Main Street's Pain, Wall Street's Gain*

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Abstract

We propose a fiscal policy expectations mechanism. When bad macro news arrives (e.g., initial jobless claims or IJC are higher than expected), investors may expect more generous government support and drive up aggregate stock prices through the expected cash flow channel. Using a time-series sample from January 2013 to March 2021, we find that this phenomenon indeed emerges when newspapers mention fiscal policy more. Using a specific sample where fiscal policy debates were unprecedentedly active (early 2020-March 2021), we find that firms that are expected to receive more fiscal support exhibit higher individual stock returns when bad IJC shocks arrive.

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Keywords: return dynamics, macroeconomic news announcement, labor news, fiscal policy expectations, COVID-19, textual analysis, cross section

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"The number of Americans filing first-time applications for unemployment benefits unexpectedly rose last week... The weekly unemployment claims report from the Labor Department on Thursday, the most timely data on the economy's health, could add impetus to President Joe Biden's push for a \$1.9 trillion package to aid the recovery from the pandemic."

— *Reuters, February 18, 2021, 8:40AM EST*[1]

1. Introduction

While actual fiscal policy bills get passed relatively infrequently, people's beliefs about the prospect of bills passing can change on a daily basis. However, there is little empirical research on the role of changing expectations about fiscal policy in the stock market.[2] In this paper, we propose a "fiscal policy expectations" mechanism in the effect of macro announcement surprises on stock returns. In a low-interest-rate, crisis environment, when Main Street suffers more than expected, investors may expect more generous federal government support through fiscal policy (FP), driving up expected future cash flow growth and stock prices.

Given the lack of futures prices or surveys to elicit high-frequency FP expectations, we provide evidence for the following two testable predictions of this mechanism and focus on the weekly initial jobless claims (IJC) announcements as the main macro events in the paper. The first prediction is that time-varying FP expectations should explain time-varying return responses to IJC shocks, particularly when the actual IJC numbers are worse than expected. In a time-series sample from January 2013 to March 2021, we construct newspaper-based measures on IJC announcement days to capture time-varying perceptions of FP. The second prediction is that firms (and industries) that are expected to receive more fiscal support should exhibit higher individual stock returns when bad IJC shocks appear, resulting in a stronger "Main Street pain, Wall Street gain" phenomenon in the cross section. We use a specific covid period (early 2020 until March 2021) with unprecedented fiscal activities as our identification strategy, and construct three granular cross sections based on a novel firm-level fiscal spending database, the actual stimulus bills, and firm fundamentals.

[1] https://www.reuters.com/business/us-weekly-jobless-claims-rise-labor-market-recovery-stalls-2021-02-18/

[2] For instance, Gomes, Michaelides, and Polkovnichenko (2013), Croce, Kung, Nguyen, and Schmid (2012a), Croce, Nguyen, and Schmid (2012b), and Croce, Nguyen, and Raymond (2021) among many others focus on the long-term equilibrium effects of actual fiscal policies on asset prices and economic variables.

Initial Jobless Claims are announced every Thursday at 8:30 a.m. Eastern Time, and IJC surprises or shocks in our paper are defined as percent differences between actual and expected IJC numbers. The higher the shocks are, the worse the news is. Our mechanism hypothesis of a *specific* cash-flow mechanism that can be generalized is motivated from two stylized facts on IJC announcement days. For one, news articles mention different topics when IJC announcements arrive over time. There are significantly heightened fiscal policy-related mentions – not monetary policy- (MP) or uncertainty-related mentions – when bad IJC news comes out after 2020, compared to the earlier years from 2013 to 2019.[3] Together with additional narrative evidence, higher FP mentions in this low-interest-rate sample are consistent with expansionary policy speculations. Second, stock returns significantly increase with IJC shocks from February 2020 to March 2021 (the end of our sample), overturning the "bad is bad" pricing. Specifically, a one standard deviation (SD) increase in the initial jobless claims (IJC) surprise leads to significant increases in the daily open-to-close market index returns of around 30 basis points. The effect mostly affects through the expected cash flow channel and is pronounced during bad IJC days.

Next, we use two empirical frameworks to test the aggregate prediction from January 2013 to March 2021. In the first empirical framework, we regress rolling return-IJC responses on rolling topic mentions of FP, MP, and uncertainty; in the second test, we construct and use non-overlapping quarterly state variables to directly interact with IJC shocks. Both tests show qualitatively and quantitatively similar results, and are robust to controlling for monetary policy and business cycle indicators (such as uncertainty). During periods in which FP mentions are one SD higher than average, stock return responses caused by a 0.1 unit increase in IJC shocks are 16-20 basis points higher than stock responses to the same increase on average IJC days. The effect mostly comes from bad IJC days, which deliver a 26-34 basis point wedge. This finding is consistent with the expansionary nature of fiscal policy during this period.

In both empirical frameworks, we also find that monetary policy expectations (gauged with either text- or survey-based measures) are typically associated with return responses to good IJC shocks. During a period in which MP mentions are one SD higher than average, the

[3]The sample starts in 2013 due to IJC news article limitations. We explain in Section 2.1.

corresponding increase in return responses is around 11-13 basis points on average IJC days and 22 basis points on good IJC days. This finding is consistent with Boyd, Hu, and Jagannathan (2005) and Elenev, Law, Song, and Yaron (2022b). In a low-interest-rate environment, interest rates should have more potential to increase, and good IJC shocks should be able to trigger such increases.

We next test the cross-section prediction. Under this fiscal policy expectation mechanism, when a bad IJC shock arrives, investors may expect the likelihood of an expansionary fiscal policy passing to increase, which could affect the expected aggregate economic growth by affecting fiscal distributions to households and firms. As it is empirically challenging to design a households cross-sectional analysis, we focus on firms/industries. In addition, we use a fiscal-active period from February 2020 to March 2021 for identification. During this period, fiscal stimulus bills received unprecedented public attention and should be economically relevant to almost all industries and firms. To capture firm-level or industry-level fiscal policy expectations, we construct cross sections based on (1) industry mentions in actual stimulus bills, (2) firm-level fiscal support promised and actually given by the Federal Government, and (3) firm-level expected fundamental suffering. Results from these three cross sections lend support to the *fiscal*-based interpretation.

Investors may infer the likelihood of a particular industry or firm receiving more fiscal support from reading industry mentions in actual stimulus bills. We search industry mentions in the major stimulus bills using industry keywords from the NAICS website. Industries mentioned more heavily in actual bills exhibit statistically higher return-IJC shock correlations, supporting our hypothesis. For instance, in our fiscal-active sample period the healthcare industry receives a considerable amount of fiscal subsidy, given the nature of the pandemic crisis, and demonstrates a high industry return-IJC shock correlation at 0.228. Several non-crisis-related industries (e.g., transportation, manufacturing) with more mentions in the actual bills also exhibit a stronger "Main Street pain, Wall Street gain" phenomenon.

Next we scrape and create a novel database from a Treasury Office website. This website includes all details about both obligated fiscal distributions and actual outlay to each firm under each legal bill from the Federal government. We focus on the three covid stimulus bills

(CARES of 3/27/2020, CAA of 12/27/2020, and ARP of 3/11/2021), where fiscal distributions are largely in the form of a Paycheck Protection Program (PPP) or forgivable loans. We are able to identify 138 companies from the S&P 500 in our government spending database. Firms that are promised larger direct emergency payments exhibit statistically higher return-IJC shock correlations. An upper 75th bin exhibits an average return-IJC correlation of 18.5%, which is statistically higher than the lowest 25th bin, which has an average correlation of 13.2%. The healthcare and air transportation industries receive the greatest fiscal spending during the pandemic, consistent with our bill-mentioning study. In an alternative identification, we find that actual distributions from the CARES act (February – April of 2020) can significantly predict return-IJC shock correlations in the following months (May 2020 – March 2021). Investors form fiscal policy expectations about future bills based on recent distributions.

In our last cross-sectional evidence, we obtain a new dataset that indexes all internet job postings from employer websites; we define changes in a firm's job postings from 2019 to April/May of 2020 as a forward-looking measure of expected covid-related losses. Firms with greater decreases in job postings exhibit a higher return-IJC shock correlation.

We conclude the paper with several extending discussions, including examining the main results using intradaily asset prices or monthly macro announcements. The results are as expected. In addition, to shed light on the mechanism, we examine how traditional portfolios known to be cash flow sensitive behave on IJC days. Note that the specific mechanism in this paper affects returns through the cash flow expectation channel. Our efforts thus far in both time-series (Section 2) and the cross section (Section 4) include decomposing stock returns, documenting lack of similar behaviors among Treasury-related assets, and directly sorting firms based on a granular fiscal spending dataset. Here, we form portfolios based on end-of-2019 levels, and find that highly cash-flow sensitive assets (i.e., small, value, high E/P, low FCF) outperform only when IJC numbers are worse than expected, that is, according to our mechanism, when more expansionary fiscal policy is expected. High leverage assets do not outperform on bad IJC days.

Related literature

Our research contributes to the economics and finance literature in several ways. First, we join the literature that shows that macro announcements matter to the stock market (e.g., Gilbert (2011), Savor and Wilson (2013), Ai and Bansal (2018), Hirshleifer and Sheng (2021), Fisher, Martineau, and Sheng (2022), among many others). In particular, our work joins existing papers that study the time series pattern of stock market reactions to macro announcement surprises. The literature typically settles on two explanations. There is a business-cycle explanation (e.g., McQueen and Roley (1993), Andersen, Bollerslev, Diebold, and Vega (2007)) that predicts that business conditions reinforce the pricing of macro shocks during contractionary times. Another strand (e.g., Boyd, Hu, and Jagannathan (2005), Elenev, Law, Song, and Yaron (2022b), Yang and Zhu (2021), and Caballero and Simsek (2021)) argues that time-varying return responses to macro news likely also depend on monetary policy expectations, which are often but not always correlated with business cycles. Our research contributes to this literature by providing empirical evidence of the existence and economic significance of a specific cash flow expectation mechanism, i.e., time-varying fiscal spending expectations.

Next, our empirical evidence also complements the existing fiscal policy literature. While there is an extensive economics literature on the macroeconomic effects of fiscal policy,[4] there is scant research on its asset pricing effects. Most studies (see Croce, Kung, Nguyen, and Schmid (2012a), Croce, Nguyen, and Schmid (2012b), Gomes, Michaelides, and Polkovnichenko (2013), Bretscher, Hsu, and Tamoni (2020), Croce, Nguyen, and Raymond (2021) and so on) focus on examining the long-term price effects of *actual* policies (tax and spending) at the quarterly or lower frequencies though the lens of an equilibrium framework. Meanwhile, Belo, Gala, and Li (2013) and Belo and Yu (2013) examine the impact of *actual* government spending and investment on the cross section of equity risk premia, and Diercks and Waller (2017)

[4]For instance, Goulder and Summers (1989), Easterly and Rebelo (1993), Perotti (1999), Mankiw (2000), Akitoby and Stratmann (2008), Leeper, Walker, and Yang (2010), Auerbach and Gorodnichenko (2012), Mertens and Ravn (2012), Correia, Farhi, Nicolini, and Teles (2013), Bhandari, Evans, Golosov, and Sargent (2017), Karantounias (2018), D'Acunto, Hoang, and Weber (2018), Bhandari, Evans, Golosov, and Sargent (2021), and many others.

and Elenev, Landvoigt, Shultz, and Van Nieuwerburgh (2022a) examine the interplay among monetary policy, fiscal policy, and risk premium. Some recent empirical papers such as Baker, Bloom, Davis, and Sammon (2021) point out the rising importance of *actual* fiscal policy news in positive short-term stock market jumps. Our research contributes by hypothesizing that fiscal policy could already affect the capital market through investor expectations, which get capitalized at a high frequency, and we use labor news announcements as an identification strategy to help "sign" investor fiscal policy expectations. In a related paper, Bianchi, Cram, and Kung (2021) examine the role of congressional tweets in changing investor expectations about a bill passing.

As an empirical contribution to future literature, we intend to continue updating new datasets used in our identifications for more general applications, such as the news-based FP mention measures and cross-sectional fiscal distributions. The remainder of the paper is organized as follows. Section 2 establishes the stylized facts about newspaper topic discussions and asset price responses on IJC announcement dates, which motivates the mechanism hypothesized in Section 3. Sections 4 and 5 test the time-series and cross-sectional prediction of the hypothesis, respectively. Section 6 presents three extending discussions. Section 7 offers concluding remarks.

2. Stylized Facts

In this section, we establish several stylized facts about newspaper topic discussions and asset price responses *on* initial jobless claims (IJC) announcement days in the recent decade. We use initial jobless claims as our primary macro announcement shock in this paper for several reasons. First, among various macro announcements in the U.S., only IJC announcements occur at a weekly frequency (08:30 a.m. Eastern Time every Thursday), and such timely releases potentially generate a better empirical identification. Second, jobless numbers are unarguably "Main Street" variables, and should matter to policymakers. We consider other (monthly) macro announcements in Online Appendix Section OE.

Our main IJC shock is defined as $IJCShock_t = \frac{IJC_t - E_{t-\Delta}(IJC_t)}{E_{t-\Delta}(IJC_t)}$, where IJC_t denotes the number of actual initial claims from last week, which is released during this week t by the Employment and Training Administration (ETA), and $E_{t-\Delta}(IJC_t)$ indicates the median survey forecasts submitted before the announcement time. Both actual and expected claims are obtained from Bloomberg. We consider only IJC announcement days that neither exhibit statistically outlying behaviors[5] nor overlap with Federal Open Market Committee meetings (FOMC) or other major macro announcements. We also consider the simple level difference $IJC_t - E_{t-\Delta}(IJC_t)$ as an alternative choice (see as in Balduzzi, Elton, and Green (2001), Kurov, Sancetta, Strasser, and Wolfe (2019), etc.).[6]

2.1. Textual analysis on IJC announcement days

We let the data speak and document topic mentions on IJC announcement days. We examine CNBC's IJC news articles, which are written and published each Thursday to describe and interpret that morning's IJC announcement. Unlike other news sources such as WSJ or Bloomberg, CNBC has a reliable website designated for Initial Jobless Claims announcements, `https://www.cnbc.com/jobless-claims/`. A team of CNBC reporters writes and publishes one article for each Thursday's IJC announcement in the morning.[7] We manually collect these CNBC IJC news articles on announcement days for as far back as is available.[8] We are able to identify 366 IJC articles from the CNBC website through March 18, 2021. Figure 1 shows the article distribution over time. In the top plot, it is noticeable that we can identify only a few articles from before 2013 on their website, while the number becomes quite stable afterward. This limits the start year of the textual analysis (here and later in Section 4) to 2013. The

[5]The two top plots in Appendix Figure A1 show the time series of our main IJC shock with and without identified statistical outliers and days overlapping with the FOMC. Specifically, box plot outlier analysis using the ×2 interquartile range rule suggests that 2020/3/19 (actual: 281K; expected: 220K; shock=27.7%), 3/26 (actual: 3.28M; expected: 1.70M; shock=93.1%) and 4/2 (actual: 6.65M; expected: 3.76M; shock=76.7%) constitute three unrepresentative shock outliers. It can be tested that our main IJC shock series is stationary and well-behaved.

[6]The obvious structural break in the level of initial claims during March and April of 2020 makes this alternative measure less favorable, as seen in bottom two plots of Appendix Figure A1.

[7]A handful of times, they share Reuters.com's articles.

[8]News on CNBC's website is not directly downloadable from well-known news aggregators (e.g., RavenPack, LexisNexis, Factiva). There are also sometimes two articles on one IJC announcement day: one that describes the announcement statistics and has a macroeconomic discussion and one that describes financial market reactions at the end of the day. We only focus on the former.

bottom plot shows a relatively stable split between bad and good IJC announcements per 60-week rolling window.

We construct time-varying topic mentions metrics of 5 general topics: Fiscal policy ("FP"), monetary policy ("MP"), economic uncertainty ("UNC"), coronavirus-related ("COVID"), and normal words that appear in describing IJC ("NORMAL"). We relegate detailed lists of keywords and empirical methodology to Online Appendix OB, and discuss important points below. First, general textbook terms that define fiscal policy – such as "fiscal policy," "tax," or "government debt" – are not typically how fiscal policy as a topic gets mentioned in labor news announcement articles. To accommodate the needs of our research, we developed a group of words that reflect discussions of government spending, grants to the states, transfers (augmented unemployment benefits), and lawmaking to capture fiscal policy mentions. For instance, when words and phrases such as "aid," "extend," "benefit," "Congress," "lawmaker," and "federal government" appear in one article, that typically reflects an ongoing fiscal discussion.[9] The second topic of interest is monetary policy. The words we choose are standard and general, such as "central bank," "inflation," and "Federal Reserve," as well as

[9]Three examples of FP mentions when actual jobless numbers are worse than expected during 2020-2021:

1. August 20, 2020 https://www.cnbc.com/2020/08/20/weekly-jobless-claims.html: *Earlier this week, more than 100* ***House Democrats*** *urged* ***House Speaker*** *Nancy Pelosi, D-Calif., to pass a smaller bill that would reinstated the* ***extra benefits****.* ***Republicans*** *have indicated they want to* ***extend*** *the* ***additional benefit*** *at a lower rate. "It's been four weeks without the* ***$600/week*** *CARES Act* ***benefits*** *for tens of millions of unemployed Americans," said Zhao. "While a handful of states are approved to disburse the new* ***$300/week benefits****, it remains unclear how quickly the* ***benefits*** *will be able to flow to unemployed Americans already facing an unsteady recovery."*

2. December 17, 2020 https://www.cnbc.com/2020/12/17/weekly-jobless-claims.html: *The recent uptick in weekly jobless claims comes as coronavirus cases surge across the country.* ***Congress****, meanwhile, is scrambling to push through new* ***legislation*** *to* ***aid*** *individuals and businesses before year-end.* ***Congressional*** *leaders on Wednesday closed in on a* ***$900 billion*** *package that would include direct* ***payments*** *to individuals.*

3. February 18, 2021 ; https://www.reuters.com/business/us-weekly-jobless-claims-rise-labor-market-recovery-stalls-2021-02-18/: *The total of those receiving* ***benefits*** *dropped by 1.3 million to 18.34 million, primarily due to a falloff in those on Covid-19 pandemic-related claims in the final week of January. However, those numbers have accelerated in early February...* ***Congress*** *is trying to negotiate a* ***$1.9 trillion White House*** *stimulus plan. Part of that proposal includes* ***extended*** *jobless* ***benefits*** *that are scheduled to run out in mid-March... The number of Americans filing first-time applications for unemployment* ***benefits*** *unexpectedly rose last week... The weekly unemployment claims report from the Labor Department on Thursday, the most timely data on the economy's health, could add impetus to* ***President*** *Joe Biden's push for a* ***$1.9 trillion package*** *to aid the recovery from the pandemic.*

Federal Reserve Chairpersons' last names, etc. The third topic is economic uncertainty, and we follow Baker, Bloom, and Davis (2016). We do not use the existing EPU index because we are interested in mentions of economic uncertainty specifically in IJC news articles published on IJC announcement days. The last two topics – coronavirus-related and normal IJC terms – we include for validation purposes. Finally, to obtain the topic mentions metrics, we use state-of-the-art "Term Frequency-Inverse Document Frequency" or "TF-IDF" scores in our textual analysis. In general, the score of a word (after stemming and lemmatization) increases proportionally to the number of times this word appears in the document (Luhn (1957)); this is offset by the number of documents in which it occurs to adjust for the fact that some words simply appear more frequently in general (Jones (1972)). TF-IDF has become the standard recommended term-weighting method, as Beel, Gipp, Langer, and Breitinger (2016)'s recent survey documents. In our research, the average of the TF-IDF scores of all words in the same topic then becomes the topic's score. Given that each IJC article is relatively short (average=327 words), we construct topic mentions metrics using groups of weeks.

To illustrate, Figure 2 considers 60-week rolling windows and shows the time-varying topic mentions, normalized by the "Normal-IJC" mentions from the same rolling window. The mentions of economic uncertainty (blue dotted) behave as expected, given the existing literature that uses other empirical methodologies (such as Jurado, Ludvigson, and Ng (2015), Baker, Bloom, and Davis (2016), and Bekaert, Engstrom, and Xu (2022)). The pattern peaks around the Brexit referendum in 2016, the China-U.S. trade war in 2018-2019, the COVID-19 peak in early 2020, and the U.S. election in late 2020. Next, the two policy mentions – fiscal (black solid) and monetary (red dashed) – show distinctive patterns. Both start at a similar level and exhibit a downward trend; they remain low during 2015 and 2016. The MP mentions on IJC announcement days visibly increased around 2017 and 2018 but then declined, with a small bump in early 2020; the level of MP mentions ends 49.0% lower than that at the beginning of the sample (t statistics of a closeness test = -3.09). Note that MP is certainly well attended to during 2020-2021, particularly before April 2020 because most of the Federal Reserve's actions through MP tools were announced before April 2020;[10] what's different here is that we are

[10]We manually collected and summarized all Federal Reserve actions from 2020 to 2021 in Appendix Ta-

interested in what CNBC discusses *specifically* on IJC announcement days, which is a cleaner measure. FP mentions are high during the fiscal cliff debate early in the sample, become and remain low until April 2020, and then significantly increase and continue to do so through the end of the sample. From the beginning to the end of the sample, FP mentions increase by 57% ($t = 2.87$) and significantly surpass MP mentions. This stylized fact is the first indication that speculations about fiscal policy become more relevant on IJC days during 2020-2021.

Figure 3 complements Figure 2 by constructing "bad" ("good") topic mentions metrics using articles on bad (good) IJC days from the same 60-week rolling window. In this plot, we normalize a topic's bad- or good-day mentions using its first value in the sample, as we are interested in the relative growth; "1.5" in the thick line means that the bad-day mentions of a particular topic increase by 50% compared to the sample's beginning. In the upper left plot of Figure 3, FP mentions grow more aggressively on bad IJC days, and are mainly responsible for explaining the upward FP pattern from Figure 2. FP mentions on good IJC days remain relatively stable and statistically similar to earlier periods. The growth of FP mentions is statistically and significantly higher on bad IJC days than on good IJC days on average (t = 2.28). Second, the pattern of MP mentions on good IJC days is mostly aligned with the overall MP pattern. It exhibits a clear hump around 2017 and 2018 relative to the 2015-2016 period, meaning that discussions about monetary policy increased when initial claims numbers were lower than expected. These point estimates also exhibit narrow 95% confidence intervals (see Figure OB1 in the online appendix).

Taken together, these empirical observations and the narratives above suggest that higher FP mentions during our sample period (2013-2021) potentially indicate higher expansionary FP expectations, as FP mentions grow mostly when bad IJC news arrives. Then, higher MP mentions, particularly on good IJC days, may be interpreted as higher contractionary MP expectations. In fact, to further support this MP interpretation, we correlate quarterly revisions in future interest rate expectations (source: Survey of Professional Forecasters) with our good- and bad-day MP mentions, and find that the correlation is 0.46*** (-0.05) with our good (bad) MP mentions. Higher MP mentions, particularly on good IJC days, may be

ble A1.

interpreted as higher contractionary MP expectations.

2.2. Asset price responses on IJC announcement days

Next, we evaluate the responses of asset prices (denoted by y_t) to IJC shocks on announcement days:

$$y_t = \beta_0 + \beta_1 IJCShock_t + \varepsilon_t. \tag{1}$$

We examine two groups of assets, stocks and discount rate-sensitive assets. To potentially control for monetary policy variations, we streamline the stylized facts by comparing two recent zero-lower-bound periods with expansionary MP: February 2020 to March 2021 (end of the paper sample), labeled as "covid," and July 2009 to December 2016, labeled as "normal" in this section. A one standard deviation (SD) above average IJC shock in the normal period corresponds to a 4.4% shock (mean 0.0% + SD 4.4%); that is, actual jobless claims are 4.4% higher than expected. A one SD above average IJC shock in the covid period corresponds to a 10.6% shock (mean 1.9% + SD 8.7%).[11]

The main result in this section highlights unusual stock return behaviors during the February 2020 to March 2021 (end of the paper sample) period. The first column of Table 1 uses the daily open-to-close log S&P 500 returns (unit: basis points; source: DataStream) as the dependent variable. During the normal period, daily open-to-close S&P 500 returns decrease by around 10 basis points as IJC shocks increase by 0.1 unit or 10%. During the covid period, market returns increase by about 31 basis points with a 10% IJC shock. That is, a one SD increase in the IJC shock corresponds to a 0.2 SD increase in daily open-to-close market returns.[12] We label this headline observation the "Main Street pain, Wall Street gain" phenomenon — bad labor news drives up stock prices. In the rest of the section, we provide evidence on pricing channels and asymmetry patterns.

[11] Detailed statistics are reported in Online Appendix Table OA1.

[12] The literature typically finds that high-frequency stock returns show the strongest reaction to announcement news shortly after the announcement, and results using daily returns tend to become weaker; we confirm this in our high-frequency evidence later in Appendix Table A6.

2.2.1. Pricing channels

We use two strategies. We decompose unexpected stock returns into changes in the discount rate (NDR) or cash flow expectations (NCF) and also closely examine discount window-sensitive asset variables, capturing both changes in level and path.

