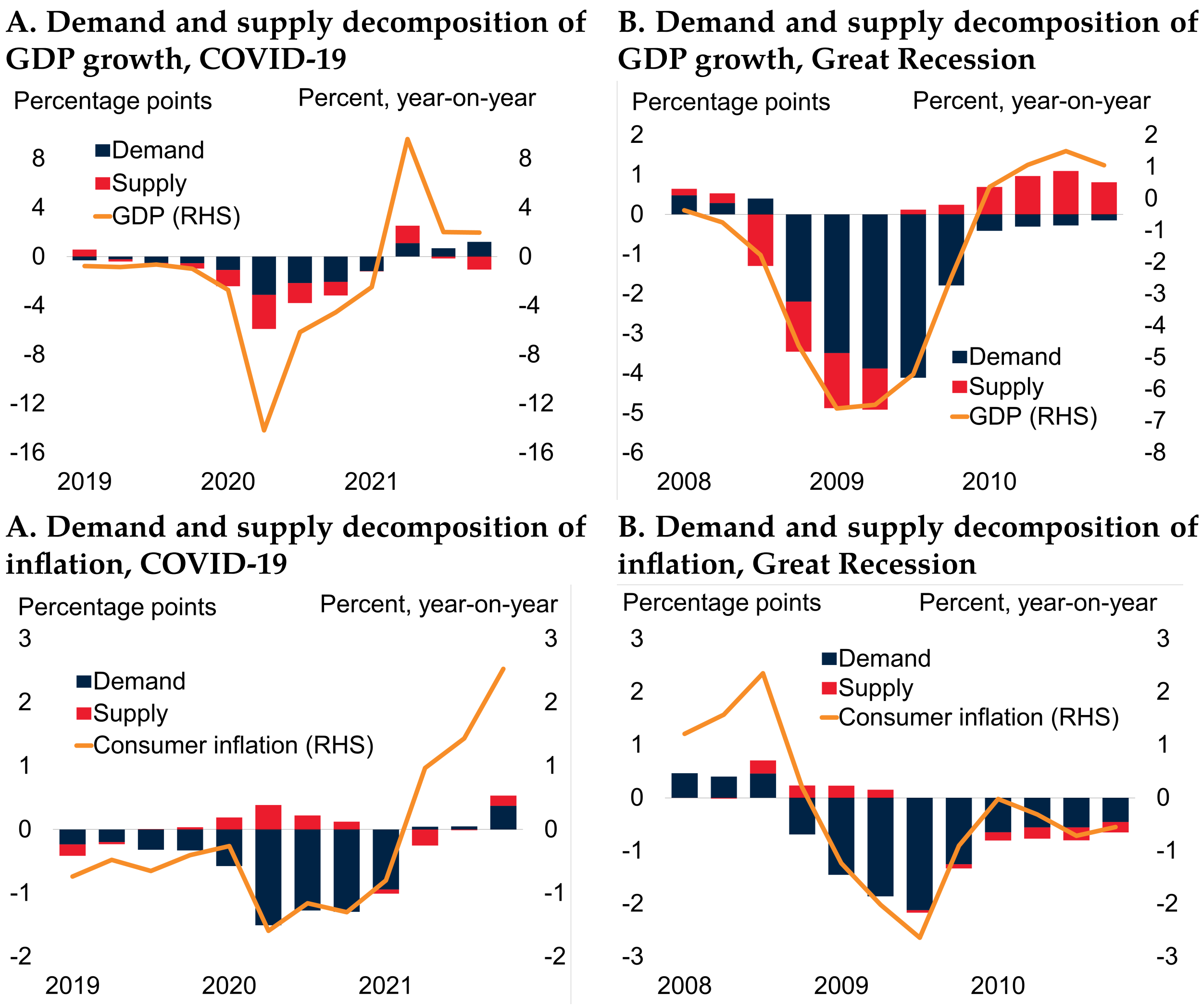
[7] The model includes other shocks that explain movements in output and inflation. Demand and supply alone account for more than half of the change in output growth in 2020.

guria and Taylor (2020) finds that financial crises are mainly demand shocks. Mian and Sufi (2009) reject prior studies' claim that productivity-driven growth was an important driver of the rapid buildup and subsequent collapse of credit during the Great Recession, but rather arguing instead that securitization was the main driver. This suggests that aggregate demand shocks are a more likely explanation for shifts in GDP during the Great Recession.