Following Campbell and Vuolteenaho (2004), we rewrite the unexpected part of market returns as NCF minus NDR:

$$\underbrace{r_{t+1} - E_t(r_{t+1})}_{\text{Unexpected return}} = \underbrace{(E_{t+1} - E_t)\sum_{j=0}^{\infty} \rho^j \Delta d_{t+1+j}}_{\equiv NCF} - \underbrace{(E_{t+1} - E_t)\sum_{j=0}^{\infty} \rho^j r_{t+1+j}}_{\equiv NDR}, \quad (2)$$

where r_{t+1} is the log S&P 500 return, Δd_{t+1} is the log changes in dividends, E_t (E_{t+1}) denotes a rational expectation at time t ($t+1$) about the future, and ρ is a discount coefficient in the log-linear approximation of stock returns. One empirical challenge is that our research question focuses on daily frequency, whereas the NCF-NDR decomposition is typically estimated at a lower frequency (i.e., monthly) in a VAR system. Estimating this VAR system at a daily frequency is not trivial for a couple of reasons. First, the choice of ρ at a daily frequency is not as straightforward as $0.95^{1/252}$.[13] Second, some variables in the state vector cannot be constructed at a daily frequency, such as the small-stock value spread. As a result, to obtain daily NCF and NDR for our purpose, we propose an easily implementable method. In a nutshell, we first estimate the monthly parameters using a modern sample from 1982/01 to 2021/04, and then use the parameters to *impute* daily NCF and NDR values using 22 non-overlapping, quasi-monthly subsamples. For instance, subsample 1 consists of daily data from Day 1, 23, 45 ...; subsample 2 consists of daily data from Day 2, 24, 46 ...; and so on.[14] Online

[13] John Campbell has argued in multiple papers, including Campbell (1996) and Campbell and Vuolteenaho (2004), that one can use the average consumption-wealth ratio to determine the discount coefficient ρ; as a result, 0.95 ($0.95^{1/12}$) is typically applied in an annual (monthly) frequency. However, the consumption-wealth ratio is, to our knowledge, not available at a daily frequency (Lettau and Ludvigson (2001)).

[14] Here are the data sources (monthly data for the VAR system, and daily data for the imputation): excess market returns from CRSP for 1982-2020 and DataStream for 2021; yield spread between 10-year and 2-year government bond yields from FRED; the log ratio of the S&P 500 price index to a ten-year moving average of S&P 500 earnings, or a smoothed PE, http://www.econ.yale.edu/~shiller/data.htm; and the small-stock value spread (VS), http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. These sources are standard, following Campbell and Vuolteenaho (2004); the smoothed PE and small-stock VS cannot be constructed at a daily frequency. In unreported results, we also considered re-estimating the monthly system within each sample, though it is unclear that this is a better strategy given the underlying assumption that parameters may be different every day. Results are not statistically different.

Appendix OC provides more details, including our replication of Campbell and Vuolteenaho (2004) using their original sample and an updated sample; one useful finding is that pure cash flow innovations exhibit an increasing power in explaining total return dynamics, going from 19% in a long pre-2000 sample to 34% in a modern sample from 1982 to 2021.

Columns (2)-(4) in Table 1 present results using unexpected stock market returns, NCF, and NDR as y_t. The unexpected return by construction equals NCF minus NDR. During the normal period, as the IJC shock increases by 0.1 unit, 8.3 bps out of the total 8.7 bps decrease in the daily stock returns can be explained by the increase in the expected future discount rate, as shown in Column (4). In contrast, during the covid period, a 0.1 unit increase in the IJC shock is associated with an increase in daily stock returns by 30 bps, and this is mostly explained through increases in expected future cash flow, as shown in Column (3).

Next, Columns (5)-(8) in Table 1 demonstrate how purely discount rate-sensitive assets respond to IJC shocks during the two separate ZLB periods. During the normal period, when the IJC shock increases (worse macro news), we mainly observe that long-term Treasury yields decrease as stock prices also generally decrease, which is consistent with the standard *risk premium* story. During the covid period, the coefficient signs and economic magnitudes for long-term yields (Column (5)), Fed Funds rate implied volatility (Column (6)), and short-term Fed Funds futures (Column (7)) remain consistent with those during the normal period.

Of course, even though both periods are at the zero lower bound, the short rate should not respond much, but the expected path might. One hypothesis is that bad macro news could correspond to expectations of a longer ZLB ahead, hence increasing the stock returns. We directly test this hypothesis by constructing a "path" variable (the difference between n- and 1-month ahead Fed Funds futures (FFF) rates) and study whether investors expect the ZLB to be less likely to be lifted when the IJC shock is higher (i.e., a negative coefficient). We again find statistically similar evidence between these two periods, and importantly we do not find the covid-period coefficient to be negative.

Panel C shows that only stock returns and NCF coefficients during the covid period in the first three columns are significantly different than those of the normal period. On IJC announcement days, the significantly stronger NCF result from the decomposition and the relatively normal responses of discount rate-sensitive assets during the covid period are the second indication in Section 2 that a different mechanism is dominating during this covid period, which potentially affects stock returns through changing future cash flow expectations.[15]

2.2.2. Asymmetry patterns

We zero in and examine stock return responses on good and bad IJC days separately. The first plot of Figure 4 illustrates that the positive β_1 in Table 1, Column (1) mainly comes from days when actual IJC numbers are higher than expected. In fact, the patterns are robust using other headline indices such as the Nasdaq 100 and Dow Jones indices. On days when actual IJC numbers are lower than expected, β_1 is visually negative for all indices except for the Nasdaq 100.[16] Table 2 formalizes this result and finds that all statistically significant and positive coefficients come from bad IJC days (see Panel A), with noticeably higher R^2s. A one SD increase in IJC shock corresponds to a 0.4 SD increase in stock returns, with the stronger effect in the Dow Jones Industrial and Transportation indices and the weakest effect in the Nasdaq 100. This table also shows some preliminary cross-section evidence as Dow Jones indices contain mostly cash-flow sensitive value firms.[17]

3. Mechanism Hypothesis

Thus far, we document a set of unusual media and asset prices responses on IJC announcement days during the covid period. Compared to earlier years, during 2020-2021 we find significantly heightened fiscal policy mentions when bad IJC news comes out. Meanwhile, during the same period, stock returns increase with IJC shocks. The effect mostly works through the expected cash flow channel and is pronounced during bad IJC days. These stylized facts motivate a specific cash-flow mechanism that can be generalized; the purpose of this paper is to document the existence of this mechanism.

We propose a fiscal policy expectations mechanism. In a low-interest-rate, crisis environ-

[15]Results are robust to using alternative IJC shocks; see Appendix Table A2.
[16]These patterns hold when we drop April 9, 2023; see Appendix Figure A2 or Table A3.
[17]We formally conduct cross section analysis in Section 6.2.

ment, when Main Street suffers more than expected, investors may expect more generous federal government support through fiscal policy, *driving up* expected future cash flow growth and stock prices. We expect this mechanism to be time-varying, as our textual analysis already shows that perceptions of policy tools do change over time (see Figure 2). During periods when FP is not the perceived dominant policy tool, the "Main Street pain, Wall Street gain" pattern in stock returns should diminish.

Unlike monetary policy expectations, we do not observe futures market or surveys to elicit high-frequency fiscal policy (FP) expectations. As a result, we test our hypothesis by examining two testable predictions. The first prediction is that time-varying FP expectations should explain time-varying return responses to IJC shocks, particularly on bad IJC days. We proxy time-varying FP expectations from 2013 to 2021 using newspaper-based measures as constructed earlier. The second prediction is that, in the cross section, firms and industries that are expected to receive more fiscal support should exhibit higher individual stock returns when bad IJC shocks appear, resulting in a stronger "Main Street pain, Wall Street gain" phenomenon. We use the covid context as our identification strategy in order to have the best chance of observing cross sections. We construct three cross sections spanning firm-level data from the Treasury registry office, the actual stimulus bill, and firm fundamentals. Some of these data sources are new to the asset pricing literature.

Our hypothesis joins, but differs from, Boyd, Hu, and Jagannathan (2005) in two major ways. First, they empirically document that rising unemployment is good news for stocks during economic expansions, which is explained by lower interest rate expectations. In our research, we propose a cash flow channel. Second, while they discuss conceptually the possibility for a cash flow channel to explain their empirical fact, we establish the empirical existence of a specific cash flow channel, which can be generalized in asset pricing models and is new to the literature. In a broader view, our paper should also complement Cieslak and Vissing-Jorgensen (2021) (documenting "Fed Put") by essentially proposing the existence of "Government Put" in the recent decade when fiscal policy and government purchases have become unprecedentedly active.

4. Mechanism: Time-series Evidence

To test the first prediction in Section 3, we use two different aggregate frameworks in Sections 4.1 and 4.2, respectively.

4.1. Test using rolling data

We project time-varying return responses to IJC shocks on time-varying topic mentions. We use an 80 IJC-day rolling window to construct return responses to IJC shocks and topic-mention scores (i.e., see construction details of the TF-IDF scores in Section 2.1). Similarly, we use rolling windows of 40 bad (good) IJC days to construct bad IJC day (good IJC day) return responses and topic-mention scores. Results are reported in Tables 3 and 4, where topic-mention scores are standardized for interpretation purposes. As discussed in Section 2.1, higher FP (MP) mentions during this sample period (2013-2021) can be mostly interpreted as more expansionary (contractionary) policy expectations.

Using all IJC days, positive loadings in Table 3 indicate that both FP and MP are counteracting forces to the normal pattern (i.e., stock returns should decrease with IJC shocks). During periods in which FP mentions are one SD higher than average, stock return responses caused by a 0.1 unit increase in IJC shocks are 16-20 basis points higher. During a period in which MP mentions are one SD higher than average, the corresponding increase in return responses is around 11-13 basis points. However, results come from different subsamples. Panel A (B) of Table 4 shows that the dynamics of fiscal (monetary) policy expectations mostly explain the dynamics of return responses to bad (good) IJC shocks. When fiscal policy is expected to be one SD more expansionary, stock return responses caused by a 0.1 unit increase in IJC shocks are 26-34 basis points higher; the Dow Jones index contributes the higher end, which is consistent with Table 2. When monetary policy is expected to tighten, stock return responses to good IJC shocks weaken.

We conduct a series of robustness tests and also produce some graphical evidence. Tables 3 and 4 consider alternative left-hand-side variables (economic magnitude and the Dow Jones

65's open-to-close return responses) and add uncertainty as a control variable. Appendix Table A4 includes three more tests that drop 4/9/2020 given the unusual number of Federal Reserve announcements on that day or consider an alternative rolling window size.

4.2. Test using non-overlapping data

We next construct and use non-overlapping quarterly state variables to directly interact with IJC shocks. The specification is as follows:

$$y_t = \beta_0 + \beta_1 IJCshock_t + \boldsymbol{\beta_2 Z_\tau} + \boldsymbol{\beta_3} IJCshock_t * \boldsymbol{Z_\tau} + \varepsilon_t, \tag{3}$$

where t and τ denote daily and quarterly frequency, respectively, y is stock returns (in basis points) on IJC announcement days, and $\boldsymbol{Z}$ is one or multiple standardized quarterly state variable(s). The unit of observation is the announcement day. The first three quarterly state variables we consider are topic mentions using the 12 articles from the same quarter (fiscal policy "FP," monetary policy "MP," and uncertainty "UNC"); similarly, we construct quarterly "bad" ("good") topic mentions measures on bad (good) IJC days within the quarter. Next, we follow Elenev, Law, Song, and Yaron (2022b) and consider the difference between the one-quarter-ahead forecast and the nowcast of the 3-month Treasury bill rate ("$\Delta Tbill3m$," $Tbill3m_{\tau+1|\tau-1} - Tbill3m_{\tau|\tau-1}$), where both forecast and nowcast are provided given the last quarter's ($\tau - 1$) information set according to the Survey of Professional Forecasters (SPF). As explained in Section 2.1, the regression sample runs from January 2013 to March 2021.

The quarterly FP and MP mentions are statistically uncorrelated during the sample period, regardless of bad or good IJC days. Also, according to SPF, investors expected the interest rate to climb around 2015 - 2018, which is consistent with the timing of the rising "bump-shaped" MP mentions (see the second plot of Figure 3). In fact, good IJC day MP mentions and $\Delta Tbill3m$ are significantly and positively correlated at 0.46***, which supports the conjecture that higher MP mentions can be interpreted as expectations of more contractionary MP during this sample period. One disadvantage of the survey-based quarterly interest rate forecast data is that we do not know when the survey was conducted, on good or bad or non-macro announcement days for instance, whereas for text-based measures we do know.

Table 5 reports the regression results of Equation (3), where the interaction coefficients are of interest.[18] First, on bad IJC announcement days, when fiscal policy mentions are one SD higher than the average, stock return responses to a 10% IJC shock are 26 basis points higher, given the significant and positive interaction estimates in Columns (1) and (2). The magnitude is consistent with Table 4. In Columns (3) and (4), we see that MP mentions and rate forecast revisions ($\Delta Tbill3m$) play an insignificant role in explaining return responses to bad IJC shocks.

Second, on good IJC announcement days, fiscal policy mentions do not explain the time-varying return responses, given insignificant interaction coefficients in Columns (5)-(8). When monetary policy mentions are one SD higher than the average, stock return responses to a -10% IJC shock are 19-30 basis points lower. This evidence is consistent with the existing monetary policy expectation story (as in Boyd, Hu, and Jagannathan (2005) and Elenev, Law, Song, and Yaron (2022b)), counteracting the "good is good" conventional pattern. In Column (8), we replace MP mentions with survey-based $\Delta Tbill3m$, and find consistent results. This is not surprising given the significant correlation between the two state variables as mentioned before.

While speculations about FP are categorically higher during 2020-2021, our results are also robust using a sample period through December 2019.[19] This is an indication that the FP state variable variations already have the ability to explain time-varying return responses to IJC shocks before 2020. What is different is that the covid-period FP speculations are strong enough to overturn the sign of return responses to IJC shocks.

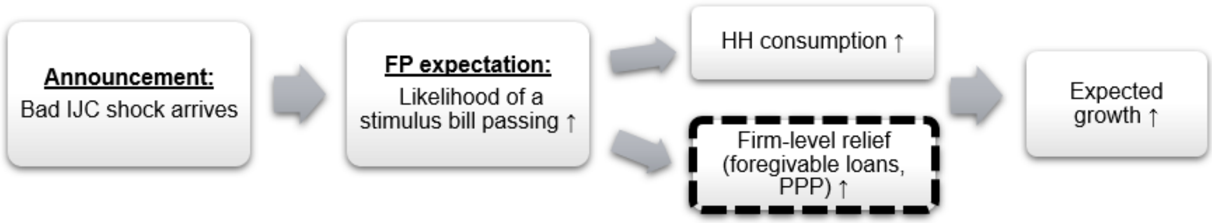
5. Mechanism: Cross-Sectional Evidence

We next test the cross-section prediction from Section 3. Under this fiscal policy expectations mechanism, when a bad IJC shock arrives, investors may expect the likelihood of an expansionary fiscal policy passing – in the case of the COVID period, a *stimulus bill passing* –

[18]We relegate univariate results to Appendix Table A5.

[19]See detailed estimation table in Online Appendix Table OA2. Interaction coefficients and statistical significance results hold.

to increase, which could affect the expected aggregate economic growth through fiscal distributions to households and to firms. As it is empirically challenging to design a cross-sectional analysis at the households level, we focus on the firm or industry level.



Specifically, we test whether firms/industries that are *expected* to receive more fiscal support exhibit higher individual stock returns when worse IJC shocks appear. Empirically, there is no granular-level fiscal expectation data;[20] in addition, the passing of fiscal policy and budget allocations typically has an irregular schedule, which makes it challenging to design dynamic sorting strategies. As a result, we use the covid context to our advantage, and test this hypothesis using a fixed period from February 2020 to March 2021 (dropping outlier IJC shocks and macro and monetary policy announcement overlaps as before). During this period, fiscal stimulus receives unprecedented public attention, and should reach almost all industries and firms, allowing us to construct cross sections.

We create three granular-level datasets that could reflect cross-sectional differences in fiscal policy expectations. A higher correlation (or sensitivity) between individual returns and IJC shocks should occur in:

1. Industries that are mentioned more in the actual stimulus bills.
2. Firms that are promised more fiscal funding by the U.S. government.
3. Firms that are expected to suffer more from covid-related impacts.

Sections 5.1, 5.2, and 5.3 present evidence using these three cross-sectional measures. We primarily consider the S&P 500 universe, consistent with our aggregate analysis. All cross-sectional tests robustly support our hypothesis.

[20]We have explored the online betting market (such as Kashi and Polymarket), and found it too lacking in reliable tokens and samples to be used for our research.

5.1. Industry mentions in actual bills

Investors may infer the likelihood of a particular firm/industry receiving more fiscal support than others from relative industry mentions in actual bills. We therefore directly search for industry mentions in the four stimulus legal bills. In addition to the three bills that were actually signed into law (CARES of 3/27/2020, CAA of 12/27/2020, ARP of 3/11/2021), the Health and Economic Recovery Omnibus Emergency Solutions (HEROES) Act passed the House on May 15, 2020 and was heavily debated in but didn't pass the Senate 6 months later. In all cases, we use the final versions of these bills (source: Congress.gov) to conduct textual analysis. We count industry keywords for each 2-digit NAICS industry, where each industry keyword list comprises words from its 6-digit NAICS website. We consider one bill at a time. Three 2-digit NAICS industries cannot be found in the S&P500 firm universe that we study, and three other industries have fewer than 5 firms.[21] We therefore focus on the remaining 14 industries with $\geq$5 firms in the S&P500 firm universe. Finally, to construct industry-level return-IJC correlations, we calculate individual stock return-IJC correlations and then calculate the simple industry average.

Figure 5 demonstrates a significant and positive relationship between industry mentions in the CARES Act on the x-axis against industry return correlations with IJC shocks on the y-axis. We focus on correlation, which can also be interpreted as economic magnitude in SDs, in order to standardize individual stock return volatility. The fitted line yields a correlation coefficient of 0.44 (SE=0.24), which is a strong result given that this comes from only 14 data points and a simple textual analysis. Results using the other three stimulus bills hold (see Appendix Figure A3); the CARES Act is particularly interesting given its early date.

The healthcare industries are among the most mentioned in the CARES Act, given the nature of the pandemic crisis, with a high industry return-IJC shock correlation at 0.228 (*p-value*=0.016). It is worth noting that there are other non-crisis-related industries with frequent mentions in the CARES Act that also exhibited high stock return-IJC shock corre-

[21] No presence: *61, Educational Services; 81, Other Services (except Public Administration); 92, Public Administration*; few firms: 2 (*11, Agriculture, Forestry, Fishing and Hunting*), 2 (*55, Management of Companies and Enterprises*), 3 (*71, Arts, Entertainment, and Recreation*) firms.

lation. One example is the transportation industry, with an industry return-IJC correlation of 0.186 (*p-value*=0.092). At least three titles in the CARES Act (e.g., Titles II, VI, XII) and five sections in the ARP Act (e.g., *Continued Assistance to Rail Workers*, *Public Transportation*, *Transportation and Infrastructure*, and *Aviation Manufacturing Jobs Protection*) heavily mention transportation-related industries.

5.2. Promised and actual fiscal spending

The previous cross-sectional evidence is the first indication of the role of fiscal policy expectations in shaping cross-industry differences in return responses to IJC shocks. In our second cross-section, we collect data from scratch to construct a new dataset of all COVID crisis-related fiscal spending to each firm (and its subsidiaries) based on public records on https://www.usaspending.gov/.[22] Intuitively, investors would expect certain firms to receive more fiscal support if they are promised to receive more or they have been distributed more support in a previous act. We explain the raw data, economic magnitude, and cross section constructions next.

USAspending uses the term "award" to indicate a forgivable grant and provides both promised / obligated amounts and actual gross outlays at the award-time level. We identify all covid-related crisis spending using the category "Disaster Emergency Fund Codes." In a clear subset category (Disaster Emergency Fund Codes = O or P), we are able to identify Paycheck Protection Program (PPP) awards — a specific labor-related fiscal support. In the raw data, a very small fraction of negative "award" amounts means that the government revoked the funding or reduced the award amount. When calculating total award amounts (promised or actual) to a firm, we produce both "All" (positive+negative amounts on records) and "Positive" (positive amounts only) measures. The Online Appendix OD provides more description of our data source and collection process.

Two patterns of awards are directly useful for our research. First, awards are sizable,

[22] This website is managed by the Treasury Office and was created as a part of the Federal Funding Accountability and Transparency Act (FFATA) of 2006. The first reliable fiscal spending data is not until late 2008.

providing direct positive cash flow for these firms. Second and more importantly, one current actual award amount is indicative of future cash flows in the subsequent supports/bills. For instance, shortly after the covid crisis began in the U.S., American Airlines received 6 billion dollars on April 21, 2020 as part of the payroll support program in the CARES Act, enacted on March 27, 2020. Then the company received another 3.3 billion dollars in obligated payroll support, authorized under Subtitle A of Title IV of the CAA, 2021.[23] In the S&P 500 universe, we identify 138 companies in our fiscal spending database.[24] Covid-related funding is highly skewed: out of the 138 companies in the S&P 500 universe who received any funding, 108 companies received less than one million dollars, 24 companies received one million to one billion dollars, and 6 companies received more than one billion dollars. The healthcare and transportation industries were promised (and actually did receive) large amounts. For other firms that we do not find matches for, fiscal support equals zero.

As a result, we construct the following three firm-level fiscal support proxies: the log of the obligated amount across all covid-related spending types, the log of the obligated amount from the Paycheck Protection Program only, and the log of the actual total gross outlays. Panel A of Table 6 calculates the firm-level fiscal support proxies and the return-IJC shock correlations using the entire sample (2020/02-2021/03). To produce a cleaner non-forward-looking bias measure, in Panel B (Panel C), we construct firm-level fiscal support proxies using awards from 2020/02 to 2020/04 (2020/05) and return-IJC shock correlations using the 2020/05 (2020/06)-2021/03 sample. Intuitively, investors would expect higher future fiscal support for firms that have already received more actual support. To the best of our knowledge, this is one of the first efforts linking this firm-level fiscal spending and PPP data to stock market data in the

[23]See the USAspending links: `https://www.usaspending.gov/award/ASST_NON_ACWS0060_2001/`; `https://www.usaspending.gov/award/ASST_NON_ATSE0233_2001/`.

[24]We create a linking file to match recipient names in government award records to Compustat company names. The major difficulty is that the government only records company names entered by applicants. These do not necessarily have to be the legal parent names used in a corporate filing. For example, Google's parent company is Alphabet in legal filings, but the PPP recipient on record is Google. To maximize our sample size, we collect company names on Yahoo! Finance by stock tickers. Then, we try both Compustat and Yahoo! Finance company names and use a fuzzy matching algorithm to find possible CUSIPs for the recipients of government funding. Finally, we manually verify whether the assignment is correct. For ones with similar names, we use the recipient address to look up the company on Google Maps to confirm that the recipient matches the Compustat company.

literature.[25]

In Column (1) of Table 6, Panel A, we show that individual stock return-IJC shock correlations increase significantly at the 1% level with firms' obligated amounts from the U.S. government. In Columns (2)-(6), we show that this result is robust using (a) positive amount items only, (b) PPP items only, and (c) actual total gross outlays. For instance, for a firm whose promised PPP amount is 10% higher than another firm, its return-IJC correlation during this period is also higher by 0.03, which is sizable given that the average correlation is 0.14. According to Figure 6-(a), where we plot the data, the economic interpretation is quite monotonic from the extensive to intensive margin. In Panels B and C of Table 6, which use non-overlapping samples, results exhibit similar coefficients and economic magnitudes but now also have predictive interpretations. For a firm whose actual award amount is 10% higher than another firm during the CARES period, its return-IJC correlation in the following months is also higher by 0.022. Plots (B) and (C) of Figure 6 similarly demonstrate the positive relationship. The overall trend remains positive, and the documented relationship appears stronger for the upper tail.

5.3. Firm crisis impact measures

More broadly speaking, investors might expect firms that are likely to be more affected by COVID-19 to receive more government support in the future. Both realized and expected impact likely would enter active policy debates and hence be meaningful in investors' formations of their cash flow expectations. Therefore, we obtain four measures to capture to what extent a firm has been and will likely continue to be negatively affected by covid as our third cross-section.

Our first measure uses a novel dataset from LinkUp that indexes all job listings directly from employer websites in real-time. We construct our first covid impact measure using changes in the number of job postings from a firm's 2019 average to its 2020 April-May average. One advantage of this measure is its foresighted nature; firms cut their job listings

[25] Other research collects PPP data at the firm level; for example, Rabetti (2022) collected PPP data for public companies from corporate filings: 10-K, 10-Q, and 8K.

when they expect weaker business prospects in the near future. We also consider realized impacts: the change in the number of employees from fiscal year (FY) 2019 to fiscal year 2020, the quarter-on-quarter growth rates of total revenue between 2019Q2 and 2020Q2 to control for seasonality, and the change in quarter-on-quarter earnings per share (basic, excluding extraordinary items) from 2019Q2 to 2020Q2.[26] Data are obtained from Compustat Annual and Compustat Quarter, and we use the number of employees from 10-Ks, as employment data are not available in 10-Qs. We obtain the ticker list of the S&P 500 for July 2021 and trace all matched PERMNOs (the CRSP identifier) through our covid data sample period from February 2020 to March 2021. We can identify 498 tickers. For robustness, we also consider revenue changes and EPS changes from FY 2019 to FY 2020 at the firm level.

For all our covid impact measures, the lower or more negative a measure is, the more a firm is (expected to be) negatively impacted by covid. Our forward-looking job posting measure tells us that almost all firms reduced their job listings by -39% on average during the initial impact of covid. The cross-firm distribution is well-behaved. Actual employment changes calculated using Compustat's fiscal year-end data in 2019 and 2020 show some positive labor growth, which is not surprising given that by the end of 2020 two rounds of stimulus packages had come in; this also makes Compustat's employment data a bit harder to interpret compared to our job posting measure. The quarterly financial measures show a wide dispersion of changes in firm revenue and EPS, with the latter being more negatively skewed (with the 5^{th} percentile at about -\$11 and the 95^{th} at \$4). Due to the skewed nature of these financial variables, we take the percentile rank of these measures in our next cross-sectional analysis (i.e., lower rank = more negative effects). Detailed summary statistics are relegated to Online Appendix Table OA3.

Table 7 reports the regression results (N=498) of projecting firm-level return-IJC correlations onto firm-level covid impact proxies. The average return-IJC correlation is significant and positive at 0.141 (or 14.1%). The regression results show significant and negative coefficients across all of our measures. That is, firms that are expected to suffer or actually suffered

[26] "2020Q2" ("2019Q2") refers to 10-Q numbers reported in 2020 (2019) July, August, or September from Compustat.

more (i.e., lower values in the independent variables) exhibit higher return-IJC correlations. To make sense of the coefficients, a one SD below average job posting change (-39%-21%=-60%) corresponds to a significant increase in return-IJC correlation of 1.87% (21%×-0.089), hence a stronger "Main Street pain, Wall Street gain" phenomenon. Considering the average correlation is 14.1%, 1.87% is a sizable cross-sectional difference. For financial variables, a quintile (20%) drop in the "suffering" rank corresponds to around a 1.2%-1.6% increase in the correlation.

The data are displayed in Figure 7 with negative slopes as expected. For illustration purposes, we split firms uniformly into 20 bins (dots); each bin contains 5% of the firms. Our main measure is in Subfigure (A). The negative slope is particularly linear and strong in the left/bottom 60 percent, and the relationship gradually flattens for firms with less covid damage in the right/top 20 percent. Companies with more severe covid damage are the firms that drive the cross-sectional "Main Street pain, Wall Street gain" phenomenon.

6. Discussions

6.1. Who gets what?

The three novel cross-sections that we construct from various data sources (bill mentioning, obligated and actual fiscal support, and expected covid damage) give our research a unique opportunity to answer a key question: During the height of fiscal activity from 2020 to early 2021, who gets what? Are these three cross-section sorting variables correlated? Figure 8 addresses these questions at the industry level.

First, we find that industries that have a larger stock market presence tend to be mentioned more in actual fiscal spending bills (see Subfigure (A)). Then, comparing bill mentions and actual covid impact, Subfigure (B) shows the majority of industries are mentioned more often in actual bills if they are more affected (see the blue circle dots and the corresponding dashed trend line). This is generally consistent with Gourinchas, Kalemli-Özcan, Penciakova, and Sander (2021) who conclude that "*fiscal support in 2020 achieved important macroeconomic* *results...preventing many firm failures.*" On the other hand, a few inconsistencies stand out, as illustrated in different colors/shapes in Subfigure (B). Healthcare industries are among the most mentioned due to the nature of the crisis, but their job posting changes do not place them among the most negatively affected firms. The finance and insurance industries are also more frequently mentioned, but mostly for a different reason; we find their keywords when a bill discusses not only the financial market but also the financing aspects of the bill. The mining industry experienced severe covid impacts; given our calculation, the average mining company (and there are 16 of them among the 498) decreased its job postings by 64% in April 2020 compared to the December 2019 level. However, the mining industry is among the least mentioned industries in the CARES Act as well as in the other three bills.

The next two plots compare bill mentions and fiscal support. Subfigure (C) proxies fiscal support by the fraction of firms in an industry that receive > $0 fiscal support (regardless of the type); and Subfigure (D) uses the log of promised PPP amounts. Both plots show statistically significant and strongly positive trends, with correlation coefficients above 0.6. Manufacturing is the only industry that seems to draw a disconnect between its mentions in the actual bills and its actual or promised fiscal support.

6.2. Cash flow sensitive portfolios

The specific mechanism in this paper affects returns through the cash flow expectations channel. To prove it, our efforts thus far in both time-series (Section 2) and the cross-section (Section 4) include decomposing stock returns, documenting lack of similar behaviors among Treasury-related assets, and directly sorting firms based on a granular fiscal spending dataset. This section joins the previous effort by examining how traditional cash-flow sensitive portfolios behave on IJC days, which builds on the brief discussion of Dow Jones vs. Nasdaq responses in Section 2.2.

We form portfolios based on several reported firm characteristics and risk proxies pre-covid (that is, as of the end of 2019); of these, some characteristics have been shown in the literature to be associated with cash flow sensitivities. The portfolio takes the return difference between the lowest and the highest quintile bins; within each quintile, value-weighted average returns can be calculated on bad, good, and non-IJC days.

The first four blue solid bars in Figure 9 demonstrate that firms with high sensitivities to market cash flow news (i.e., small size, high B/M, high E/P, low free cash flow) outperform when IJC numbers are worse than expected, that is, according to our mechanism, when more expansionary fiscal policy is expected. On the other hand, such highly cash-sensitive firms perform worse on good IJC days (red shaded bars) or non-announcement days (hollow bars) than on bad IJC days, which is as expected. Bar magnitude on non-bad IJC days is consistently smaller than on bad IJC days, which is expected as we learn from previous sections that FP expectations and mentions are weak when good labor news arrives.

We also sort on firms' pre-covid leverage or riskiness conditions, where leverage is defined as (long-term debt+short-term debt) divided by shareholder equity.[27] We find that the low-minus-high leverage portfolio shows significant and positive returns on good IJC days, which is consistent with the monetary policy expectation channel that we document above. When good IJC news arrives, investors may expect monetary policy to tighten, which would be proportionally worse news for highly leveraged firms. We also find that the low-minus-high leverage portfolio shows close to zero and insignificant returns on both bad and non-IJC days, which indicates that leverage or riskiness is not the channel that creates the paper's headline phenomenon.

6.3. Main results through the lens of alternative frequencies

In this section, we provide two robustness tests of our main results through the lens of intra-daily futures prices and monthly macro announcement data, respectively. First, we follow the literature (e.g., Kurov, Sancetta, Strasser, and Wolfe (2019) and Elenev, Law, Song, and Yaron (2022b)) and construct cumulative returns of E-minis from 8:00 a.m. ET (30 minutes before the IJC announcement time) to several representative time stamps during the day: 8:25 a.m. (pre-announcement), 8:35 a.m. (shortly after the announcement), 12:30 p.m. (four hours after

[27] Our leverage and free-cash-flow variables are correlated at -0.01 in the S&P 500 universe.

the announcement), and 3:30 p.m. (shortly before market close). Appendix Tables A6 and A7 use S&P500 and Dow Jones futures, respectively. Consistent with the literature, we find no pre-announcement drift for labor news during both the normal and covid periods. During the normal period, futures decrease significantly with IJC shocks, beginning 5 minutes after the announcement; the effect remains statistically strong until noon. This effect is robust when we evaluate bad and good IJC days separately or together. In the covid period (see the right panel), futures prices still decrease with IJC shocks at 8:35 a.m., but with a much smaller magnitude, and eventually, they increase with IJC shocks, with a significant and positive coefficient. The coefficients during the covid period are significantly *higher* for all of our post-announcement time stamps than during the normal period. This evidence indicates a counteracting force in place. Furthermore, we find a similar message (compared to our daily evidence) that the positive price responses mostly come from bad IJC days.

Second, we use monthly announcements of unemployment rates and non-farm payrolls, two other often-studied labor variables (see Fisher, Martineau, and Sheng (2022)), to test our main result. What is most relevant to our paper is that we are able to statistically reject the null hypothesis that stock returns exhibit the same directional responses to monthly labor news surprises before and after 2020. For instance, as shown in Appendix Figure A4, stock returns during the covid period increase with bad unemployment rate news, holding a correlation at 0.793***, which is statistically higher than the correlation during the normal period, 0.035. We conduct a separate analysis using 7 monthly macro announcements in Online Appendix Section OE. The fact that not all macro announcements show similar patterns – for instance, inflation does not – provides further support to the fiscal policy mechanism.

7. Conclusion

Our paper starts with establishing a few stylized facts. Compared to earlier years, during 2020-2021, there are significantly heightened fiscal policy mentions when bad IJC news comes out, and stock returns increase with IJC shocks. In addition, the IJC effect mostly influences stock returns through the expected cash flow channel and is pronounced during bad IJC days. Given these stylized facts, we hypothesize a *specific* cash-flow mechanism that can be generalized, and provide empirical evidence of it in time series and cross section tests. Time-varying fiscal policy expectations, gauged by a newspaper-based topic measure, significantly explain the time variation in return responses to IJC shocks on announcement days, after controlling for monetary policy and uncertainty measures. In the cross section, firms that are expected to receive more fiscal support exhibit higher individual stock returns when bad IJC shocks appear, hence a stronger "Main Street pain, Wall Street gain" phenomenon in their respective stock prices. Our paper contributes to the literature by empirically establishing a specific state variable that counteracts the conventional wisdom of the pricing of macro shocks. During certain times and cross sections, investors appear to incorporate more fiscal policy expectations into asset pricing.

Future research should examine the macroeconomic effects and welfare effects of fiscal policy expectations. The fact that people have fiscal policy expectations when bad news arrives could feed back to the macro economy through consumption behaviors, labor options, and borrowing decisions, as we observe in the inflation hikes and the Great Resignation during late 2021 and 2022. In addition, while the covid crisis triggered an unprecedented adverse shock to the labor market, the capital market gain due to investor anticipation of fiscal stimulus is not trivial in dollar terms. From February 2020 to March 2021, the average daily capital gain in the S&P 500 market is 73 billion dollars on bad IJC days, 18 billion dollars on good IJC days, and 44 billion dollars on non-IJC days (see details in Online Appendix Table OA4).

Overall, our work implies that the distributional effect of fiscal policy could also transmit through this expectations channel, which gets capitalized at a high frequency. An optimal fiscal stimulus should consider it for the fairness and overall welfare effects of public policies.

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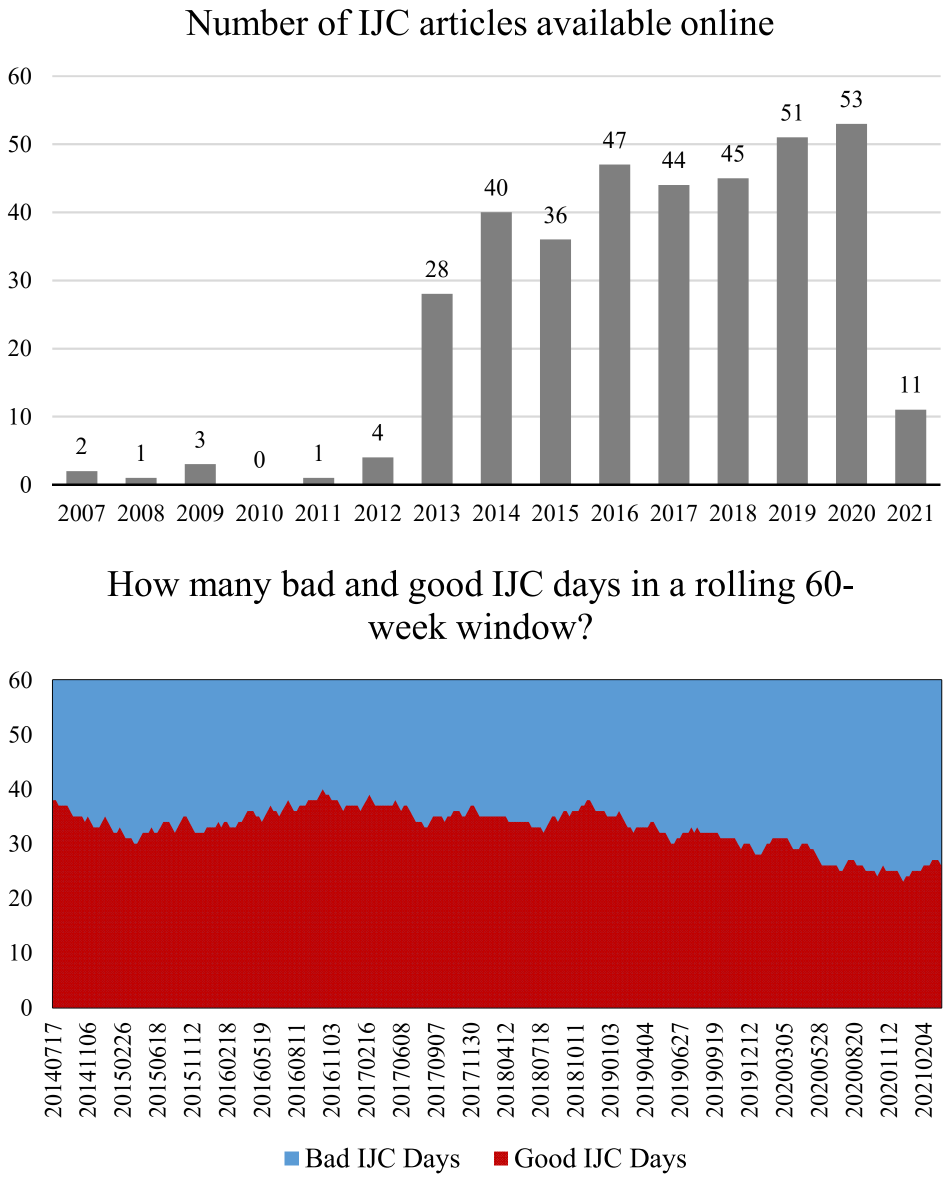


Figure 1: Summary of CNBC jobless claim articles through the IJC announcement date on 2021/3/18 (the end of our sample).

The data collection process is described in Section 2.1 and additional description is available in Online Appendix OB. Top plot: number of articles each year. Bottom plot: take a rolling 60-week window (time stamp=last day of the rolling window) and calculate the number of articles with bad IJC surprises (blue) and good IJC surprises (red). The last 60-week rolling window is from 20200130 (exclude) to 20210318 (include). Source: https://www.cnbc.com/jobless-claims/.

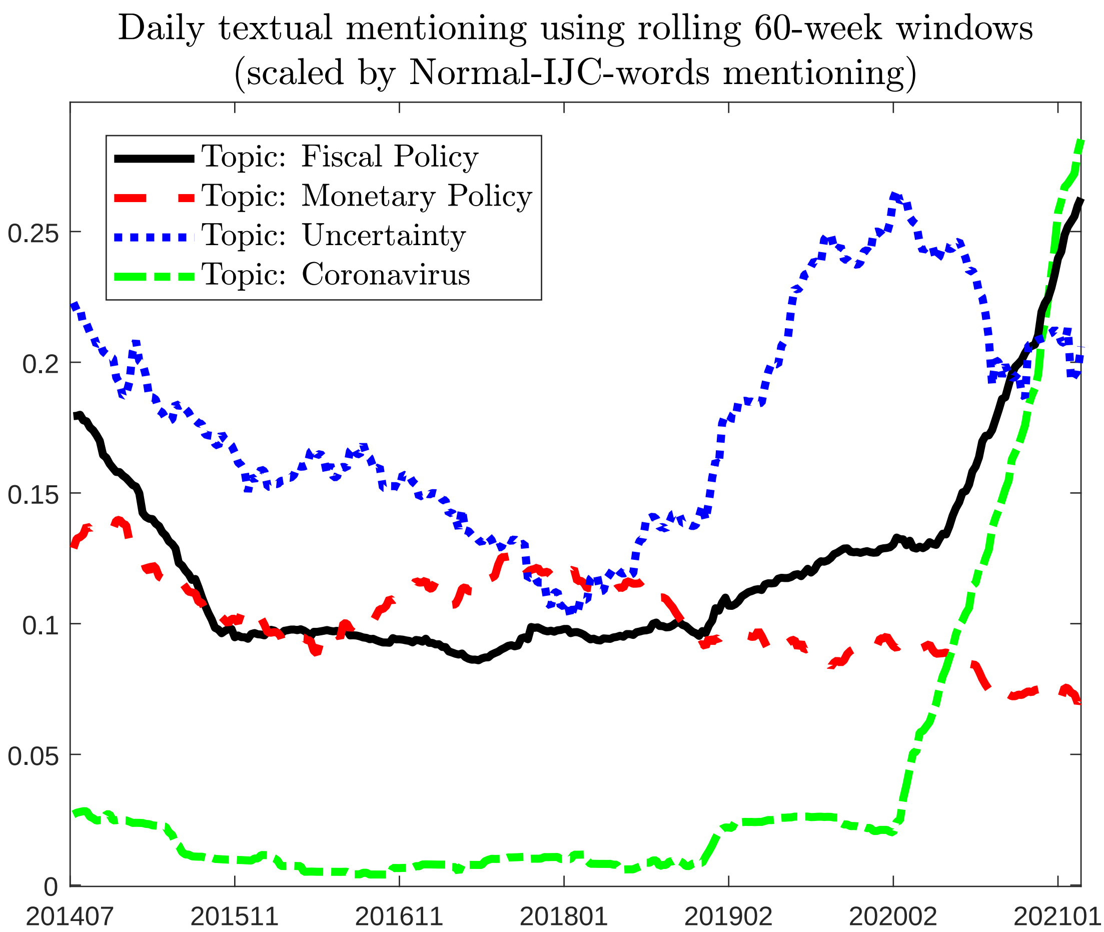


Figure 2: What do people talk about on IJC announcement days?

This figure shows the topic mentions in rolling 60-week windows of news articles released on IJC announcement days, where the four topic mentions are scaled by mentions of normal IJC words (see Section 2.1 and Online Appendix OB for more details). 0.2 in the y-axis means that this topic's keywords are mentioned 20 times per 100 normal IJC words. The timestamp refers to the last day of the rolling window.

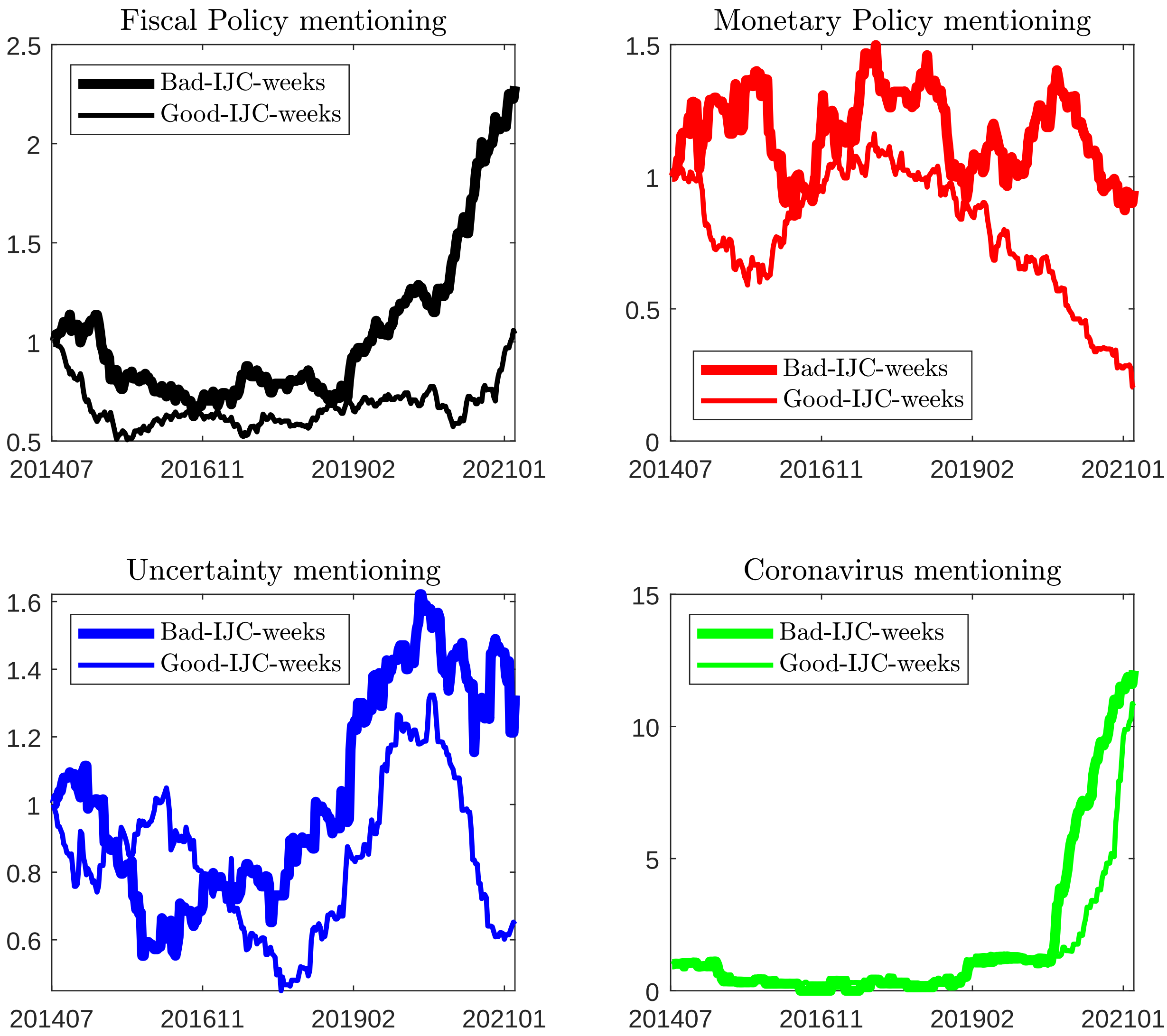


Figure 3: What do people talk about on bad and good IJC announcement days?

This figure complements Figure 2 and shows the relative topic mentions on bad (thick lines) and good (thin lines) IJC days within the same 60-week rolling window. For interpretation purposes, each line is scaled with the first value in its series. 1.5 in the y-axis means that mentions of this topic during, e.g., bad days are 50% higher than at the beginning of the sample. The timestamp always refers to the last day of the rolling window.

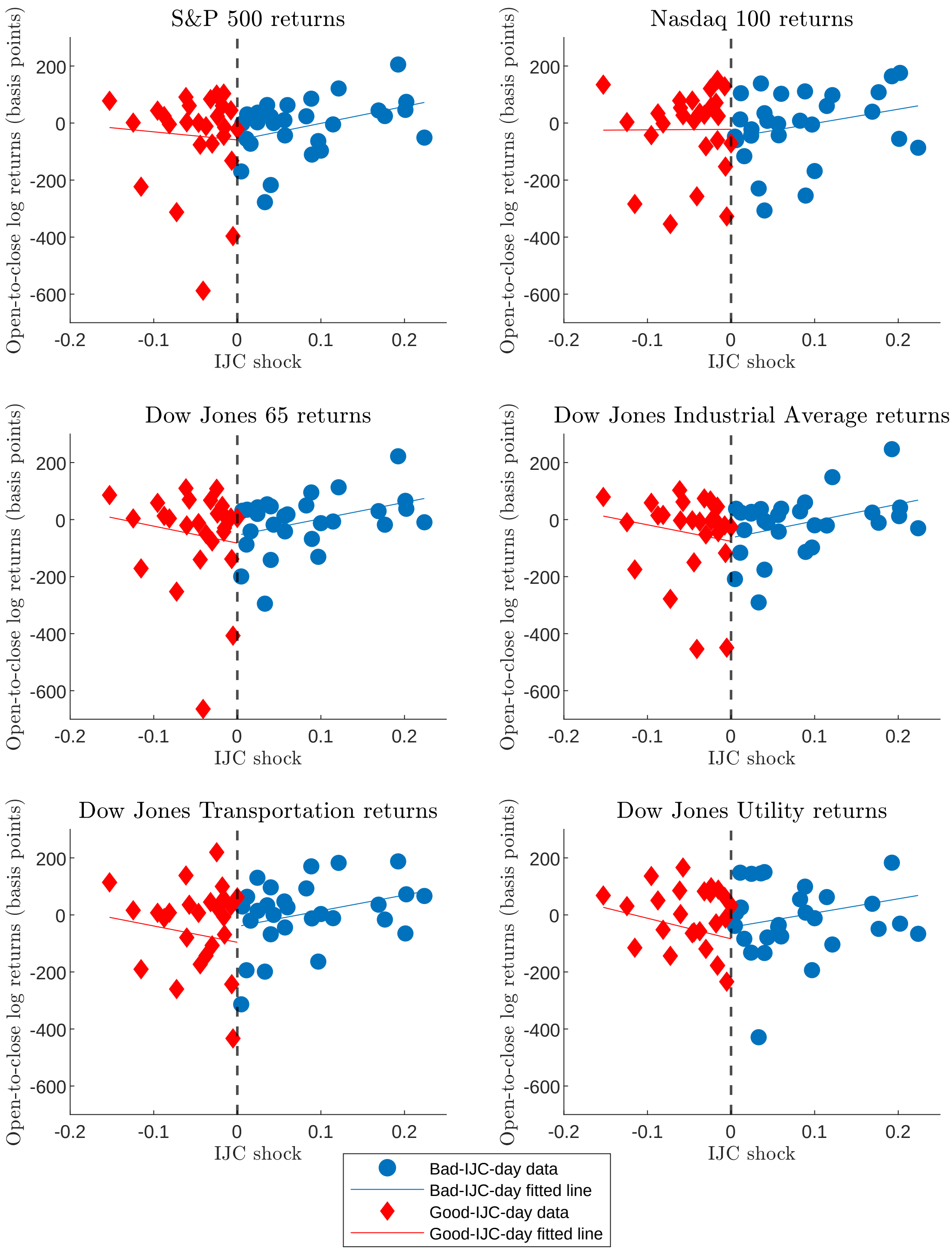


Figure 4: Relation between daily open-to-close stock returns and IJC shocks from February 2020 to March 2021 (the end of our sample).