The historical decompositions from the SBVAR model generally corroborate our review of transcripts of earnings calls that swings in demand and supply sentiments were large and shifted quickly into negative territory in 2020. Also, while demand recovered in 2021, supply again turned negative. The relative importance of supply tends to dominate in the case of earnings calls, but does not link directly to activity. In the case of the Great Recession, the shift in demand and supply sentiments supports the greater importance of demand. However, the earlier supply shift is not clear from earnings calls.

In the case of inflation, the historical decomposition shows that demand and supply shocks countered each other during the COVID-19 pandemic, dampening the decline in consumer price inflation. The relatively larger role of demand also occurs in the case of inflation. As a consequence, annual inflation fell from 2 percent on an annual basis in 2020Q1 to 0.7 percent in 2020Q2, and rebounded quickly. During the Great Recession, the decline in inflation was more protracted, falling from 2.5 percent in 2008Q4 to -0.3 percent in 2009Q3, with demand and supply both contributing to the decline.

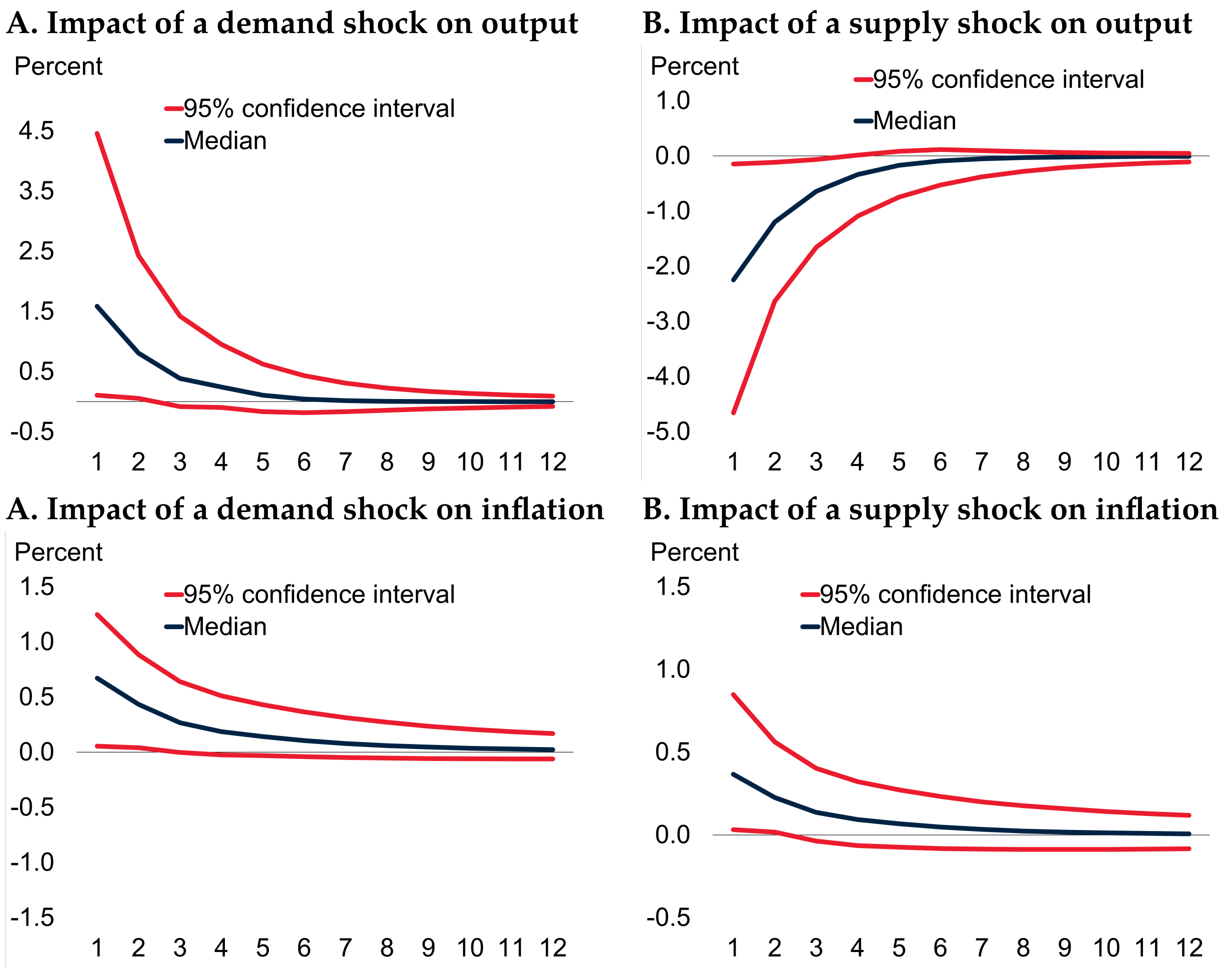
Figure 5: Demand and supply from VAR



Source: Authors' calculations.