This figure complements Table 2 and also excludes IJC shock outlier days (2020/3/19, 3/26, 4/2).

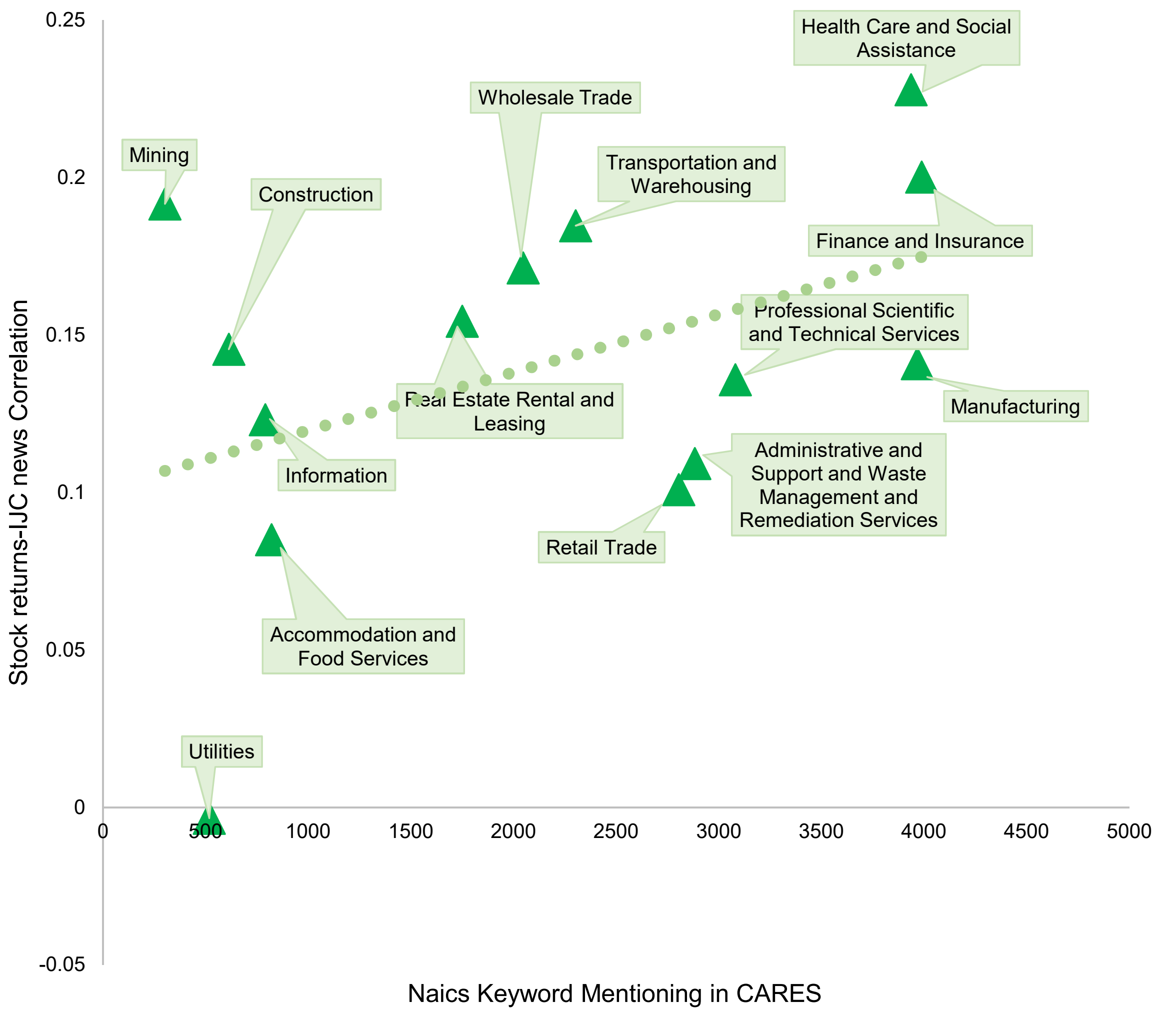
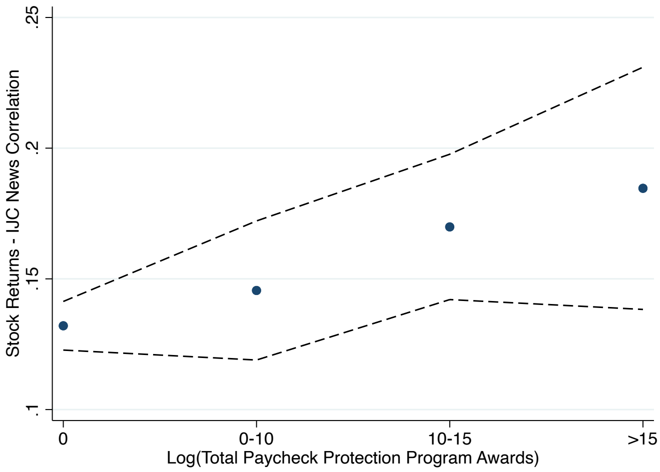
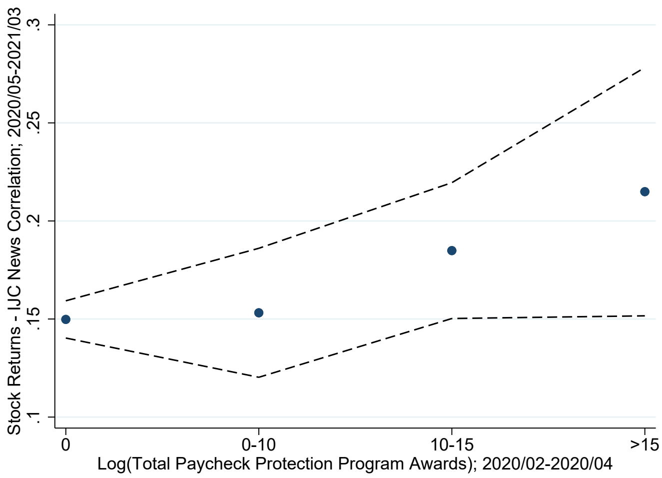


Figure 5: Cross-section evidence: Industry keyword mentions in CARES and return-IJC correlations.

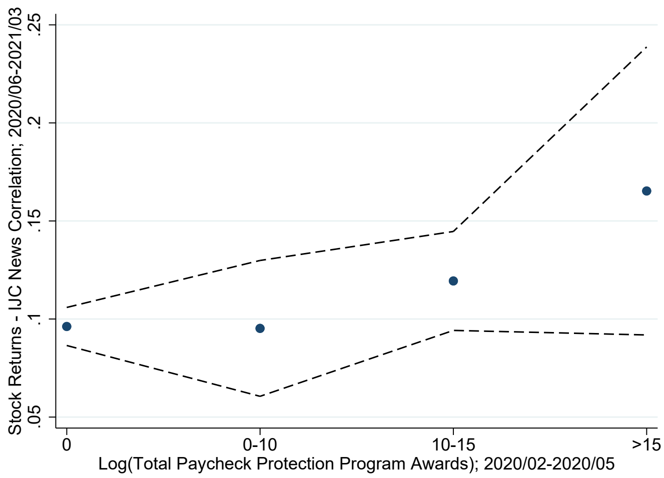
This figure depicts the relationship between industry return-IJC shock correlations and their mentions in the actual final Coronavirus Aid, Relief, and Economic Security (CARES) Act. **Construction of industry-level correlation (y-axis)**: we calculate correlations between individual stock returns and the IJC shocks of the S&P 500 stocks that we are able to identify for all three cross-sections in this paper from February 2020 to March 2021. (As before, we drop shock outliers and major macro and monetary policy announcement dates.) We then calculate the industry average. We use 2-digit NAICS codes to classify firms. Six industries have fewer than 5 firms representing them among the S&P 500 stocks, and they are therefore excluded from this analysis. **Construction of industry mentions in the actual bill (x-axis)**: We use words that appear on the 6-digit NAICS industry classification webpages as keywords for 2-digit NAICS industries. For instance, keywords for "21 Mining" are obtained from `https://www.naics.com/six-digit-naics/?v=2017&code=21`. Then, we identify mentions of this industry in the actual bills (after cleaning the data, including stemming in the bill texts). **CARES Act**: This bill was initially introduced in the House of Representatives on January 24, 2019 as H.R. 748 as the Middle Class Health Benefits Tax Repeal Act of 2019; it passed the House on July 17, 2019. It then passed the Senate as the Coronavirus Aid, Relief, and Economic Security Act on March 25, 2020, and was signed into law by President Donald Trump on March 27, 2020. In Appendix Figure A3, we reproduce the same plot using the HEROES, CAA, and ARP acts as robustness tests. The fitted line above yields a significant and high correlation of 0.44 (SE=0.24).



(A) Full sample, as in Panel A of Table 6



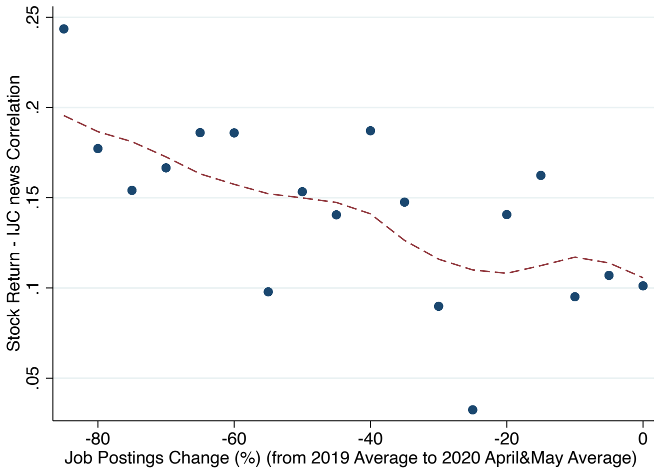
(B) Non-overlapping sample, as in Panel B of Table 6



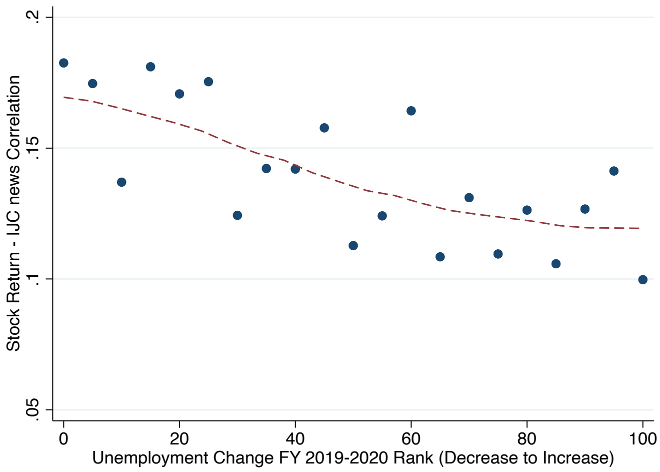
(C) Non-overlapping sample, as in Panel C of Table 6

Figure 6: Cross-section evidence: Obligated Paycheck Protection Program awards and return-IJC correlations.

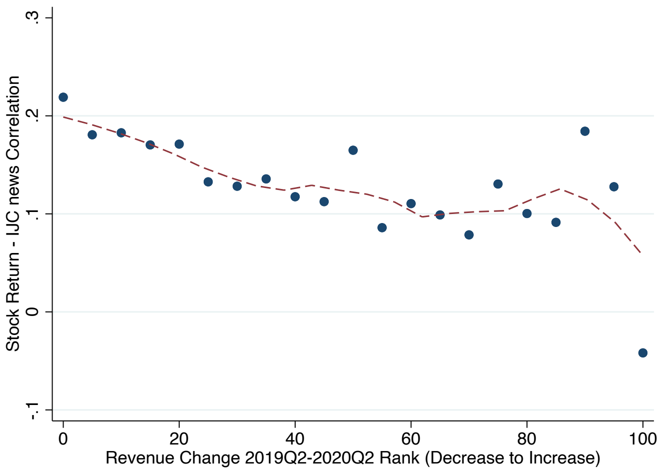
This figure complements Column (3) in each of the three panels in Table 6, depicting the relationship between return-IJC correlations and covid-related crisis funding awards using the full sample in (A) and non-overlapping samples in (B) and (C). For demonstration, we sort firms into four groups by their obligated PPP award amounts calculated during various periods (as discussed in Table 6): Not a covid funding recipient (log(award+1)=0); log(award+1) from 0 to 10; log(award+1) from 10 to 15; and log(award+1) above 15. The dashed lines indicate the actual 90% confidence interval.



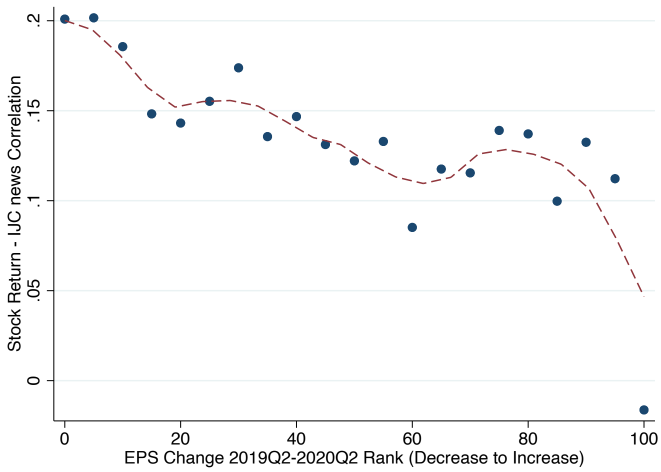
(A)



(B)



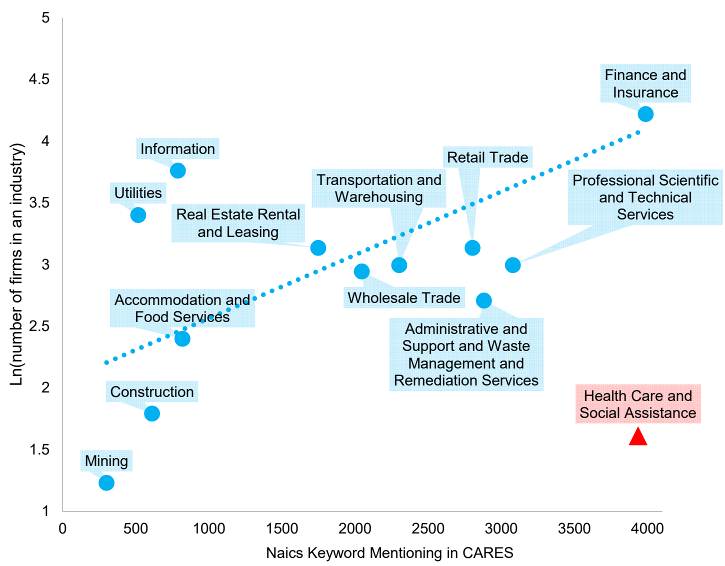
(C)



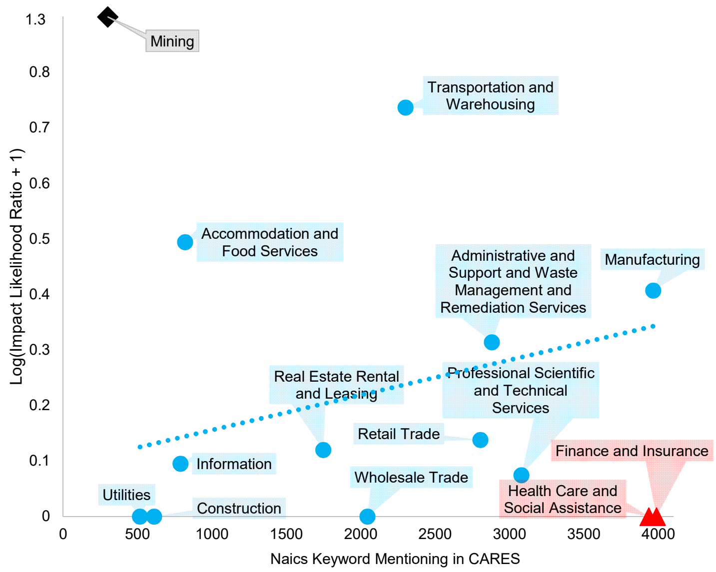
(D)

Figure 7: Cross-section evidence: covid damage and return-IJC correlations.

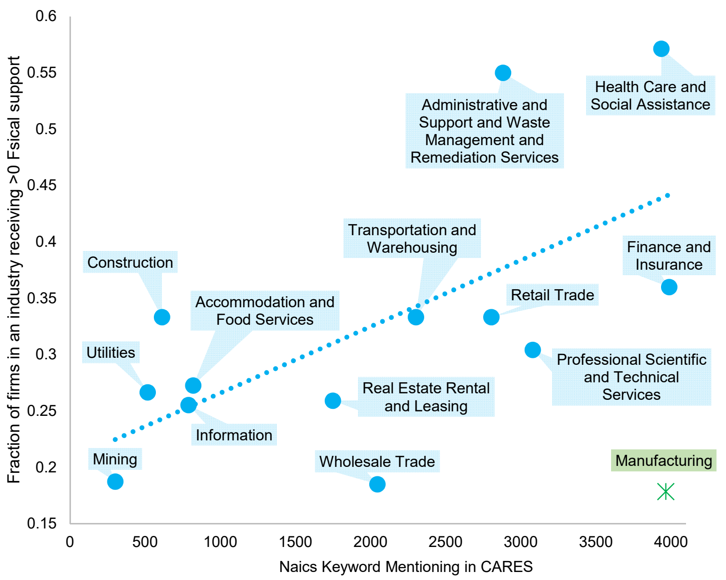
This figure shows the relationship between four firm covid impact measures (x-axis) and firm stock return reactions to IJC shocks (y-axis). We group all firms (498 of the S&P 500 firms) into 20 bins (5% each). We explain the constructions in Section 5.3. Each dot represents the average correlation in each bin, and the red dashed line is the kernel fitted line. Firms that suffer more (i.e., are closer to the left end of the x-axis) show a stronger "Main Street pain, Wall Street gain" phenomenon (captured by the higher SD changes in individual stock returns given a 1 SD IJC shock). The x variable in Subfigure (A) is the raw change in the number of all-internet job postings, where, for example, -80 indicates that job postings decreased by 80% between 2019 and April/May of 2020. The x variables in Subfigures (B)-(D) are ranks of employment changes, revenue changes, and earnings per share (EPS) changes, respectively; employment changes compares fiscal year 2019 and 2020 (due to data availability), whereas revenue and EPS changes compare 2019Q2 and 2020Q2 (to capture the initial effects of COVID-19). We use rank in the x-axis due to the skewness of firm-level data (see summary statistics in Online Appendix Table OA3).



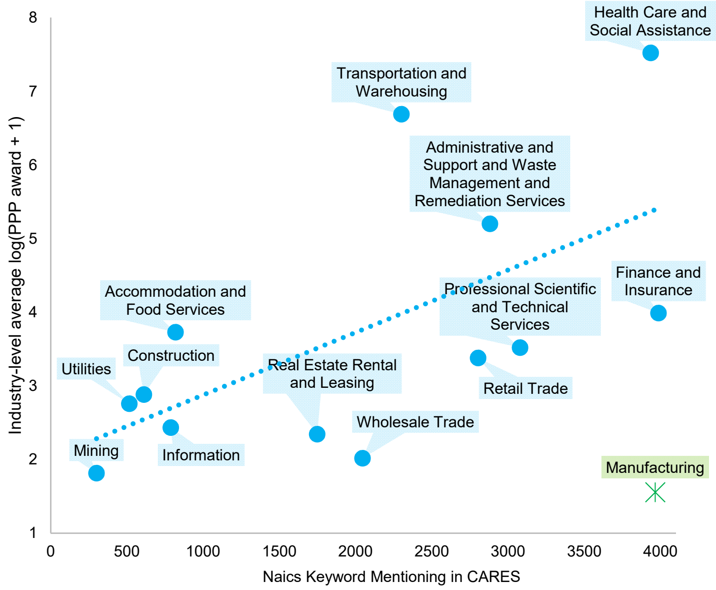
(A) y-axis: Industry presence in S&P500 (our 498 firm pool)



(B) y-axis: Industry covid impact likelihood ratio



(C) y-axis: Fiscal support to each industry (fraction of firms)



(D) y-axis: Fiscal support to each industry (amount)

Figure 8: Comparison across three cross-sectional dimensions at the industry level: Who gets what?

This figure compares an industry's bill mentions with (A) its presence in the stock market, (B) its expected covid impact, and (C,D) its fiscal supports. **Y-axes:** (A) uses the log of the number of firms within the S&P500 universe; (B) constructs a log of an Impact Likelihood Ratio, which represents the likelihood for this industry to fall in the most damaged 15% compared to its likelihood to be in the least damaged 50%, where the damage measure uses changes in job postings: $Ratio = \frac{Prob(\#\text{Firm in the most damaged 15\%})}{Prob(\#\text{Firm in the least damaged 50\%})}$; (C) calculates the fraction of firms in an industry that receive any covid-related spending out of its total presence in the S&P 500 firms; (D) calculates the average obligated log(PPP+1) across all firms in an industry. The fitted lines from (A)-(D) yield the following positive correlations, respectively: 0.66, 0.30, 0.65, 0.63.

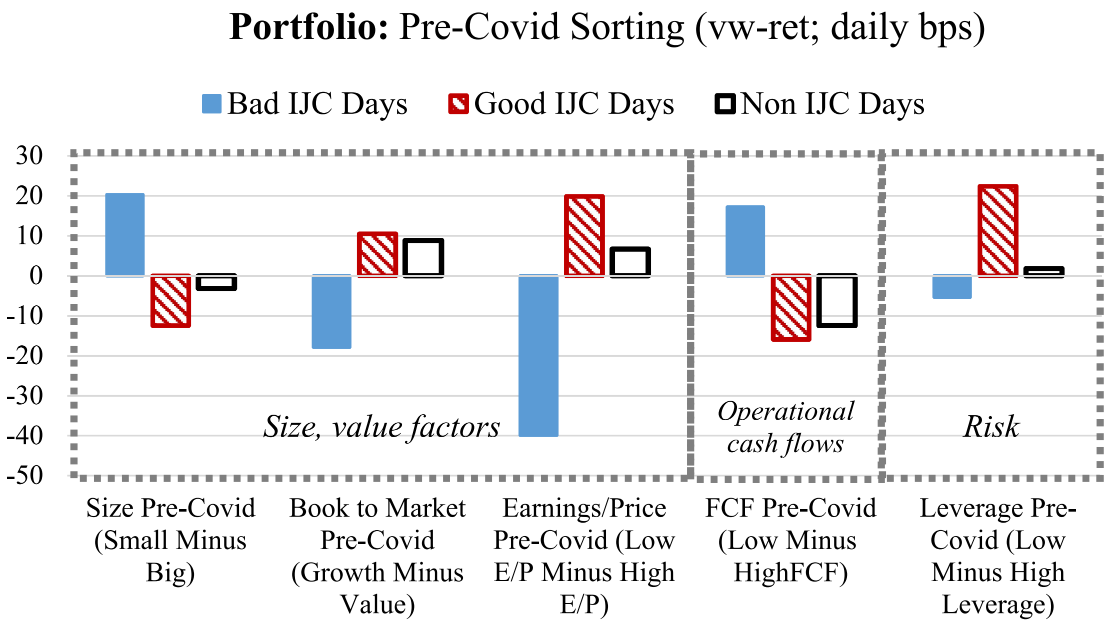


Figure 9: Traditional firm characteristics.

We sort S&P500 firms into 5 bins based on firms' end-of-2019 characteristics: (1) standard size and value factor (B/M, E/P); (2) free cash flows (FCF=operating cash flow (OANCF)-gross capital expenditures (CAPX)); (3) risk (leverage=(long-term debt+short-term debt)/share holder equity). The portfolio takes the return difference between the lowest (lowest-size, lowest-B/M, lowest-E/P, lowest-FCF, lowest-leverage) and the highest quintile bins. In each portfolio, average returns can be calculated using bad IJC days (when the actual IJC number is higher/worse than expected), good IJC days (when the actual IJC number is lower/better than expected), and non-IJC days. Returns are in basis points; our sample period runs from February 2020 to March 2021, excluding 03/19, 03/26, 04/02, and 04/09 of 2020 and FOMC overlaps. Robustness using equal weights is shown in Online Appendix Figure OA1.

Table 1: Stylized Facts: Pricing Channel.

This table presents stylized facts about asset price responses to IJC shocks, as discussed in Section 2.2. **Panels:** In Panels A and B, we consider two non-overlapping, post-Global Financial Crisis, zero-lower-bound (ZLB) sample periods. See more discussions in Section 2. Panel C presents the t statistics of the coefficient difference. **Initial jobless claim (IJC) shock:** Our main IJC shock is defined as $\frac{IJC_t - E_{t-\Delta}(IJC_t)}{E_{t-\Delta}(IJC_t)}$, where both the actual IJC_t and survey median forecast $E_{t-\Delta}(IJC_t)$ are obtained from Bloomberg. We exclude identified IJC outlier days (3/19/2020, 3/26/2020, and 4/2/2020). **Left-hand-side variables are stocks and discount rate-sensitive assets:** (1) "S&P500" denotes the daily open-to-close log returns (unit: basis points; source: DataStream); (2) unexpected returns; (3) changes in expectations of future cash flow growth or NCF; (4) changes in expectations of future discount rate or NDR; the unit for all of these is basis points. By design, NCF minus NDR yields the total unexpected return. (5) "Chgs in 10-yr Yield" denotes the first differences in the 10-year Treasury Yield (unit: annual percents; source: DataStream). (6) "Chgs in Treasury IV" denotes the first differences in the Treasury implied volatility (unit: annual percents; source: CBOE). (7) "Chgs in 1m-ahead Fed Funds futures rates" denotes the changes in daily Fed Funds futures (FFF) rates (unit: annual percents; source: DataStream). (8) "Chgs in FFF paths" denotes the changes in the daily spread between long-term and 1m FFF rates, where we consider 6m, 9m, and 12m as longer-term proxies (unit: annual percents; source: data of specific horizons from DataStream). **Reporting:** "IJC shock coeff." reports the regression coefficients with robust standard errors and R-squared displayed in the following rows. "SD chngs per 1SD shock" shows the standard deviation (SD) changes in the LHS variable given 1 SD IJC shock. ***, p-value <1%; **, <5%; *, <10%.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)		
	S&P500	**Unexpected Return**	**NCF**	**NDR**	**Chgs in 10-yr Yield**	**Chgs in Treasury IV**	**Chgs in 1m FFF**	**Chgs in FFF paths**		
								6m-1m	**9m-1m**	**12m-1m**
Panel A. "Normal" zero-lower-bound period: 2009/07-2016/12										
IJC shock coeff.	-97.163	-86.736	-3.993	**82.743***	**-0.207*****	-1.786	0.003	0.014	**0.035****	**0.061****
(SE)	(107.303)	(106.271)	(79.224)	**(48.330)**	**(0.060)**	(1.813)	(0.010)	(0.011)	**(0.017)**	**(0.024)**
SD chngs per 1SD shock	-0.042	-0.037	-0.002	**0.037**	**-0.167**	-0.137	0.019	0.06	**0.10**	**0.12**
R^2%	0.18%	0.15%	0.00%	**0.55%**	**2.78%**	1.36%	0.04%	0.42%	**0.96%**	**1.44%**
Panel B. "Covid" zero-lower-bound period: 2020/02-2021/03										
IJC shock coeff.	**307.916***	299.961	**298.903****	-1.058	-0.087	-2.182	0.029	0.0154	0.0175	**0.024***
(SE)	**(186.945)**	(186.761)	**(133.464)**	(103.733)	(0.066)	(2.342)	(0.022)	(0.010)	(0.011)	**(0.012)**
SD chngs per 1SD shock	**0.197**	0.192	**0.197**	-0.001	-0.177	-0.121	0.103	0.09	0.10	**0.15**
R^2%	**3.90%**	3.68%	**7.56%**	0.00%	3.13%	1.46%	1.06%	0.73%	1.06%	**2.11%**
Panel C. t test statistics of coefficient equality, Covid-Normal										
t stats.	**1.88**	**1.80**	**1.95**	-0.73	1.27	-0.14	1.09	0.09	-0.87	-1.36

Table 2: Stylized Facts: Asymmetry.

This table presents stylized facts about asset price responses to IJC shocks, as discussed in Section 2.2. In the asymmetry analysis, we split the 2020/02-2021/03 period into days when actual IJC numbers are higher than expected (bad days) and days when actual IJC numbers are lower than or equal to the expected numbers (good days). The first three columns use the same LHS variables as in Table 1. The next six columns use the open-to-close log returns of various major stock market indices and are expressed in basis points as before; Nasdaq and Dow Jones indices (30=industrial; 20=transportation; 15=utility) are downloaded from Datastream. The coefficient in row "IJC shock coeff." indicates the sensitivity of open-to-close log returns to IJC shocks on bad IJC days (Panel A) or good IJC days (Panel B). See other notation details in Table 1. ***, p-value <1%; **, <5%; *, <10%.

	(1) **S&P500**	(2) **Unexpected Return**	(3) **NCF**	(4) **NDR**	(5) **Nasdaq100**	(6) **DowJones65**	(7) **DowJones30 Indus.**	(8) **DowJones20 Transp.**	(9) **DowJones15 Util.**
Panel A. Sample: Bad IJC days (IJC shock>0)									
IJC shock coeff.	**591.829****	**585.113****	**479.568****	-105.545	498.523	**575.072****	**589.960****	**549.662***	498.755
(SE)	**(264.162)**	**(262.050)**	**(224.735)**	(154.879)	(324.814)	**(263.722)**	**(291.756)**	**(312.686)**	(468.282)
SD chngs per 1SD shock	**0.400**	**0.395**	**0.265**	-0.072	0.275	**0.392**	**0.387**	**0.321**	0.231
R^2%	**15.97%**	**15.68%**	**17.40%**	1.97%	7.56%	**15.33%**	**14.97%**	**10.31%**	5.32%
Panel B. Sample: Good IJC days (IJC shock<=0)									
	S&P500	**Unexpected Return**	**NCF**	**NDR**	**Nasdaq100**	**DowJones65**	**DowJones30 Indus.**	**DowJones20 Transp.**	**DowJones15 Util.**
IJC shock coeff.	-284.332	-284.763	-98.065	186.698	19.183	-595.586	-579.157	-572.759	-721.799
(SE)	(661.380)	(663.087)	(437.385)	(325.010)	(795.692)	(598.092)	(609.090)	(746.336)	(524.516)
SD chngs per 1SD shock	-0.069	-0.069	-0.028	0.044	0.005	-0.141	-0.159	-0.103	-0.132
R^2%	0.48%	0.48%	0.13%	0.67%	0.00%	1.99%	2.54%	1.07%	1.75%

Table 3: Time-Series Mechanism Test Using Rolling Windows: All IJC Days.

This table projects time-varying stock return responses to IJC shocks on various time-varying topic mentions, where time-varying variables are obtained using rolling 80-week windows. Three return responses are considered – the rolling S&P 500 return coefficient, the rolling S&P 500 economic magnitude (SD changes in returns given a 1 SD IJC shock), and the rolling Dow Jones 65 return coefficient. Each topic mentions variable (fiscal policy (FP), monetary policy (MP), and uncertainty (UNC) (see Section 2.1 for our topic mentions calculation) is standardized in these regressions for interpretation purposes; Newey-West standard errors (Newey and West (1987)) and SD changes in return responses given a 1 SD change in topic mentions are reported as well. Due to news file availability, our sample runs from January 2013 to March 2021. Appendix Table A4 provides more robustness tests. ***, p-value <1%; **, <5%; *, <10%.

LHS:	(1) **Rolling coeff. of S&P500 on IJC shock**	(2) **Economic Magnitude**	(3) **Rolling coeff. of S&P500 on IJC shock**	(4) **Rolling coeff. of DJ65 on IJC shock**
Constant	**59.984*** **	**0.044*** **	**59.984*** **	**82.621*** **
(NWSE)	(19.733)	(0.012)	(19.825)	(18.678)
FP (standardized)	**197.735*** **	**0.116*** **	**197.993*** **	**161.616*** **
(NWSE)	(26.342)	(0.015)	(25.522)	(17.990)
SD chngs	1.278	1.256	1.280	1.213
MP (standardized)	**110.275*** **	**0.065*** **	**109.519*** **	**125.082*** **
(NWSE)	(23.606)	(0.015)	(30.270)	(15.908)
SD chngs	0.713	0.708	0.708	0.939
UNC (standardized)			-1.468	
(NWSE)			(26.867)	
SD chngs			-0.009	
R2 Ordinary	63.9%	61.2%	63.9%	47.4%
R2 Adjusted	63.6%	60.9%	63.5%	47.0%
N	271	271	271	271

Table 4: Time-Series Mechanism Test Using Rolling Windows: Bad Versus Good IJC days.

This table complements Table 3 and shows the results using rolling windows of 40 bad IJC days in Panel A and 40 good IJC days in Panel B. See other table details in Table 3. Appendix Table A4 provides more robustness tests. ***, p-value <1%; **, <5%; *, <10%.

	Panel A. Bad IJC days				Panel B. Good IJC days			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
LHS:	**Rolling coeff. of S&P500 on IJC shock**	**Economic Magnitude**	**Rolling coeff. of S&P500 on IJC shock**	**Rolling coeff. of DJ65 on IJC shock**	**Rolling coeff. of S&P500 on IJC shock**	**Economic Magnitude**	**Rolling coeff. of S&P500 on IJC shock**	**Rolling coeff. of DJ65 on IJC shock**
Constant	21.676	**0.039*** **	21.676	-15.925	**-28.104** **	0.007	**-28.104***	50.763
(NWSE)	(37.687)	(0.015)	(32.373)	(63.498)	(14.202)	(0.007)	(14.630)	(31.618)
FP (standardized)	**262.104*** **	**0.147*** **	**267.237*** **	**342.343*** **	**80.747*** **	**0.030*** **	**95.429*** **	**-76.688***
(NWSE)	(39.129)	(0.030)	(37.908)	(55.398)	(17.666)	(0.005)	(20.288)	(41.357)
SD chngs	1.072	1.020	1.093	1.161	0.329	0.342	0.389	-0.221
MP (standardized)	87.471	0.037	**109.981***	**162.777** **	**223.482*** **	**0.082*** **	**185.234*** **	**217.792*** **
(NWSE)	(53.977)	(0.038)	(58.153)	(66.699)	(13.943)	(0.008)	(13.723)	(28.567)
SD chngs	0.358	0.254	0.450	0.552	0.911	0.929	0.755	0.627
UNC (standardized)			27.691				**-65.367*** **	
(NWSE)			(33.634)				(15.275)	
SD chngs			0.113				-0.266	
R2 Ordinary	57.5%	63.1%	58.3%	48.0%	54.4%	56.3%	57.5%	62.3%
R2 Adjusted	56.8%	62.5%	57.1%	47.0%	53.8%	55.7%	56.7%	61.8%
N	116	116	116	116	155	155	155	155

Table 5: Time-Series Mechanism Test Using Non-Overlapping State Variables.

This table reports the results of the following regression:

$$y_t = \beta_0 + \beta_1 IJCshock_t + \boldsymbol{\beta_2 Z_\tau} + \boldsymbol{\beta_3} IJCshock_t * \boldsymbol{Z_\tau} + \varepsilon_t,$$

where t and τ denote weekly and quarterly frequency, respectively, y stock returns (in basis points) and $\boldsymbol{Z}$ standardized state variable(s) of interest. The first three state variables are textual mentions using articles published within the same quarter (fiscal policy (FP), monetary policy (MP), and uncertainty (UNC)); using the same textual analysis methodology described before, we use all bad (good) days within the quarter and obtain a quarterly bad (good) measure. Next, we consider the difference between the one-quarter-ahead forecast and the nowcast of the 3-month Treasury bill rate ("$\Delta Tbill3m$"), where both forecast and nowcast are provided given the last quarter's information set (source: Survey of Professional Forecasters, or SPF). Due to news file availability, our sample runs from January 2013 to March 2021. Univariate regression results are shown in Appendix Table A5. We drop quarters when textual UNC mentions are missing. ***, p-value <1%; **, <5%; *, <10%.

	Panel A. Bad IJC days				Panel B. Good IJC days			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
LHS:	**S&P500**	**DJ65**	**DJ65**	**DJ65**	**S&P500**	**DJ65**	**DJ65**	**DJ65**
Constant	4.065	7.929	7.699	6.339	-1.612	-3.276	-9.455	-14.982
(SE)	(8.539)	(8.318)	(8.371)	(8.249)	(10.916)	(11.098)	(11.576)	(12.269)
IJC shock	-52.565	-67.039	-61.911	-36.733	67.661	32.727	-15.999	-109.268
(SE)	(146.232)	(133.391)	(135.418)	(130.245)	(196.004)	(195.249)	(193.050)	(199.728)
Quarterly FP (standardized)	**-16.552****	**-17.148****	**-21.850****	**-19.740****	20.197	14.157	10.032	18.586
(SE)	**(7.647)**	**(7.327)**	**(9.236)**	**(8.944)**	(13.305)	(12.790)	(12.108)	(14.060)
IJC shock*Quarterly FP (standardized)	**258.381*****	**257.325****	**330.973****	**261.428****	371.513	267.787	213.641	379.719
(SE)	**(99.014)**	**(102.349)**	**(155.214)**	**(132.472)**	(241.694)	(225.272)	(216.226)	(251.795)
Quarterly MP (standardized)	-6.252	-7.119	-9.225		2.103	8.599	9.028	
(SE)	(6.912)	(7.029)	(7.416)		(9.674)	(9.836)	(9.531)	
IJC shock*Quarterly MP (standardized)	58.787	131.390	168.610		190.288	**303.040***	**299.116****	
(SE)	(118.594)	(126.131)	(143.970)		(156.953)	**(160.200)**	**(150.107)**	
Quarterly $\Delta Tbill3m$ (standardized)				-0.344				**30.094****
(SE)				(8.524)				**(14.617)**
IJC shock*Quarterly $\Delta Tbill3m$ (standardized)				-47.979				**671.552****
(SE)				(141.554)				**(280.509)**
Quarterly UNC (standardized)			7.736	3.177			**26.363***	**28.829****
(SE)			(10.615)	(11.291)			**(14.504)**	**(14.468)**
IJC shock*Quarterly UNC (standardized)			-130.822	-62.590			**428.631***	**484.923****
(SE)			(194.985)	(182.359)			**(246.072)**	**(235.473)**

Table 6: Cross-Section Mechanism Test: Fiscal Stimulus Spending at the Firm Level from February 2020 to March 2021.

This table projects the individual return-IJC shock correlation on the log of covid relief funding promised or provided by the U.S. government, at the firm level (note that correlation is statistically equivalent to SD interpretation):

$$Corr^i = \beta_0 + \beta_1 log(1 + Covid\_Funding^i) + \epsilon^i.$$

Panels: The three panels differ in terms of the sample periods for which we calculate $Corr^i$ and $log(1 + Covid\_Funding^i)$. Panel A uses the full sample from February 2020 to March 2021 (excluding 03/19, 03/26, 04/02, and 04/09/2020, as elsewhere in the paper). Panels B and C use non-overlapping samples to compute variables, and hence have predictive interpretations. **Columns:** Columns (1) and (2) use the *obligated* amount (i.e., promised awards) of all covid spending; Columns (3) and (4) use the *obligated* amount from the Paycheck Protection Program only; Columns (5) and (6) use the *actual* total gross outlay (awards distributed de facto). Note that the dataset contains a small number of negative amounts, which are related to decisions to revoke funding or to entry error revisions, and we have no way to differentiate the two; therefore, Columns (1), (3), and (5) use all records, while Columns (2), (4), and (6) remove records with negative values when calculating firm-level award amounts. See other data and construction details in Section 5.2. ***, p-value <1%; **, <5%; *, <10%.

Dependent variable:	Return-IJC Shock Correlation					
Obligated or actual:	Obligated Amount		Obligated Amount		Actual Amount	
Award type:	All		Paycheck Protection		All	
	(1)	(2)	(3)	(4)	(5)	(6)
	All	Positive	All	Positive	All	Positive
Panel A: Full sample to compute $Corr^i$ and $log(1 + Covid\_Funding^i)$						
Coefficient β_1	0.247***	0.246***	0.284***	0.285***	0.311***	0.290***
(SE)	(0.091)	(0.090)	(0.095)	(0.095)	(0.099)	(0.095)
Panel B: 2020/05-2021/03 for $Corr^i$, 2020/02-2020/04 for $log(1 + Covid\_Funding^i)$						
Coefficient β_1	0.226**	0.218**	0.215*	0.235**	0.203*	0.224**
	(0.108)	(0.106)	(0.115)	(0.115)	(0.119)	(0.111)
Panel C: 2020/06-2021/03 for $Corr^i$, 2020/02-2020/05 for $log(1 + Covid\_Funding^i)$						
Coefficient β_1	0.238**	0.215**	0.226**	0.226**	0.234**	0.235**
	(0.103)	(0.101)	(0.110)	(0.110)	(0.112)	(0.105)

Table 7: Cross-Section Mechanism Test: Covid Impact Measures at the Firm Level.

This table projects return-IJC shock correlations on various covid impact measures. The sample uses IJC announcement days from February 2020 to March 2021 (excluding 03/19, 03/26, 04/02, and 04/09/2020, as elsewhere in the paper); as explained in Section 5.3, we are able to identify 498 S&P500 firms with our covid impact measures. **Firm-/industry-level covid impact measures:** (1) raw changes in the number of all internet job postings, e.g., -0.8 would mean that firm job postings decreased by 80% between 2019 and April/May of 2020; (2) employment changes from fiscal year (FY) 2019 to FY 2020 by percentile rank; (3) revenue changes from 2019Q2 to 2020Q2 by percentile rank; (4) earnings per share (EPS) changes from 2019Q2 to 2020Q2 by percentile rank; (5) revenue changes from FY 2019 to FY 2020 by percentile rank; (6) EPS changes from FY 2019 to FY 2020 by percentile rank. The online job posting data used in (1) is from a proprietary source (LinkUp); the rest of the data is obtained from Compustat Annual and Compustat Quarter (source: WRDS). Overall, the lower the measure, the larger the initial impact a firm/industry experienced. Summary statistics of these six measures are provided in Online Appendix Table OA3. Standard errors are reported in parentheses; ***, p-value <1%; **, <5%; *, <10%.

	Dependent Variable:	Return-IJC Shock Correlation
	DV calculation sample:	**All-IJC**
	DV Mean:	0.141
	DV SD:	0.114
1 (Main Measure)	Job Postings Change;	**-0.089*** **
	2019 Average-2020/04-05 Average, 4-digit NAICS	**(0.023)**
2	Employment Change; FY 2019-2020	**-0.060*** **
		(0.017)
3	Revenue Change; 2019Q2-2020Q2	**-0.081*** **
		(0.018)
4	EPS Change; 2019Q2-2020Q2	**-0.080*** **
		(0.017)
5	Revenue Change FY2019-2020	**-0.105*** **
		(0.017)
6	EPS Change FY 2019-2020	**-0.056** **
		(0.018)

A. Additional Figures and Tables

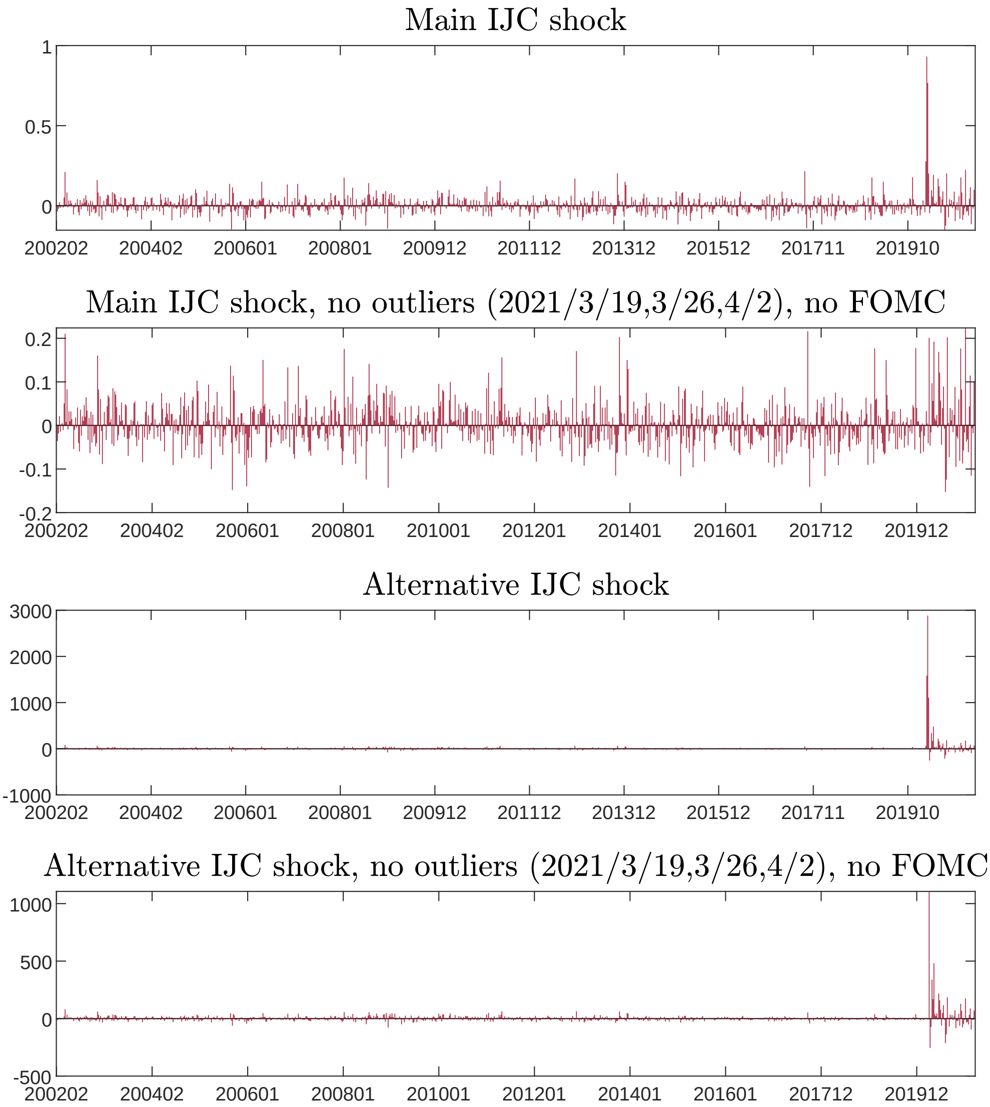


Figure A1: Time series of main IJC shocks ($\frac{IJC_t - E_{t-\Delta}(IJC_t)}{E_{t-\Delta}(IJC_t)}$) and alternative IJC shocks ($IJC_t - E_{t-\Delta}(IJC_t)$), with or without the identified outliers and FOMC days.