Note: Historical decomposition of real GDP growth and consumer price 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.

The impulse response functions show the median response of growth and inflation to demand and supply shocks (figure 6). A positive demand shock leads to a significant increase in GDP growth and consumer price inflation. The effects remain significant for up to quarters. A positive supply shock leads to a statistically significant increase in GDP growth and a decrease in consumer price inflation.

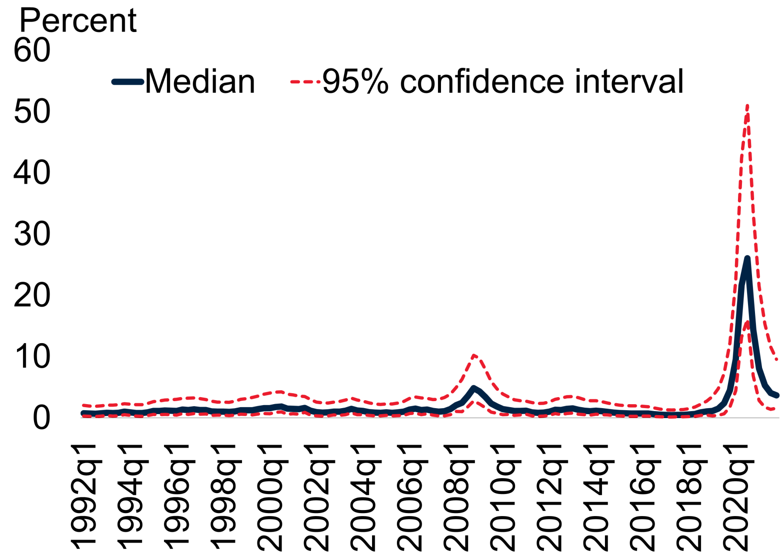
Figure 6: Impulse response functions, SBVAR



Source: Authors' calculations.

The VAR model also provides a perspective on uncertainty given the inclusion of stochastic volatility (figure 7). During the COVID-19 shock, output (and equally true of inflation) volatility was 13 times larger than the average from 1992 to 2021 (excluding the Great Recession and the COVID-19 pandemic), and four times larger than during the Great Recession. When economic conditions are more stable, the standard deviation of output is about 1.2 percent. The relative size of uncertainty during the pandemic to a longer-run average is slightly larger in the VAR model than the uncertainty observed in the transcripts of earnings calls. The VAR model also assigns substantially more uncertainty during the pandemic than the Great Recession.