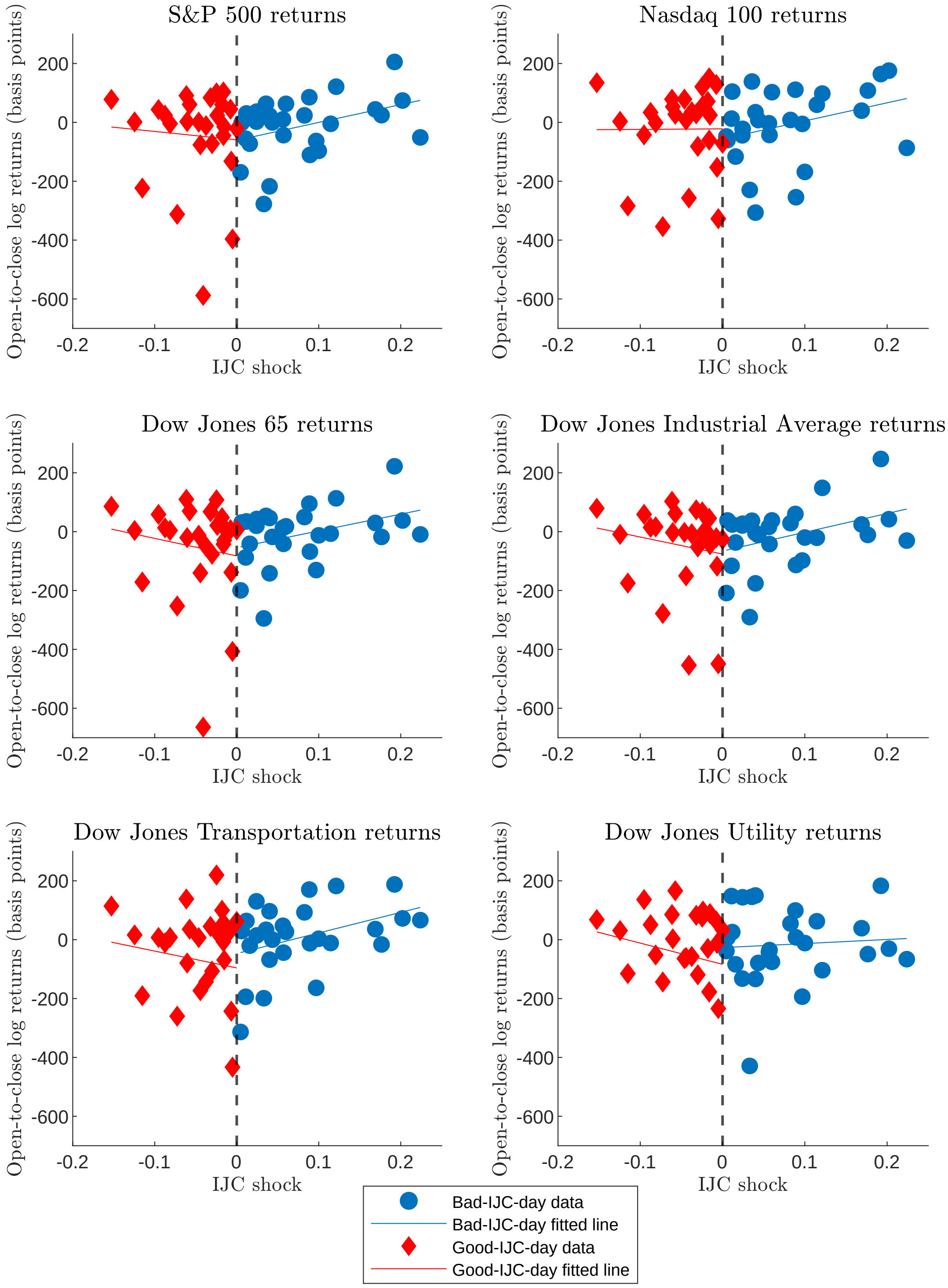
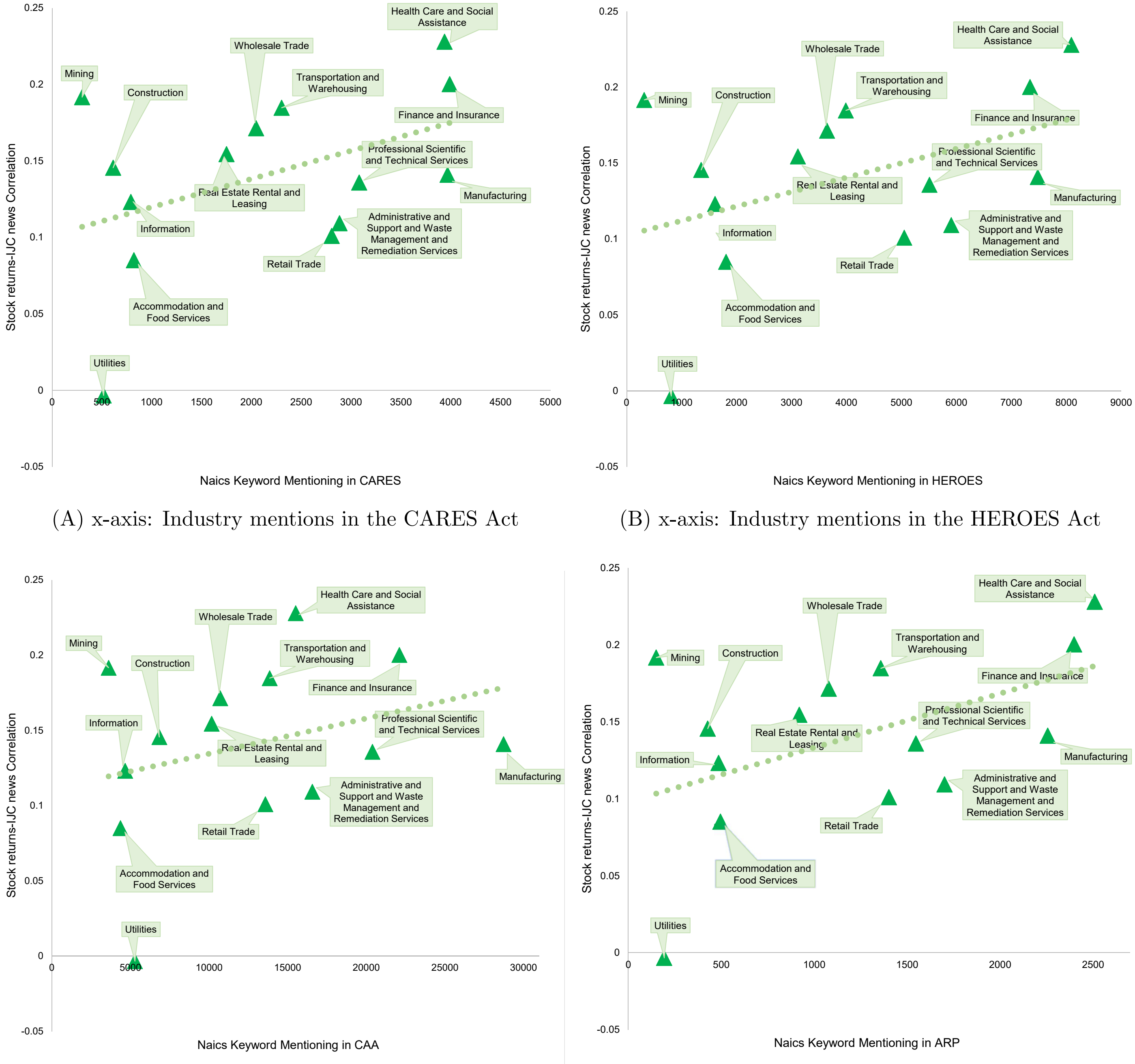


Figure A2: Robustness for Figure 4: Relation between stock returns and IJC shocks from February 2020 to March 2021, excluding IJC shock outliers (2020/3/19, 3/26, 4/2) and the major Federal Reserve announcement day (2020/4/9).



(A) x-axis: Industry mentions in the CARES Act

(B) x-axis: Industry mentions in the HEROES Act

(C) x-axis: Industry mentions in the CAA

(D) x-axis: Industry mentions in the ARP Act

Figure A3: Robustness evidence for Figure 5: Industry mentions in actual bills.

This figure extends Figure 5 using three other bills besides the CARES Act. The y-axis shows the correlation between returns and IJC shocks; the x-axis shows industry mentions in four major acts from 2020 to early 2021, where industry keywords use the 6-digit NAICS industry description on https://www.naics.com/search/. **Acts**: (A) CARES was initially introduced in House of Representatives on January 24, 2019 as H.R. 748 (Middle Class Health Benefits Tax Repeal Act of 2019); it passed the House on July 17, 2019. It passed the Senate as the Coronavirus Aid, Relief, and Economic Security Act on March 25, 2020, and was signed into law by President Donald Trump on March 27, 2020. (B) The HEROES Act was introduced in House of Representatives on May 12, 2020 as H.R. 6800; it passed the House on May 15, 2020. (C) The CAA was a spending bill, H.R. 133, for the fiscal year ending September 30, 2021, and was the product of weeks of intense negotiations and compromise between Democrats and Republicans; it passed Congress on December 21, 2020, and was signed into law by President Donald Trump on December 27, 2020. (d) The ARP Act was introduced in House of Representatives on January 14, 2021 as H.R. 1319; it passed the House on February 27, 2021, passed the Senate on March 6, 2021, and was signed into law by President Joe Biden on March 11, 2021. **The fitted lines from (A) to (D)** yield significant and positive correlations of 0.44, 0.43, 0.31, and 0.50, respectively.

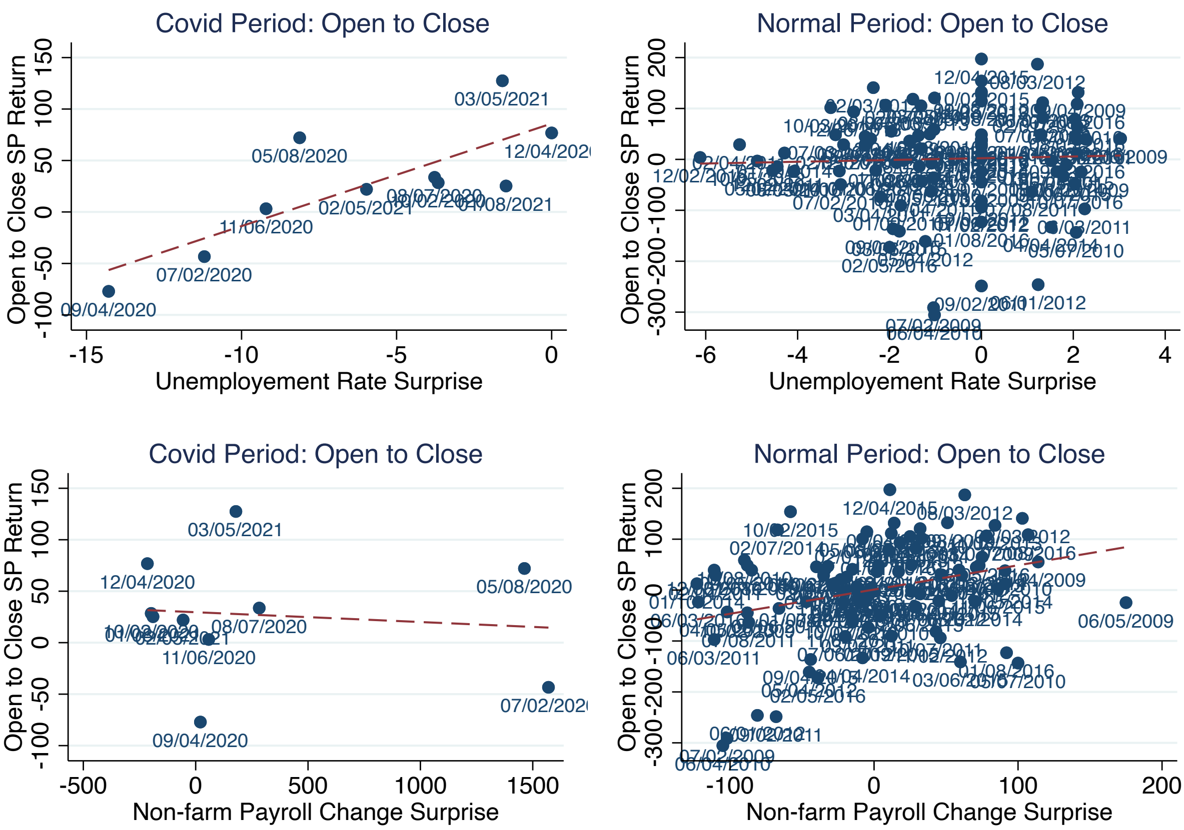


Figure A4: Scatter plot of monthly unemployment announcement surprises and announcement day open-to-close returns. Covid and normal periods are as defined in the main paper.

Table A1: Timeline of all Federal Reserve actions from March 15, 2020 to the end of 2021. (Unshaded lines: Monetary policy actions. Shaded lines: Fiscal policy implementations.)

Date	**Federal Reserve Action Timeline**
3/15/2020	The Fed Funds rate cut to zero https://www.federalreserve.gov/newsevents/pressreleases/monetary20200315a.htm
3/15/2020	Quantitative easing (large scale asset purchases) https://www.federalreserve.gov/newsevents/pressreleases/monetary20200315a.htm
3/15/2020	Encourage use of the discount window https://www.federalreserve.gov/newsevents/pressreleases/bcreg20200316a.htm
3/15/2020	Flexibility in bank capital requirements https://www.federalreserve.gov/newsevents/pressreleases/monetary20200315b.htm
3/15/2020	Coordinated international action to lower pricing on US dollar liquidity swap arrangements https://www.federalreserve.gov/newsevents/pressreleases/monetary20200315c.htm
3/17/2020	Creation of a commercial paper funding facility (CPFF) https://www.federalreserve.gov/newsevents/pressreleases/monetary20200317a.htm
3/17/2020	Creation of a primary dealer credit facility (PDCF) https://www.federalreserve.gov/newsevents/pressreleases/monetary20200317b.htm
3/18/2020	Creation of a money market mutual fund liquidity facility (MMLF) https://www.federalreserve.gov/newsevents/pressreleases/monetary20200318a.htm
3/19/2020	US dollar liquidity swap arrangements extended to more international central banks https://www.federalreserve.gov/newsevents/pressreleases/monetary20200319b.htm
3/20/2020	Frequency of US dollar liquidity swap operations updated to daily https://www.federalreserve.gov/newsevents/pressreleases/monetary20200320a.htm
3/20/2020	MMLF will now accept municipal debt https://www.federalreserve.gov/newsevents/pressreleases/monetary20200320b.htm
3/23/2020	Fed accouces extensive new measures to support the economy 1. Expands its quantitative easing program 2. Establishes three new emergency lending facilities: PMCCF, SMCCF, TALF 3. Expands two existing programs: CPFF, PDCF https://www.federalreserve.gov/newsevents/pressreleases/monetary20200323b.htm
3/23/2020	Technical changes to total loss absorbing capacity (TLAC) https://www.federalreserve.gov/newsevents/pressreleases/bcreg20200323a.htm
3/24/2020	Fed delays implementation of foreign banking organization maximum daily overdraft rule https://www.federalreserve.gov/newsevents/pressreleases/other20200324a.htm
3/24/2020	Fed scales back non-critical oversight https://www.federalreserve.gov/newsevents/pressreleases/bcreg20200324a.htm
3/26/2020	Fed provides reporting relief for small principal institutions https://www.federalreserve.gov/newsevents/pressreleases/bcreg20200326b.htm
3/26/2020	New York Fed To Buy Commercial Mortgage-Backed Securities https://www.newyorkfed.org/markets/opolicy/operating$_{p}olicy_{2}$00326
3/31/2020	Fed Establishes New Temporary Repo Facility https://www.federalreserve.gov/newsevents/pressreleases/monetary20200331a.htm
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4/1/2020		Fed loosens bank capital requirements https://www.federalreserve.gov/newsevents/pressreleases/bcreg20200401a.htm
4/6/2020	Fiscal	Fed implements CARES Act community bank capital ratio https://www.federalreserve.gov/newsevents/pressreleases/bcreg20200406a.htm
4/9/2020	Fiscal	Fed announces three new emergency lending facilities designed to implement the relief provided by the CARES Act, support the work of Treasury and the Small Business Administration (SBA): 1. Paycheck Protection Program liquidity facility (PPPFL) 2. Main Street Business Lending Program 3. Municipal Liquidity Facility https://www.federalreserve.gov/newsevents/pressreleases/monetary20200409a.htm
4/23/2020	Fiscal	Fed Commits to Transparent Disclosure of Companies Receiving Financial Aid through the liquidity and lending facilities using Coronavirus Aid, Relief, and Economic Security, or CARES, Act funding https://www.federalreserve.gov/newsevents/pressreleases/monetary20200423a.htm
4/23/2020	Fiscal	Fed to expand access to PPPLF Program https://www.federalreserve.gov/newsevents/pressreleases/monetary20200423b.htm
4/27/2020	Fiscal	Fed expands access to municipal lending facility https://www.federalreserve.gov/newsevents/pressreleases/monetary20200427a.htm
4/30/2020	Fiscal	Fed expands Main Street Lending Program https://www.federalreserve.gov/newsevents/pressreleases/monetary20200430a.htm
5/11/2020	Fiscal	Fed releases term sheet for municipal liquidity facility clarifying pricing https://www.federalreserve.gov/newsevents/pressreleases/monetary20200511a.htm
5/15/2020	Fiscal	Fed provides first report to congress on PPPLF facility https://www.federalreserve.gov/monetarypolicy/ppplf.htm
5/15/2020		Fed loosens bank capital requirement (again) https://www.federalreserve.gov/newsevents/pressreleases/bcreg20200515a.htm
5/19/2020	Fiscal	Main Street Business Lending Program and Municipal Liquidity Facility Programs to commence end of may https://www.federalreserve.gov/newsevents/testimony/powell20200519a.htm
6/3/2020	Fiscal	Municipal Liquidity Facility opens and access once again expanded https://www.federalreserve.gov/newsevents/pressreleases/monetary20200603a.htm
6/8/2020	Fiscal	Fed significantly expands access to proposed Main Street Lending Facility https://www.federalreserve.gov/newsevents/pressreleases/monetary20200608a.htm
6/15/2020	Fiscal	Main Street Lending Facility opens for lender registration https://www.bostonfed.org/news-and-events/press-releases/2020/.. ../federal-reserves-main-street-lending-program-opens-for-lender-registration.aspx?source=email
6/15/2020		Fed expands SMCCF, begins buying debt directly from large corporations https://www.newyorkfed.org/newsevents/news/markets/2020/20200615?source=email
6/15/2020	Fiscal	Fed requests feedback on extending Main Street Lending Program to Nonprofits https://www.federalreserve.gov/newsevents/pressreleases/monetary20200615b.htm
7/17/2020	Fiscal	Fed begins purchasing loans through Main Street Lending Program; opens program to non-profits https://www.federalreserve.gov/newsevents/pressreleases/monetary20200717a.htm
10/30/2020	Fiscal	Fed lowers main street lending program minimum loan amount to $100,000 https://www.federalreserve.gov/newsevents/pressreleases/monetary20201030a.htm
11/3/2021		Fed announces that it will reduce pace of asset purchases https://www.federalreserve.gov/newsevents/pressreleases/monetary20201030a.htm

Table A2: Robustness Evidence for Table 1: Pricing Channels.

This table complements Table 1 and considers the alternative IJC shock $IJC_t - E_{t-\Delta}(IJC_t)$ (see Online Appendix Table OA1 for useful summary statistics). The left panel uses Table 1's sample (without IJC outliers, FOMC, and other macro overlaps); the right panel uses the main IJC shock and a further conservative sample by dropping 2020/4/9, on which a series of new Federal Reserve announcements were made regarding CARES implementation (see Online Appendix Table A1). See other table details in Table 1. ***, p-value <1%; **, <5%; *, <10%.

		Unexpected return	NCF	NDR	Unexpected return	NCF	NDR
	Without:	*outliers, FOMC, macro*			*outliers, FOMC, macro, 2020/4/9*		
	IJC shock:	*Alternative IJC shock*			*Main IJC shock*		
Normal Period	IJC shock	-0.301	-0.011	**0.290****	-86.736	-3.993	**82.743***
	(SE)	(0.308)	(0.230)	**(0.146)**	(106.271)	(79.224)	**(48.330)**
	SD chngs per 1SD shock	-0.046	-0.002	**0.046**	-0.037	-0.002	**0.037**
	R^2%	0.23%	0.00%	**0.87%**	0.15%	0.00%	**0.55%**
COVID Period	IJC shock	**0.116***	**0.193*****	**0.077***	293.619	**255.330***	-38.289
	(SE)	**(0.069)**	**(0.056)**	**(0.043)**	(200.020)	**(136.448)**	(102.640)
	SD chngs per 1SD shock	**0.161**	**0.276**	**0.105**	0.181	**0.163**	-0.023
	R^2%	**2.59%**	**14.85%**	**3.97%**	3.25%	**5.28%**	0.19%

Table A3: Robustness Evidence for Table 2: Asymmetry and Assets.

This table complements Table 2 and further drops the 2020/4/9 announcement. See other table details in Table 2. ***, p-value <1%; **, <5%; *, <10%.

Panel A. Sample: Bad IJC days (acutal jobless claims are higher than expected; IJC shock>0)

	Unexpected return	**NCF**	**NDR**	**S&P500**	**Nasdaq100**	**DowJones65**	**DowJones30 Indus.**	**DowJones20 Transp.**	**DowJones15 Util.**
IJC shock coeff.	**605.067****	**405.563***	-199.504	**605.976****	**614.599***	**569.768***	**637.584***	**699.891****	138.197
(SE)	**(295.111)**	**(237.545)**	(139.586)	**(297.848)**	**(349.733)**	**(295.475)**	**(327.831)**	**(310.094)**	(349.430)
SD chngs per 1SD shock	**0.387**	**0.214**	-0.130	**0.387**	**0.320**	**0.368**	**0.394**	**0.387**	0.070
R^2%	**14.97%**	**12.16%**	6.75%	**14.99%**	**10.22%**	**13.58%**	**15.49%**	**14.98%**	0.49%

Panel B. Sample: Good IJC days (actual jobless claims are lower than expected; IJC shock<=0)

	Unexpected return	**NCF**	**NDR**	**S&P500**	**Nasdaq100**	**DowJones65**	**DowJones30 Indus.**	**DowJones20 Transp.**	**DowJones15 Util.**
IJC shock coeff.	-284.763	-98.065	186.698	-284.332	19.183	-595.586	-579.157	-572.759	-721.799
(SE)	(663.087)	(437.385)	(325.010)	(661.380)	(795.692)	(598.092)	(609.090)	(746.336)	(524.516)
SD chngs per 1SD shock	-0.069	-0.028	0.044	-0.069	0.005	-0.141	-0.159	-0.103	-0.132
R^2%	0.48%	0.13%	0.67%	0.48%	0.00%	1.99%	2.54%	1.07%	1.75%

Table A4: Robustness Evidence for Tables 3 and 4: The Relationship Between Return Responses and Topic Mentions from Rolling Windows.

This table complements Tables 3 and 4 and shows three more robustness results, namely Robustness (4)-(6). To summarize:

- Robustness (1), (2), and (3) are already reported in Tables 3 and 4: using economic magnitude (in standard deviation rather than basis points), including uncertainty mentions, and using Dow Jones 65 open-to-close returns.
- Robustness (4), here: we drop 2020/4/9 from the rolling windows (rather than dropping the rolling window sample that ends with 2020/4/9). On 2020/4/9 the Federal Reserve made a series of new announcements regarding CARES Act implementation (see Appendix Table A1).
- Robustness (5), here: using all IJC days with a 60-day rolling window rather than an 80-day. Table format follows Table 3.
- Robustness (6), here: we use 30-IJC-day rolling windows to calculate both the rolling return responses to bad or good IJC shocks (LHS) and the rolling bad or good topic mentions (RHS). Table format follows Table 4.

See other table details in Table 4. ***, p-value <1%; **, <5%; *, <10%.

	Robustness (4). Without 4/9/2020			Robustness (5). Using all IJC days, 60-day rolling window			
Rolling sample:	All IJC	Bad IJC	Good IJC	All IJC days			
LHS:		**Rolling coeff. of S&P500 on IJC shock**		**Rolling coeff. of S&P500 on IJC shock**	**Economic Magnitude**	**Rolling coeff. of S&P500 on IJC shock**	**Rolling coeff. of DJ65 on IJC shock**
Constant	**58.887*** **	**23.363**	**-28.104** **	**80.077*** **	**0.055*** **	**80.077*** **	**100.474*** **
(NWSE)	(19.777)	(38.104)	(14.202)	(27.141)	(0.016)	(26.795)	(32.249)
FP (standardized)	**196.988*** **	**266.987*** **	**80.747*** **	**195.727*** **	**0.120*** **	**198.501*** **	**156.699*** **
(NWSE)	(26.419)	(40.847)	(17.666)	(55.901)	(0.034)	(60.942)	(36.551)
SD chngs	1.277	1.060	0.329	0.965	0.985	0.979	0.821
MP (standardized)	**110.794*** **	86.098	**223.482*** **	**85.890***	**0.057***	73.968	**96.702*** **
(NWSE)	(23.765)	(55.953)	(13.943)	(49.697)	(0.032)	(58.588)	(37.222)
SD chngs	0.718	0.342	0.911	0.424	0.467	0.365	0.507
UNC (standardized)						-27.766	
(NWSE)						(35.181)	
SD chngs						-0.137	
R^2% Ordinary	61.2%	63.1%	56.3%	57.5%	54.4%	63.9%	48.0%
R^2% Adjusted	60.9%	62.5%	55.7%	56.8%	53.8%	63.6%	47.0%
N	270	115	155	287	287	287	287

Robustness (6). Using 30-day rolling window, rather than 40-day								
	Panel A. Bad IJC days				Panel B. Good IJC days			
LHS:	**Rolling coeff. of S&P500 on IJC shock**	**Economic Magnitude**	**Rolling coeff. of S&P500 on IJC shock**	**Rolling coeff. of DJ65 on IJC shock**	**Rolling coeff. of S&P500 on IJC shock**	**Economic Magnitude**	**Rolling coeff. of S&P500 on IJC shock**	**Rolling coeff. of DJ65 on IJC shock**
Constant	26.148	**0.043****	26.148	-21.049	-21.804	**0.014***	-21.804	55.948
(SE)	(34.686)	(0.018)	(41.297)	(57.473)	(21.682)	(0.007)	(22.154)	(38.930)
FP (standardized)	**219.121*****	**0.143*****	**217.644*****	**336.411*****	**88.139****	**0.030****	**91.026****	**-62.317**
(SE)	(70.437)	(0.043)	(58.475)	(52.234)	(37.225)	(0.012)	(35.732)	(58.837)
SD chngs	0.704	0.768	0.699	0.946	0.274	0.260	0.283	-0.153
MP (standardized)	**13.566**	**0.016**	**-5.074**	**128.061**	**259.975*****	**0.093*****	**250.954*****	**269.209*****
(SE)	(88.622)	(0.053)	(68.803)	(78.896)	(36.750)	(0.009)	(47.655)	(43.227)
SD chngs	0.044	0.085	-0.016	0.360	0.808	0.816	0.780	0.662
UNC (standardized)			**-36.881***				-18.482	
(SE)			(22.140)				(29.449)	
SD chngs			-0.118				-0.057	
R^2% Ordinary	57.5%	57.5%	57.5%	57.5%	57.5%	57.5%	57.5%	57.5%
R^2% Adjusted	56.7%	56.7%	56.7%	56.7%	56.7%	56.7%	56.7%	56.7%
N	125	125	125	125	165	165	165	165

Table A5: Robustness Evidence for Table 5: Mechanism and Quarterly State Variables.