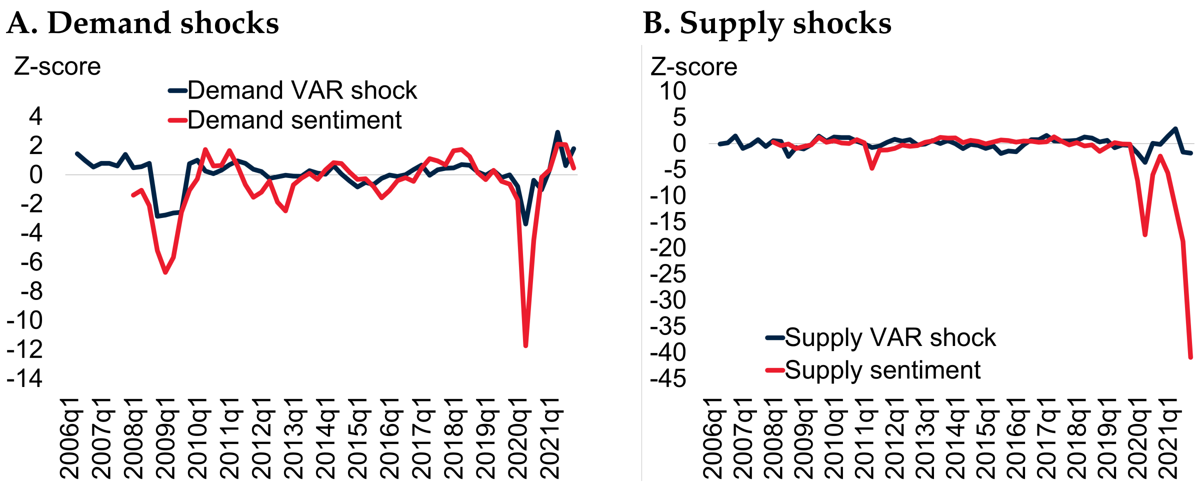
Figure 7: Output uncertainty



Source: Authors' calculations.

Lastly, the structural shocks from the VAR model can be compared with the sentiment measures generated from the earnings calls (figure 8). Structural demand shocks from the VAR and the sentiment demand measure have a strong positive correlation (0.78). While absolute magnitudes differ, both methods clearly distinguish demand. However, the timing of the demand shifts surrounding the European debt crisis in 2011-12 diverge somewhat. The supply measures are less well correlated (0.34), suggesting differences in the nature of the supply shock around both the COVID-19 pandemic and the Great Recession.

Figure 8: Demand and supply comparisons



Source: Authors' calculations.
A.B. Structural demand and supply shocks from the Bayesian VAR model are four-quarter moving averages and standardized for ease of comparison to the sentiment measures. The sentiment series reflect z-scores.

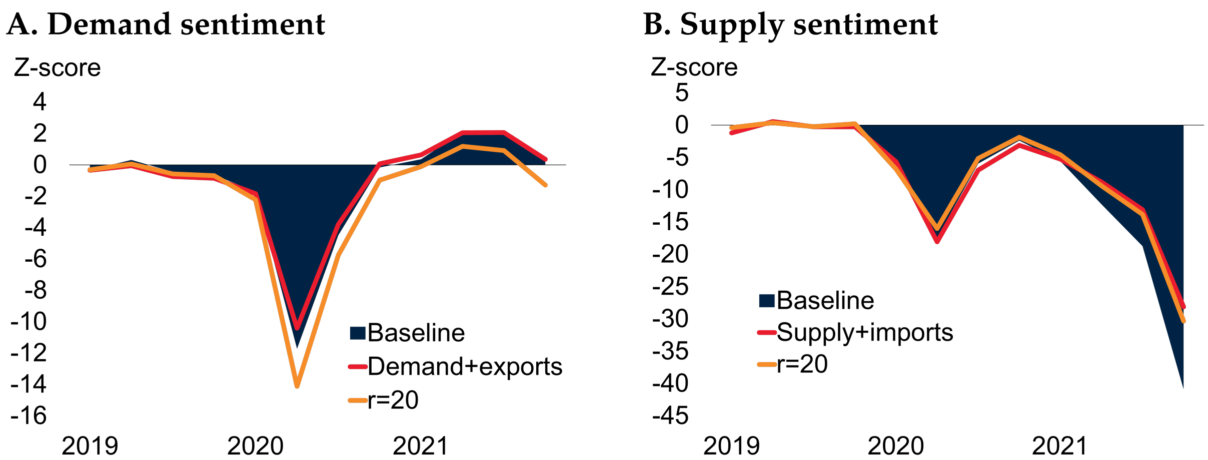
5 Robustness

5.1 Sentiment measures

The sentiment measures are partly functions of choices about how to collate textual information. This section looks at the sensitivity of demand and supply sentiment to r, and to the keywords that are used to identify demand and supply discussions.