This table reports the results of the following regression:

$$y_t = \beta_0 + \beta_1 IJCshock_t + \beta_2 Z_\tau + \beta_3 IJCshock_t * Z_\tau + \varepsilon_t,$$

where t and τ denote daily and quarterly frequency, respectively, y stock returns (in basis points), and Z a standardized state variable of interest. The first three state variables are textual mentions using articles within the same quarter (fiscal policy (FP), monetary policy (MP), uncertainty (UNC)); with the same textual analysis methodology as mentioned before, we use all bad (good) days within the quarter and obtain a quarterly bad (good) measure. Next, we consider the difference between the one-quarter-ahead forecast and the nowcast of the 3-month Treasury bill rate ("$\Delta Tbill3m$") and recession probability ("$\Delta Recess$"), where both forecast and nowcast are provided given last quarter's information set (source: Survey of Professional Forecasters, or SPF). ***, p-value <1%; **, <5%; *, <10%.

	Panel A. Bad IJC days					Panel B. Good IJC days				
▶ **Quarterly state variable (standardized):**	**FP**	**MP**	**UNC**	**$\Delta Tbill3m$**	**$\Delta Recess$**	**FP**	**MP**	**UNC**	**$\Delta Tbill3m$**	**$\Delta Recess$**
▶ *Source:*	*CNBC textual analysis*			*SPF survey data*		*CNBC textual analysis*			*SPF survey data*	
	LHS: S&P500 daily returns (basis points)									
Constant	2.962	-2.311	1.007	0.632	-0.990	-4.445	-1.760	-6.520	-3.484	-5.043
(SE)	(8.084)	(8.016)	(8.591)	(8.047)	(7.776)	(9.412)	(9.793)	(11.973)	(9.987)	(9.194)
IJC shock	-35.536	186.045	56.968	64.823	100.272	-26.926	48.280	66.756	19.794	3.020
(SE)	(135.442)	(127.284)	(153.385)	(123.666)	(129.078)	(184.845)	(191.510)	(232.282)	(197.491)	(192.266)
State variable	**-17.491****	-5.074	-9.298	5.011	**9.130***	**20.797***	2.979	**29.943***	8.517	**40.709****
(SE)	**(7.557)**	(6.824)	(8.335)	(7.187)	**(5.080)**	**(12.474)**	(8.830)	**(15.962)**	(10.907)	**(20.053)**
Interaction	**258.382*****	-30.503	213.611	**-219.424***	**-136.354****	363.772	159.268	502.839	124.815	**856.506****
(SE)	**(90.750)**	(112.333)	(136.517)	**(117.790)**	**(59.652)**	(231.668)	(157.862)	(338.148)	(225.727)	**(369.300)**
	LHS: Dow Jones daily returns (basis points)									
Constant	6.343	1.769	4.607	4.055	2.900	-2.948	-1.605	-8.902	-3.537	-4.634
(SE)	(7.914)	(7.957)	(8.444)	(7.984)	(7.686)	(9.628)	(9.707)	(12.265)	(9.928)	(9.034)
IJC shock	-34.205	164.523	50.199	62.933	84.275	-19.831	31.471	6.194	-0.867	-16.505
(SE)	(123.073)	(126.081)	(144.149)	(122.901)	(119.288)	(187.882)	(181.619)	(237.954)	(187.733)	(182.221)
State variable	**-17.519****	-6.163	-10.837	7.084	8.113	13.937	11.021	**29.719***	15.995	**45.972****
(SE)	**(7.437)**	(6.990)	(8.448)	(7.306)	(5.869)	(12.206)	(8.948)	**(16.352)**	(10.682)	**(19.485)**
Interaction	**243.349****	46.081	203.833	-201.915	**-125.484****	238.650	**301.688***	492.411	322.768	**983.782*****
(SE)	**(95.140)**	(115.303)	(139.151)	(126.739)	**(62.901)**	(216.905)	**(154.373)**	(346.405)	(217.330)	**(356.423)**

Table A6: High-Frequency Evidence Using E-Mini S&P 500 Futures Prices.

This table provides the intraday return responses of E-mini S&P500 futures prices on IJC shocks. Intraday returns (in basis points) are calculated using a start time of 8:00 a.m. Eastern Time and an end time of interest. From left to right: pre-announcement, 8:25 a.m. ET; shortly after the announcement, 8:35 a.m. ET; noon, 12:30 p.m. ET; shortly before market close, 3:30 p.m. ET. The left four columns display results using our normal period (2009/07-2016/12); the right four columns use the covid period (2020/02-2021/03, dropping the outliers of the IJC shocks). Row "Closeness (Covid-normal)?" provides t-statistics comparing the covid period coefficient and the normal period coefficient, with bold t-stats indicating one-sided 10% significance. High-frequency futures data are from Tick Data. See other notation details in Table 1. ***, p-value <1%; **, <5%; *, <10%.

Start time	8:00:00 AM –				8:00:00 AM –			
End time	8:25:00 AM	8:35:00 AM	12:30:00 PM	3:30:00 PM	8:25:00 AM	8:35:00 AM	12:30:00 PM	3:30:00 PM
Sample	***Normal period***				***COVID period***			
Panel A. All IJC days								
IJC shock coeff.	-19.994*	-162.170***	-125.895	-130.037	-4.513	-30.910	280.975*	344.150
(SE)	(10.931)	(26.354)	(81.490)	(98.474)	(20.560)	(48.857)	(170.177)	(212.995)
SD chngs per 1SD shock	-0.071	-0.307	-0.074	-0.060	-0.032	-0.115	0.240	0.231
Closeness (Covid-normal)?					0.66	**2.36**	**2.16**	**2.02**
Panel B. Bad IJC days								
IJC shock coeff.	-11.540	-138.013***	-98.389	-114.292	10.187	66.602	354.704	578.006**
(SE)	(19.334)	(46.605)	(169.397)	(209.667)	(45.598)	(95.204)	(258.371)	(275.692)
SD chngs per 1SD shock	-0.036	-0.205	-0.045	-0.040	0.052	0.175	0.338	0.421
Closeness (Covid-normal)?					0.44	**1.93**	1.47	**2.00**
Panel C. Good IJC days								
IJC shock coeff.	5.960	-75.468	18.927	-59.043	-7.745	-119.204	170.943	-148.880
(SE)	(34.266)	(65.639)	(186.399)	(246.221)	(56.448)	(94.310)	(490.906)	(747.502)
SD chngs per 1SD shock	0.011	-0.083	0.006	-0.015	-0.028	-0.247	0.055	-0.038
Closeness (Covid-normal)?					-0.21	-0.38	0.29	-0.11

Table A7: High-Frequency Evidence Using E-Mini Dow Futures prices.

This table provides the intraday return responses of E-mini Dow futures prices on IJC shocks. Intraday returns (in basis points) are calculated using a start time of 8:00 a.m. Eastern Time and an end time of interest. From left to right: pre-announcement, 8:25 a.m. ET; shortly after the announcement, 8:35 a.m. ET; shortly after noon, 12:30 p.m. ET; shortly before market close, 3:30 p.m. ET. The left four columns display results using our normal period (2009/07-2016/12); the right four columns use the covid period (2020/02-2021/03, dropping the outliers of the IJC shocks). Row "Closeness (Covid-normal)?" provides t-statistics comparing the covid period coefficient and the normal period coefficient, with bold t-stats indicating one-sided 10% significance. High-frequency futures data are from Tick Data. See other notation details in Table 1. ***, p-value <1%; **, <5%; *, <10%.

Start time	8:00:00 AM –				8:00:00 AM –			
End time	8:25:00 AM	8:35:00 AM	12:30:00 PM	3:30:00 PM	8:25:00 AM	8:35:00 AM	12:30:00 PM	3:30:00 PM
Sample	***Normal period***				***COVID period***			
Panel A. All IJC days								
IJC shock coeff.	-16.888	-151.213***	-139.207*	-138.867	-7.741	-45.530	303.572*	356.293*
(SE)	(10.798)	(24.540)	(83.709)	(102.110)	(25.425)	(54.429)	(165.106)	(211.937)
SD chngs per 1SD shock	-0.066	-0.300	-0.080	-0.064	-0.050	-0.155	0.250	0.235
Closeness (Covid-normal)?					0.33	**1.77**	**2.39**	**2.10**
Panel B. Bad IJC days								
IJC shock coeff.	9.263	-114.518***	-170.965	-185.154	-1.801	48.179	421.878*	632.505**
(SE)	(19.101)	(40.706)	(179.002)	(227.507)	(56.386)	(105.108)	(238.705)	(290.869)
[t]	[0.485]	[-2.813]	[-0.955]	[-0.814]	[-0.032]	[0.458]	[1.767]	[2.175]
SD chngs per 1SD shock	0.031	-0.180	-0.074	-0.064	-0.008	0.115	0.406	0.439
Closeness (Covid-normal)?					-0.19	1.44	**1.99**	**2.21**
Panel C. Good IJC days								
IJC shock coeff.	-6.064	-111.963*	3.763	-47.306	-27.246	-183.772*	-31.505	-460.172
(SE)	(35.163)	(67.031)	(186.831)	(250.003)	(59.533)	(105.761)	(469.415)	(699.902)
SD chngs per 1SD shock	-0.012	-0.126	0.001	-0.012	-0.100	-0.347	-0.010	-0.117
Closeness (Covid-normal)?					-0.31	-0.57	-0.07	-0.56

Online Appendices for “Main Street’s Pain, Wall Street’s Gain”

OA. Additional Tables and Figures

Table OA1: Summary Statistics for Initial Jobless Claims (IJC) Shocks

This table shows summary statistics for IJC shocks in two period samples of interest (as mentioned in the main paper):

Name	*Time range*	*Monetary policy conditions*
Covid period	*2020/02-2021/03*	*Expansionary/Zero lower bound*
Normal period	*2009/07-2016/12*	*Expansionary/Zero lower bound*

Our main IJC shock is defined as $\frac{IJC_t - E_{t-\Delta}(IJC_t)}{E_{t-\Delta}(IJC_t)}$, where IJC_t (unit: 1 thousand claims) indicates the actual initial claims from last week (ending Saturday) released by the Employment and Training Administration (ETA) on Thursday of current week t, and $E_{t-\Delta}(IJC_t)$ indicates the median survey forecast submitted up to shortly before the announcement at time $t-\Delta$. Both actual and expected claims are obtained from Bloomberg. Our alternative shock is defined as $IJC_t - E_{t-\Delta}(IJC_t)$. The first half of the table reports the min, max, and several percentile values during each period; the second half of the table reports the mean, standard deviation, skewness, and N using IJC shocks during all, bad, or good IJC days during the subsample. We exclude identified IJC outlier days (3/19/2020, 3/26/2020, and 4/2/2020).

	Percent changes (Main IJC shocks)		Difference (Alternative IJC shocks)	
	Normal period	***COVID period***	***Normal period***	***COVID period***
Min	-0.117	-0.153	-38	-255
1st	-0.091	-0.152	-33	-254
5th	-0.067	-0.112	-25	-131
10th	-0.053	-0.083	-18	-78
25th	-0.026	-0.038	-10	-30
50th	-0.003	0.005	-1	1
75th	0.025	0.058	8	68
90th	0.054	0.131	19	171
95th	0.079	0.190	25	213
99th	0.144	0.223	49	477
Max	0.203	0.224	64	481
Mean	0.000	0.019	0.209	43.954
Mean-Bad	0.036	0.083	12.949	135.482
Mean-Good	-0.030	-0.049	-10.720	-54.615
SD	0.044	0.087	15.766	188.383
SD-Bad	0.033	0.068	12.187	218.860
SD-Good	0.024	0.040	8.696	63.375
Skewness	0.672	0.550	0.701	3.577
Skewness-Bad	1.930	0.738	1.876	3.401
Skewness-Good	-1.023	-0.946	-0.990	-1.872
N-Total	379	54	379	54
N-Bad	175	28	175	28
N-Good	204	26	204	26

Table OA2: Robustness to Time-Series Results: Pre-2020

This table replicates Table 5 using a pre-covid sample from January 2013 to December 2019. See other table details in Table 5. ***, p-value <1%; **, <5%; *, <10%.

	Panel A. Bad IJC days				Panel B. Good IJC days			
LHS:	**S&P500**	**DJ65**	**DJ65**	**DJ65**	**S&P500**	**DJ65**	**DJ65**	**DJ65**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	4.651	6.956	6.231	6.575	5.706	7.100	5.742	5.729
(SE)	(8.934)	(8.845)	(8.928)	(8.436)	(9.378)	(9.647)	(9.377)	(8.170)
IJC shock	56.860	10.944	18.043	7.265	-22.809	-41.915	-111.428	45.972
(SE)	(172.568)	(170.836)	(172.136)	(163.215)	(197.038)	(216.164)	(205.028)	(161.241)
Quarterly FP (standardized)	-11.121	-19.204	**-26.338***	**-26.355***	**20.928***	17.992	8.896	20.483
(SE)	(13.392)	(13.258)	**(15.686)**	**(15.005)**	**(12.003)**	(12.167)	(13.709)	(13.657)
IJC shock*Quarterly FP (standardized)	297.860	**318.041***	**391.789***	**373.602***	199.703	119.307	-166.861	349.523
(SE)	(184.004)	**(182.158)**	**(214.750)**	**(215.830)**	(247.473)	(248.223)	(290.234)	(259.581)
Quarterly MP (standardized)	-1.789	1.150	-0.762		-6.009	0.558	4.364	
(SE)	(9.179)	(9.087)	(9.452)		(7.442)	(7.920)	(7.927)	
IJC shock*Quarterly MP (standardized)	-104.347	-33.355	1.341		171.781	**307.397***	**435.025****	
(SE)	(200.126)	(198.117)	(212.869)		(163.171)	**(177.556)**	**(176.547)**	
Quarterly UNC (standardized)			9.242	8.133			14.119	10.919
(SE)			(10.651)	(10.997)			(10.372)	(9.951)
IJC shock*Quarterly UNC (standardized)			-124.231	-134.177			**414.955***	246.376
(SE)			(214.286)	(207.299)			**(216.806)**	(198.200)
Quarterly $\Delta Tbill3m$ (standardized)				-0.836				13.583
(SE)				(8.497)				(9.194)
IJC shock*Quarterly $\Delta Tbill3m$ (standardized)				-81.286				**420.827****
(SE)				(191.704)				**(209.817)**

Table OA3: Summary Statistics of Raw Covid-Impact Measure Across 498 Firms.

		p5	p25	p50	p75	p95	Mean	SD
1	Job Postings Change; 2019 Average-2020 April&May Average , 4-digit NAICS	-0.75	-0.50	-0.40	-0.31	-0.12	-0.40	0.20
2	Employment Change; FY 2019-2020	-0.23	-0.05	0.00	0.06	0.23	0.02	0.24
3	Revenue Change; 2019Q2-2020Q2	-0.41	-0.08	0.01	0.10	0.41	0.02	0.47
4	EPS Change; 2019Q2-2020Q2	-9.88	-1.95	-0.17	1.01	5.00	-0.93	7.64
5	Revenue Change; FY2019-2020	-0.40	-0.09	-0.01	0.07	0.32	0.02	0.60
6	EPS Change; FY 2019-2020	-11.23	-1.93	-0.37	0.72	4.02	-1.45	8.27

Correlation Matrix	Employment Rank	Revenue Rank	EPS Rank	Revenue Rank (Q)	EPS Rank (Q)	Job Post Change (4-digit)
Employment Rank	1.00					
Revenue Rank	0.66	1.00				
EPS Rank	0.34	0.57	1.00			
Revenue Rank (Q)	0.61	0.86	0.52	1.00		
EPS Rank (Q)	0.36	0.57	0.72	0.54	1.00	
Job Post Change (4-digit)	0.23	0.28	0.28	0.28	0.24	1.00

Table OA4: Cumulative and Average Daily Capital Gains in the U.S. Stock Market.

This table calculates the simple cumulative and average daily capital gains of S&P500 stocks on bad, good, and non-IJC days, during the covid period and during a general non-covid period. Average daily capital gains are cumulative capital gains divided by the number of days, capturing what the average daily capital gains are during these three non-overlapping groups of days. In particular, for the first two columns, this table considers IJC surprise days that are economically sizable when calculating the average for clearer identification during each period (i.e., actual-expectation $> 10K$ or $\leq -10K$, which according to Table OA1 corresponds to around $> 75th$ or $\leq 25th$).

Covid (2020/02-2021/03)	**Bad-IJC**	**Good-IJC**	**Non-IJC**
Cumulative capital gain (unit: million US dollars)	\$2,104,650	\$368,150	\$10,383,020
(SE)	(\$63,095)	(\$79,965)	(\$31,267)
N of days	29	21	235
Average daily capital gain (unit: million US dollars)	\$72,574	\$17,531	\$44,183
(SE)	(\$2,176)	(\$3,808)	(\$133)
General non-Covid (2000/01-2020/01)	**Bad-IJC**	**Good-IJC**	**Non-IJC**
Cumulative capital gain (unit: million US dollars)	\$491,732	\$1,978,888	\$6,260,015
(SE)	(\$6,486)	(\$5,735)	(\$2,192)
N of days	235	251	4193
Average daily capital gain (unit: million US dollars)	\$2,092	\$7,884	\$1,493
(SE)	(\$28)	(\$23)	(\$1)

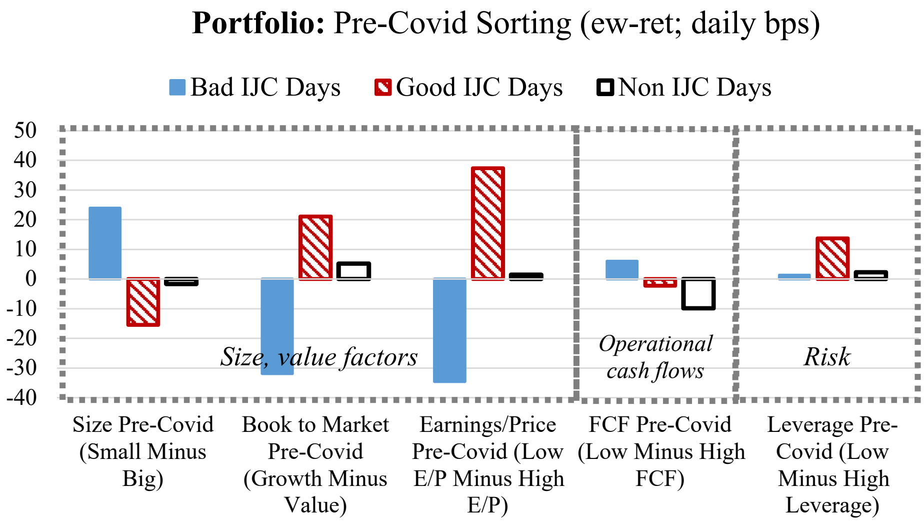


Figure OA1: Robustness Evidence for Figure 9: Portfolio Returns.

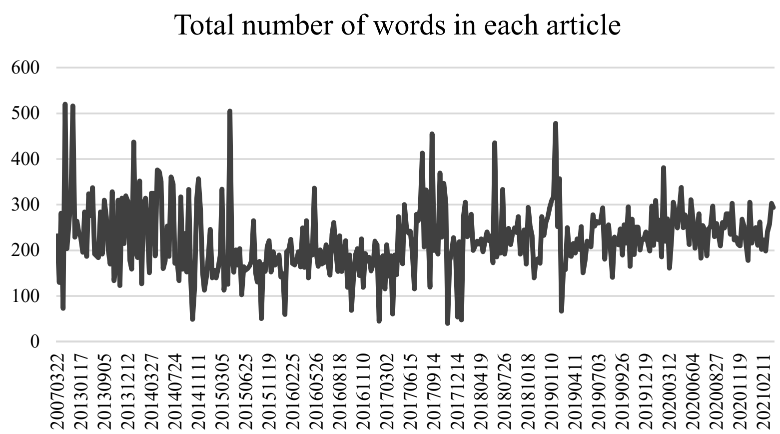
The first two plots provide robustness results for Figure 9 using equal weights. See other details in Figure 9.

OB. Details on Textual Analysis

OB.1. Web-scraping steps for CNBC jobless claims articles

To prepare a list of all articles on CNBC about weekly jobless claims, the first step is to download initial jobless claims announcement dates. We obtain them from Bloomberg in a tabulated version that provides both actual and survey medians. Once those articles are tabbed in the Excel file as per the dates, we go to `cnbc.com` and search for "Weekly Jobless Claims" with a specific date and then identify the articles. We often find dates that have multiple articles with the same keywords, i.e., jobless claims articles for the same dates; some are entirely related to the stock market, futures market, etc. We select only those articles that are categorized under the *US Economy* or *Economy* headers, as we need texts describing the economic environment (hence, a state variable), rather than texts describing current or possible market reactions. The search is finalized manually after using the Google search package on Python; as that package typically finds not only CNBC articles but also other news articles that may be referring to CNBC, we need manual effort to finalize it.

Once we have the final list of dates and corresponding URL links on CNBC, we scrape the articles using a package called BeautifulSoup, which is a Python package for pulling data out of HTML and XML files.



OB.2. Texts by topic

Table OB1 summarizes the keywords for each of the five topics; their variants are also considered in the search. The time variation in the topic mentions (using either the rolling rule or the non-overlapping quarterly rule) is insignificantly different after deleting one word at a time for Fiscal Policy, Monetary Policy, Coronavirus-related, and Normal-IJC topics. Figure OB1 drops one keyword at a time from the FP and MP lists, and recalculates the 60-week rolling topic mentions scores; as noted in the main paper, "bad," for instance, uses all weeks within the same 60-week interval that correspond to bad IJC announcements. As in Figure 3, we standardize the series with its first data value for interpretation purposes (that is, 1.5 means that the mentions are 50% higher than the same topic's 2013-2014 value). Both the min-max bandwidths (see the top four plots in Figure OB1) and the 95% confidence intervals (see the bottom four plots in Figure OB1) are tight relative to the overall fluctuations.

OB.3. TF-IDF scores to identify topic mentions

To begin, we read all the txt files in the folder and store them in a list call. We then replace the "$" sign with the word "dollar." After that, we extract all the file names and store them in another list. As the file names are the dates of the reports, we can then store the years and dates of all the file names in different lists. With these lists, we can create a data frame with year, date, and content.

First, we convert each report to a list of lowercase and tokenized words using `gensim.utils.simple_preprocess()`. Then we remove all the stop words and words that are shorter than 3 characters from the list of tokens. The stop words are given by `gensim.parsing.preprocessing.STOPWORDS`, including "much," "again," "her," etc. With the list of tokens, we then use functions `WordNetLemmatizer()` from *nltk* to group different inflected forms of a word as a single item based on the dictionary from *nltk*'s *WordNet*. For example, "better" becomes "good." We indicate that we want the verb form of the word when it is possible. Using `PorterStemmer()`, also from *nltk*, we reduce all the words to their root form. For instance, "government" becomes "govern."

In the next step, we use the *TfidfVectorizer* from the *sklearn* package with the parameters "`min_df=2`" and "`ngram_range= (1,2)`" to create a TF-IDF matrix with the feature name as the column and the TF-IDF score for a word in a specific report as the rows. With "`min_df=2`," we filter out words that appear in fewer than 2 of the reports. The parameter "`ngram_range= (1,2)`" gives us both unigrams and bigrams.

After obtaining the TF-IDF matrix, we then transform it by first summing up the TF-IDF score for each word in all reports and then sorting the matrix by the TF-IDF score from high to low. Based on our needs, we can slice the data frame that contains all of the reports by either year or quarter, and then repeat the steps mentioned above to get a TF-IDF matrix for each period.

Table OB1: Topic Keywords.