First, we set r–the range around mentions of demand and supply to determine sentiment to 20 instead of the benchmark value of 10. Figure 9 shows that the sentiment measure is robust to choices of r 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, and {supply, imports} mentions to identify supply. The series are plotted as the red-dashed lines in figure 9. 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.

Figure 9: Robustness: Demand and supply sentiment measures



Source: Authors' calculations.
A.B. The figure illustrates the demand and supply sentiment series based on alternative measurement methods. Shaded areas show the benchmark measure, red lines show the series using an alternative keyword list for demand and supply, and orange lines show the series constructed by an extended range of words surrounding each mention of keywords. See section 2.1 for details about the construction of benchmark series.

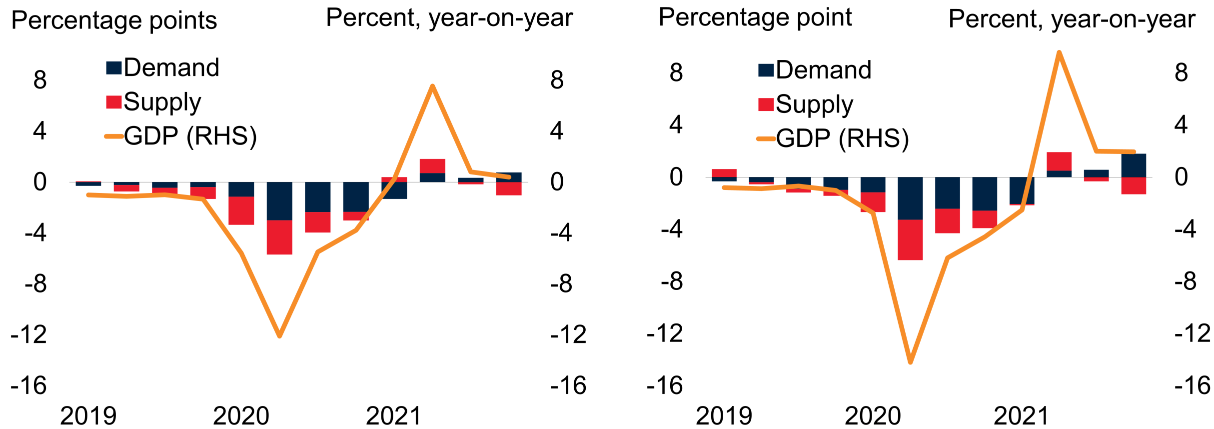
5.2 A Structural Bayesian VAR model

To test the robustness of the demand and supply decomposition, 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 better reflects the contribution of economies to overall activity and links more appropriately 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 stimulating the economy in the years since the 2009 Great Recession and therefore 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).

Figure 10: Robustness: Demand and supply from SBVAR

A. Demand and supply decomposition of GDP growth, GDP-weighted

B. Demand and supply decomposition of GDP growth, shadow policy rate



Source: 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 from a model-determined constant.

The historical decomposition is generally robust to using GDP weights instead of market capitalization, with the relative share of demand and supply the same–55 percent demand-related during the 2020 pandemic-induced collapse in the cases of market capitalization and GDP weights (figure 10). The results from the Great Recession differ somewhat, but still show that demand shocks account for the overwhelming share of GDP at about 96 percent (instead of about 87 percent in the benchmark case) of the 2009 collapse. In the case of inflation, the GDP-weighted model shows a similar offsetting role for demand and supply during the COVID-19 pandemic, with larger demand shocks driving down inflation overall. The historical decomposition is also generally robust to using the shadow policy rate instead of nominal policy rates, with the relative share of demand accounting for 55 percent of the 2020 collapse in output when using the shadow policy rates.

6 Conclusion

This study examines demand, supply, and uncertainty over time, with an emphasis on the 2009 Great Recession and the COVID-19 pandemic. Our method for decomposing economic shocks combines two different approaches. First, we identify demand and supply sentiment, and uncertainty at a global level by applying NLP methods to analyze earning call transcripts 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 disruptions during the pandemic were large, with significant variance across sectors.

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 them to movements in output and inflation. The model results corroborate the findings of the textual analysis and show that both demand and supply played an important role in driving growth and inflation outcomes. While both reflect significant increases in uncertainty during the COVID-19 pandemic, the VAR suggests that this uncertainty was significantly higher during the COVID-19 pandemic.

Recent debate over the nature of economic shocks has important implications for the optimal design of macroeconomic policies. We show that both demand and supply played an important role in the collapse of output during the COVID-19 pandemic. Our results also reveal important heterogeneity across sectors that policy makers can use to design targeted relief to those firms most impacted by future events while limiting possible side effects, such as lower productivity due to the misallocation of capital and labor.

References

Baker, Scott R, Nicholas Bloom, and Steven J Davis, "Measuring economic policy uncertainty," *The Quarterly Journal of Economics*, 2016, *131* (4), 1593–1636. 1, 2, 25

__ , __ , __ , **and Stephen J Terry**, "Covid-induced economic uncertainty," Technical Report, National Bureau of Economic Research 2020. 3

Balleer, Almut, Sebastian Link, Manuel Menkhoff, and Peter Zorn, "Demand or Supply? Price Adjustment Heterogeneity during the Covid-19 Pandemic," *International Journal of Central Banking, forthcoming*, 2022. 4

Baqaee, David and Emmanuel Farhi, "Supply and demand in disaggregated Keynesian economies with an application to the Covid-19 crisis," *American Economic Review*, 2022, *112* (5), 1397–1436. 3

Bekaert, Geert, Eric Engstrom, and Andrey Ermolov, "Aggregate demand and aggregate supply effects of covid-19: A real-time analysis," *Available at SSRN 3611399*, 2020. 17

Benguria, Felipe and Alan M Taylor, "After the panic: Are financial crises demand or supply shocks? Evidence from international trade," *American Economic Review: Insights*, 2020, *2* (4), 509–26. 17

Bernanke, Ben S, "Irreversibility, uncertainty, and cyclical investment," *The Quarterly Journal of Economics*, 1983, *98* (1), 85–106. 13

Bick, Alexander, Adam Blandin, and Karel Mertens, "Work from home after the COVID-19 Outbreak," 2020. 14

Blanchard, Olivier Jean, "A traditional interpretation of macroeconomic fluctuations," *The American Economic Review*, 1989, pp. 1146–1164. 7, 17

__ **and Danny Quah**, "The Dynamic Effects of Aggregate Demand and Supply Disturbances," *The American Economic Review*, 1989, *79* (4), 655–673. 17

Bloom, Nick, Stephen Bond, and John Van Reenen, "Uncertainty and investment dynamics," *The Review of Economic Studies*, 2007, *74* (2), 391–415. 13

Brinca, Pedro, Joao B Duarte, and Miguel Faria e Castro, "Measuring Sectoral Supply and Demand Shocks during COVID-19," *FRB St. Louis Working Paper*, 2020, (2020-011). 4

del Rio-Chanona, R Maria, Penny Mealy, Anton Pichler, Francois Lafond, and J Doyne Farmer, "Supply and demand shocks in the COVID-19 pandemic: An industry and occupation perspective," *Oxford Review of Economic Policy*, 2020, *36* (Supplement_1), S94–S137. 3

Dieppe, Alistair, Romain Legrand, and Björn Van Roye, "The BEAR toolbox," 2016. 7

Dietrich, Alexander M, Keith Kuester, Gernot J Müller, and Raphael Schoenle, "News and uncertainty about COVID-19: Survey evidence and short-run economic impact," *Journal of Monetary Economics*, 2022, *129*, S35–S51. 4

Eichenbaum, Martin S, Sergio Rebelo, and Mathias Trabandt, "The macroeconomics of epidemics," *The Review of Financial Studies*, 2021, *34* (11), 5149–5187. 4

Fornaro, Luca and Martin Wolf, "Covid-19 Coronavirus and Macroeconomic Policy," 2020. 3

Gali, Jordi, "How well does the IS-LM model fit postwar US data?," *The Quarterly Journal of Economics*, 1992, *107* (2), 709–738. 17

Gentzkow, Matthew, Bryan Kelly, and Matt Taddy, "Text as data," *Journal of Economic Literature*, 2019, *57* (3), 535–74. 2, 9

Gosselin, Marc-André and Temel Taskin, "What can earnings calls tell us about the Canadian output gap and inflation?," *Bank of Canada Staff Discussion Papers*, 2023. 3

Gottlieb, Charles, Jan Grobovšek, Markus Poschke, and Fernando Saltiel, "Lockdown accounting," *The BE Journal of Macroeconomics*, 2021, *22* (1), 197–210. 4

Guerrieri, Veronica, Guido Lorenzoni, Ludwig Straub, and Iván Werning, "Macroeconomic implications of COVID-19: Can negative supply shocks cause demand shortages?," *American Economic Review*, 2022, *112* (5), 1437–74. 3

Hassan, Tarek A, Stephan Hollander, Laurence van Lent, and Ahmed Tahoun, "Firm-level political risk: Measurement and effects," *The Quarterly Journal of Economics*, 2019, *134* (4), 2135–2202. 2

Hassan, Tarek Alexander, Stephan Hollander, Laurence van Lent, and Ahmed Tahoun, "Firm-level exposure to epidemic diseases: Covid-19, SARS, and H1N1," Technical Report, National Bureau of Economic Research 2020. 1, 3, 5, 25

Hassan, Tarek, Stephan Hollander, Laurence van Lent, and Ahmed Tahoun, "The global impact of Brexit uncertainty," Technical Report, Center for Economic Policy Research 2021. 3

Jacquier, Eric, Nicholas G Polson, and Peter E Rossi, "Bayesian Analysis of Stochastic Volatility Models," *Journal of Business & Economic Statistics*, 1994, *12* (4), 371–389. 8

Jurado, Kyle, Sydney C Ludvigson, and Serena Ng, "Measuring uncertainty," *American Economic Review*, 2015, *105* (3), 1177–1216. 12, 13

Kirby, Patrick and L Maliszewska, "The Impact of COVID-19 on Global Value Chains," 2020. 4

Lenza, Michele and Giorgio E Primiceri, "How to estimate a vector autoregression after March 2020," *Journal of Applied Econometrics*, 2022, *37* (4), 688–699. 5, 8

Lorenzoni, Guido, "A Theory of Demand Shocks," *American Economic Review*, 2009, *99* (5), 2050–84. 3

Loughran, Tim and Bill McDonald, "When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks," *The Journal of Finance*, 2011, *66* (1), 35–65. 6, 8

Meyer, Brent H, Brian Prescott, and Xuguang Simon Sheng, "The impact of the COVID-19 pandemic on business expectations," *International Journal of Forecasting*, 2022, *38* (2), 529–544. 4

Mian, Atif and Amir Sufi, "The consequences of mortgage credit expansion: Evidence from the US mortgage default crisis," *The Quarterly Journal of Economics*, 2009, *124* (4), 1449–1496. 18

Papanikolaou, Dimitris and Lawrence DW Schmidt, "Working remotely and the supply-side impact of Covid-19," *The Review of Asset Pricing Studies*, 2022, *12* (1), 53–111. 14

Pindyck, Robert S, "Capital risk and models of investment behaviour," in "Economic modelling in the OECD countries," Springer, 1988, pp. 103–117. 13

Wu, Jing Cynthia and Fan Dora Xia, "Measuring the macroeconomic impact of monetary policy at the zero lower bound," *Journal of Money, Credit and Banking*, 2016, *48* (2-3), 253–291. 23

Appendix A. Sample excerpts from selected earnings calls

Ford Motor Company, 29-Oct-20
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**.
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.
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.
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.
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.

Zoom Video Communications, 3-Jun-20
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.

Norwegian Cruise Line Holdings Ltd., 20-Feb-20
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 **virus**es 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.

Advanced Micro Devices, Inc., 28-Apr-20
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.