Fiscal Policy	**Monetary Policy**	**Uncertainty**	**Coronavirus-related**	**Normal-IJC**
aid	bank	economy	bar	american
assist	bernanke	uncertainty	biden	application
benefit	central bank		case	average
billion	chair		coronavirus	claim
business	chairman		covid	data
compensation	consumer price		emergency	department
congress	federal reserve		hospital	economy
democrat	inflation		hotel	economist
dollar	monetary		lockdown	employ
eligible	mortgage		pandemic	end
expansion	powell		recovery	expect
expire	rate		relief package	file
extend	treasury bond		restaurant	initial
extra	treasury yield		restrict	jobless
federal government	yellen		shutdown	labor
fiscal (policy)			social distance	level
government			stimulus check	market
health care			stimulus package	million
job			trump	month
lawmaker			vaccine	number
legislation			virus	percent
negotiate				percentage
package				receive
paycheck				report
president				survey
program				thursday
republican				unemploy
senate				week
state				year
trillion				
washington				
white house				

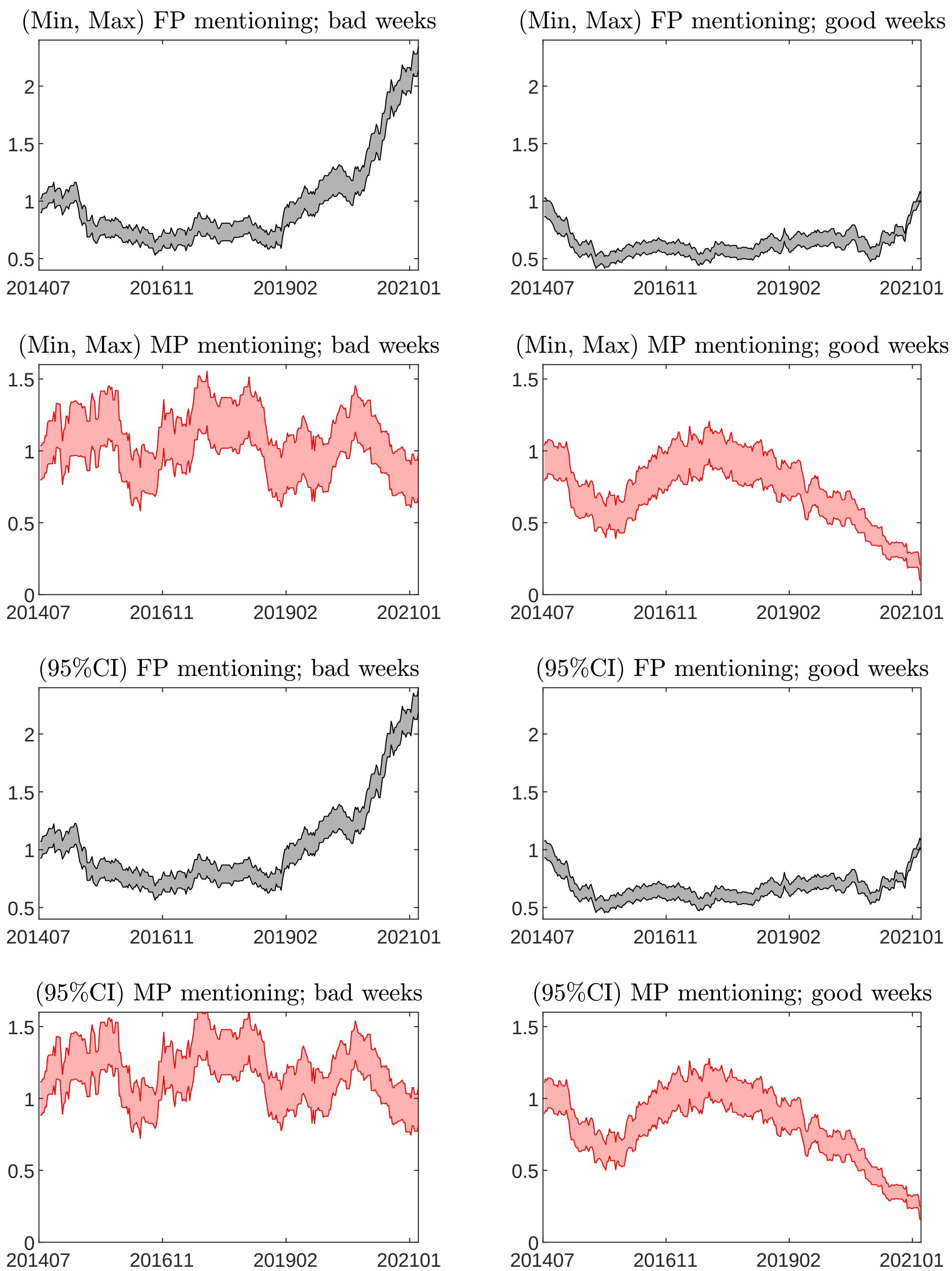


Figure OB1: Jackknife exercise of the scaled rolling topic mention values. This table complements Figure 3 in the main text and provides measurement uncertainty. In this plot, we drop one keyword at a time and recalculate the bad and good rolling topic mentions scores using all bad and good IJC announcement weeks within the same 60-week interval. The top four plots show the min-max bandwidth. The bottom four plots show a 95% confidence interval using the standard deviation of the recalculated mention scores, omitting one at a time.

OC. Imputing Daily Cash Flow and Discount Rate Shocks Using Monthly Campbell and Vuolteenaho (2004) Decomposition

We first conduct four estimation exercises to (a) replicate the Campbell and Vuolteenaho (2004) results using their exact sample and data sources and (b) extend the framework to samples up to 2021/04. We also consider using cumulative daily open-to-close returns within the same month as an alternative monthly return, given that some parts of our paper need to focus on intradaily returns. Samples are summarized in Table OC1. Estimation results using monthly data are provided in Table OC2. Figure OC1 shows the dynamics of the cash flow and the inverse (or minus) discount rate news from Sample 4.

In the second step, we use the monthly parameters estimated from Sample 4 to impute daily NCF and NDR results using 22 non-overlapping, quasi-monthly samples. For instance, subsample 1 uses daily data from days 1, 23, 45 ...; subsample 2 uses daily data from days 2, 24, 46 ...; and so on. We also considered re-estimating the monthly system within each subsample; results are very close and are not statistically differentiable. The data sources for our daily data are: for excess market returns, CRSP for 1982-2020 and Datastream for 2021; for the yield spread between 10-year and 2-year government bond yields, FRED; for the log ratio of the S&P500 price index to a ten-year moving average of S&P500 earnings, or a smoothed PE, `http://www.econ.yale.edu/~shiller/data.htm`; for the small-stock value spread (VS), `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`. These sources are standard, following Campbell and Vuolteenaho (2004); smoothed PE and small-stock VS cannot be constructed at the daily frequency, and hence we use monthly values.

Moment properties of cash flow and discount rate news are reported in Table OC3. Using the original Campbell and Vuolteenaho (2004) sample (1928/12-2001/12), our replication shows that 92% (19%) of the total return variability is explained by the NDR (NCF), and NDR and NCF are weakly negatively correlated, which makes sense in a model where a good real economic shock can decrease the discount rate (and risk variables) while increasing expected future cash flow growth. In our modern sample (1982/01-2021/04), we find that NDR (NCF) now explains 31% (34%), with a positive covariance between NDR and NCF. Results are robust using only open-to-close stock market returns.

Table OC1: Four Monthly Estimation Samples.

Sample	Name	Start	End	N (month)	N (day)
1	CV2004 original sample (returns)	1928/12	2001/12	877	-
2	Long sample (returns)	1928/12	2021/04	1109	-
3	Short sample (returns)	1982/01	2021/04	472	9916
4	Short sample (add together daily open-to-close returns)	1982/01	2021/04	472	9916

Table OC2: Estimation Results, Formatted as in Campbell and Vuolteenaho (2004)'s Table 2. Notations: log excess market return, r^e; log excess cumulative, open-to-close market return, $r^{e,oc}$; term yield spread, TY; price-earnings ratio, PE; small-stock value spread, VS. The first five columns report coefficients on the five explanatory variables and the remaining columns show R^2 and F statistics. Bootstrapped standard errors are in parentheses (2,500 simulated realizations).

Sample 1: CV original sample (return); 1928/12-2001/12							
	Constant	r^e_t	TY_t	PE_t	VS_t	$R^2(\%)$	$Fstat$
r^e_{t+1}	0.070	0.094	0.007	-0.016	-0.015	2.784	6.2
(SE)	(0.020)	(0.034)	(0.003)	(0.005)	(0.006)		
TY_{t+1}	-0.014	0.013	0.884	-0.021	0.087	82.717	1042.1
	(0.099)	(0.163)	(0.016)	(0.026)	(0.028)		
PE_{t+1}	0.022	0.515	0.003	0.994	-0.004	99.041	22485.0
	(0.013)	(0.022)	(0.002)	(0.004)	(0.004)		
VS_{t+1}	0.022	0.104	0.002	-0.001	0.989	98.126	11403.6
	(0.019)	(0.031)	(0.003)	(0.005)	(0.005)		
Sample 2: Long sample (return); 1928/12-2021/04							
	Constant	r^e_t	TY_t	PE_t	VS_t	$R^2(\%)$	$Fstat$
r^e_{t+1}	0.060	0.097	0.005	-0.013	-0.012	2.266	6.4
(SE)	(0.018)	(0.030)	(0.002)	(0.004)	(0.005)		
TY_{t+1}	-0.069	0.004	0.932	0.007	0.060	88.750	2175.4
	(0.084)	(0.142)	(0.011)	(0.021)	(0.025)		
PE_{t+1}	0.023	0.505	0.002	0.993	-0.004	99.132	31489.9
	(0.012)	(0.020)	(0.002)	(0.003)	(0.003)		
VS_{t+1}	0.029	0.109	0.000	-0.003	0.988	97.868	12658.7
	(0.017)	(0.028)	(0.002)	(0.004)	(0.005)		
Sample 3: Short sample (return); 1982/01-2021/04							
	Constant	r^e_t	TY_t	PE_t	VS_t	$R^2(\%)$	$Fstat$
r^e_{t+1}	0.049	0.070	0.001	-0.007	-0.013	1.190	1.4
(SE)	(0.025)	(0.046)	(0.003)	(0.007)	(0.014)		
TY_{t+1}	-0.052	-0.405	0.929	-0.076	0.232	90.311	1085.8
	(0.147)	(0.270)	(0.016)	(0.040)	(0.080)		
PE_{t+1}	0.045	0.438	-0.001	0.989	-0.004	99.114	13039.9
	(0.017)	(0.031)	(0.002)	(0.005)	(0.009)		
VS_{t+1}	0.013	0.108	0.000	0.014	0.964	93.536	1685.7
	(0.024)	(0.045)	(0.003)	(0.007)	(0.013)		
Sample 4: Short sample (open-to-close return); 1982/01-2021/04							
	Constant	$r^{e,oc}_t$	TY_t	PE_t	VS_t	$R^2(\%)$	$Fstat$
$r^{e,oc}_{t+1}$	0.056	0.028	0.002	-0.007	-0.020	1.441	1.7
(SE)	(0.023)	(0.046)	(0.002)	(0.006)	(0.012)		
TY_{t+1}	-0.046	-0.480	0.929	-0.077	0.228	90.316	1086.6
	(0.148)	(0.302)	(0.016)	(0.040)	(0.080)		
PE_{t+1}	0.039	0.476	-0.002	0.989	-0.001	99.094	12745.2
	(0.017)	(0.036)	(0.002)	(0.005)	(0.009)		
VS_{t+1}	0.013	0.079	0.000	0.015	0.963	93.490	1673.0
	(0.025)	(0.050)	(0.003)	(0.007)	(0.013)		

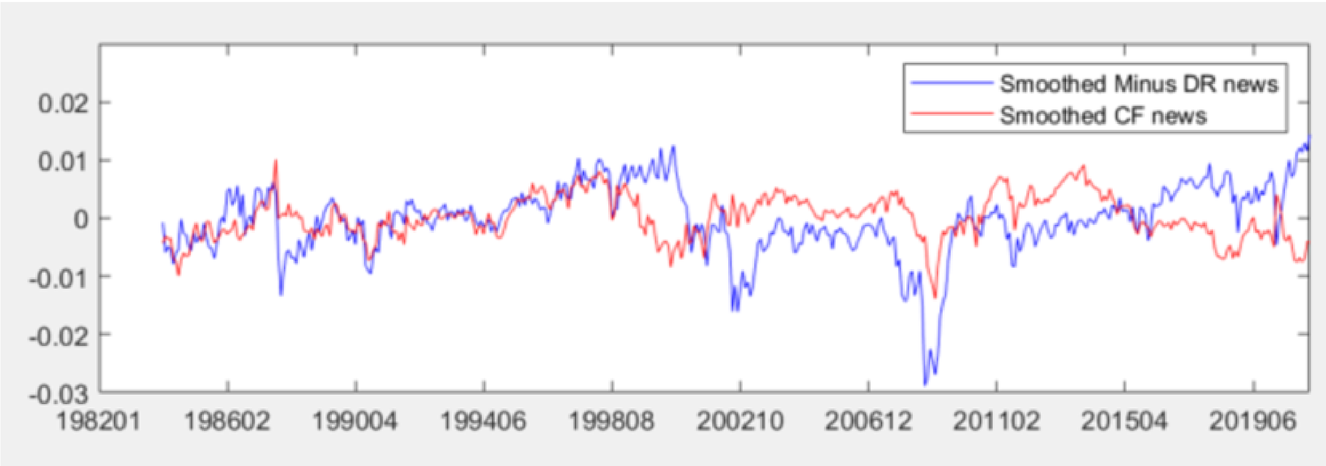


Figure OC1: Replication of Figure 1 of Campbell and Vuolteenaho (2004) using our Sample 4: Cash flow and the minus discount rate news, smoothed with a trailing exponentially weighted moving average and estimated from Sample 4. The decay parameter is set at 0.08 per month. Estimation details are in Table OC2.

Table OC3: Cash Flow and Discount Rate News Moments and Stock Return Variance Decomposition. The first four rows of each of the four blocks replicate Table 3 of Campbell and Vuolteenaho (2004). The three numbers in the fifth row sum to 1: var(r) = var(NCF) + var(NDR)-2*cov(NCF, NDR). For instance, in Sample 1, var(NCF) explains 19.1% of total return variance, var(NDR) explains 92.0%, and -2*cov(NCF, NDR) explains -11.1%.

	Sample 1			Sample 2		
	NCF	NDR	NCF,NDR	NCF	NDR	NCF,NDR
Std/Corr	0.02412	0.05298	0.13237	0.02571	0.04340	-0.12449
	(0.00095)	(0.00244)	(0.06036)	(0.00101)	(0.00174)	(0.05281)
Var/Cov	0.00058	0.00281	0.00017	0.00066	0.00188	-0.00014
	(0.00005)	(0.00025)	(0.00008)	(0.00005)	(0.00015)	(0.00006)
r^e shock variance decomposition	19.1%	92.0%	-11.1%	23.4%	66.7%	9.8%
	Sample 3			Sample 4		
	NCF	NDR	NCF,NDR	NCF	NDR	NCF,NDR
Std/Corr	0.02626	0.02513	-0.52161	0.02237	0.03129	-0.09314
	(0.00157)	(0.00146)	(0.03847)	(0.00118)	(0.00175)	(0.07812)
Var/Cov	0.00069	0.00063	-0.00034	0.00050	0.00098	-0.00007
	(0.00008)	(0.00007)	(0.00005)	(0.00005)	(0.00011)	(0.00005)
r^e shock variance decomposition	34.3%	31.4%	34.3%	31.1%	60.8%	8.1%

OD. Covid-Related Government Spending Data for Compustat Companies

USAspending.gov provides a complete collection of awards distributed by all federal government agencies from Fiscal Year (FY) 2002 onwards. The covid-related award-level government spending data is available to download in the Custom Account Data section in the Download Center, which provides 85 variables, including awarding agency, obligated amount, gross outlay amount, recipient name, recipient's parent name, and recipient address for each award entry. In our research, we primarily focus on the obligated amount and gross outlay amount; obligated amount refers to the funding promised by the government but not yet paid, while gross outlay amount refers to the award the company actually received. The obligated amount contains some negative values as the government might adjust promised funding allocations from time to time.

We obtain the list of Compustat companies traded in January 2020 and match them with recipients' names in covid-related government awards. To locate relevant records, we create company name mapping between the recipient (parent) names in USAspending.gov and Compustat companies. Compustat names are legal names for corporate filings but might not be the names commonly used or the subsidiary companies that receive government awards. For example, Alphabet Inc. is the listed company name; however, Google might be the company that receives awards. We use stock tickers in Compustat and further obtain company names from Yahoo! Finance to achieve better mapping results.

Then we implement a fuzzy matching algorithm to identify the two recipient (parent) names with the highest similarity for each Compustat company (both legal Compustat names and Yahoo! Finance names). One CUSIP (company identifier in Compustat) can be linked to multiple recipients. In USAspending data, company names might not be unique (for example, company names with and without the "Inc" suffix can refer to the sample); also, some typos or different expressions (for example, with and without comma) exist in the recipient company names.

We further manually validate our mapping file based on company names and recipient addresses in government records; namely, we use Google Maps to locate the establishment and check whether this establishment belongs to the Compustat company. After manual verification, we identify 11,018 records for 1670 Compustat companies matched with recipient (parent) names in covid spending records at the time of writing in FY 2020. Table OD1 presents the summary statistics.

Table OD1: Summary of Covid-Related Spending in 2020 (in Millions of Dollars)

	Mean	STDEV	Min	Max	Median	10th Pct	90th Pct
Gross Outlay Amount	74753.69	1177.15	-0.02	32.1	0.01	0	0.93
Obligated Amount	46459.43	934.66	-34116.31	21.71	0.01	-0.05	1.52

OE. Relationship Between Monthly Macro Announcement Surprises and Daily Open-to-Close Returns

As discussed in our analysis in Section 2, the advantage of focusing on *weekly* initial jobless claims announcements is twofold. First, it is the most timely-released data on the economy's health, and there are 54 weekly announcement data points from February 2020 to March 2021 (end of our sample) after teasing out outliers and FOMC overlaps. Second, the "Main Street" interpretation of IJC shocks is unambiguous, whereas that may not be the case for inflation surprises or industrial production surprises, for instance.

In this section, we first test the "Main Street pain, Wall Street gain" phenomenon (Section 2) using *monthly* macro announcement surprises, particularly alternative unemployment macro variables (i.e., unemployment rates and non-farm payrolls) in Section OE.1. This external validation then also potentially offers a unique cross-macro variable perspective that can help us further test our mechanism hypothesis (Section 4), as some macro variables may be more sensitive to fiscal spending than others. Our theory would predict that this phenomenon should be more pronounced when bad news about how Main Street is doing arrives. We compare the phenomenon across seven mainstream macro variables in Section OE.2. For this monthly variable analysis, we drop macro data corresponding to March 2020 (abnormal underestimates of the impact of covid lockdowns) and May 2020 (abnormal underestimates of the rebound) – both can be identified as outliers using box plot analysis. Given that different macro variables may be released at different times of day, we simply use daily open-to-close returns in this external validation exercise. Here are some examples: at 8:30 a.m. ET, or before the market opens, variables such as non-farm payrolls (Bureau of Labor Statistics, BLS), the unemployment rate (BLS), CPI (BLS), retail sales (Bureau of the Census, BC), and industrial production (Federal Reserve Board), etc. are released; at 10:00 a.m. ET variables such as the manufacturing index (Institute of Supply Management), the consumer confidence index (Conference Board), etc. are released.

OE.1. Monthly unemployment macro variables

The two top plots of Figure OE1 provide the exact scatter plots of unemployment rate (UR) surprises (higher means actual unemployment rate is higher than expected, i.e., bad news) and daily open-to-close market returns on announcement days during our covid period (2020/02-2021/03) on the left and during an identified normal period (2009/07-2016/12, as motivated in Section 2) on the right. During the normal period, the relationship between UR surprise and open-to-close returns is mild, which is consistent with the literature; during the covid period, the relationship becomes upward sloping, consistently suggesting that announcement-day returns increase with UR surprises.

In fact, this positive relationship can be tested statistically and is significantly different from its normal period counterpart. Table OE1 shows the correlation coefficients between seven mainstream monthly macro surprises (constructed from their respective announcement days) and daily open-to-close S&P 500 returns. As shown in Panel A, when bad monthly labor news arrives (i.e., a higher-than-expected unemployment rate or a lower-than-expected change in non-farm payrolls), the daily stock return response is significantly less negative or more positive during the covid period than it normally is. For instance, the correlation between unemployment surprises and stock returns during the covid period is significant and positive (0.793***), which is a strong result given that there are only 11 data points after taking out days with overlapping events. On the other hand, its normal period counterpart is typically found to be statistically insignificant and approximately zero, partially due to the rounded numbers forecasters typically enter for unemployment

Table OE1: External Validation: Correlations Between Monthly Macro Announcement Surprises and Daily Open-to-Close S&P500 Returns.

	(1) *Bad macro news:*	(2) *"Normal"*	(3) *"Covid"*	(4) Phenomenon?
Panel A: Employment				
Unemployement Rate	> 0	0.035	**0.793*** **	X, Reject
Change in Non-farm Payroll	< 0	**0.306*** **	-0.108	X, Reject
Panel B: Manufacturing, Consumption/Consumer				
ISM Manufacturing	< 0	**0.341*** **	**-0.569***	X, Reject
Retail Sales	< 0	0.026	-0.207	X
Consumer Confidence Index	< 0	0.072	-0.174	X
Panel C: Other news				
CPI Change	*Depends*	-0.107	**0.499*** **	
Industrial Production	< 0	-0.018	0.338	

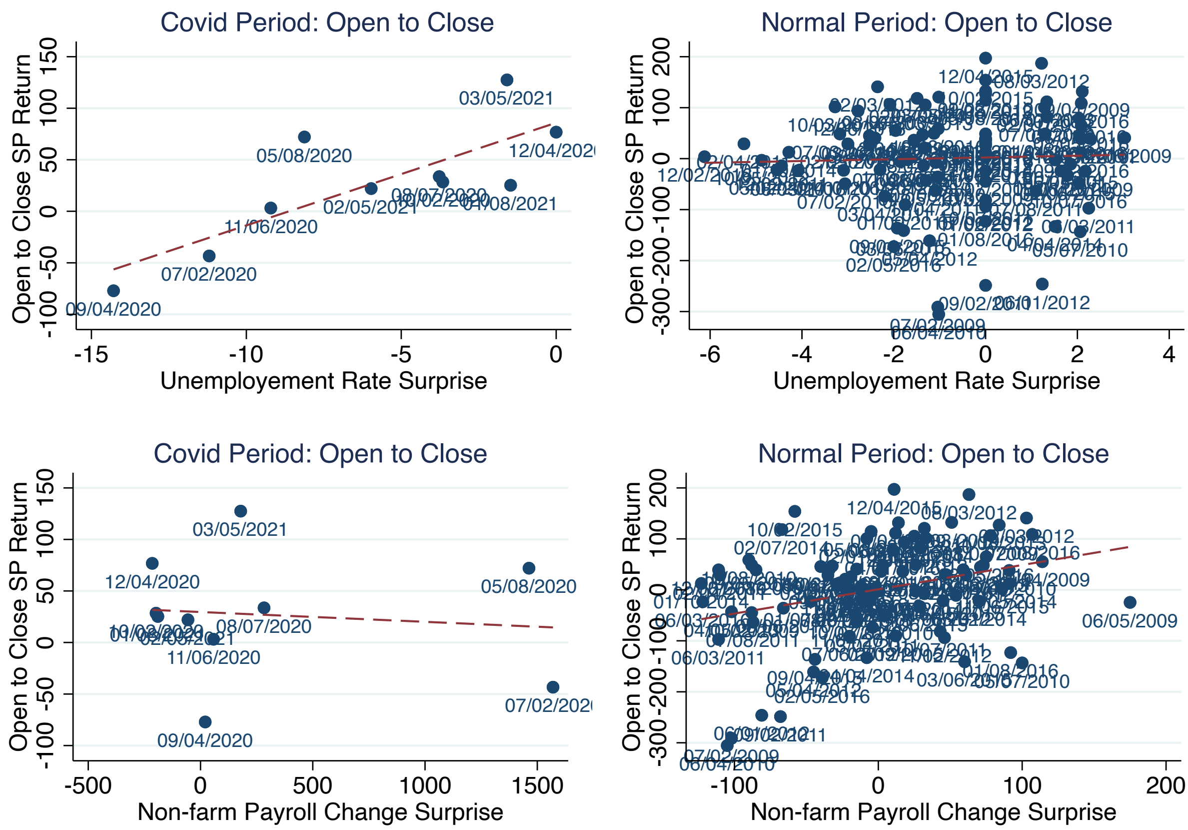


Figure OE1: Unemployment news and daily open-to-close returns.

rates. An equality test of two correlation coefficients can be rejected at the 5% level. Similarly, lower-than-expected changes in non-farm payrolls normally cause lower stock returns, but during covid can cause higher stock returns; an equality test is also rejected.

OE.2. The phenomenon across macro variables

We compare the above described phenomenon across 5 other monthly macro variables across manufacturing, consumption, inflation, and growth. In Panel B of Table OE1, we find that bad news about manufacturing, consumption, or consumer confidence indicators normally would decrease stock returns, hence yielding positive coefficients in the normal period. However, during the covid period, bad macro news is associated with higher stock prices, a result that is particularly strong for manufacturing news (-0.569*). As a result, evidence from these two panels – where macro announcements likely paint a health report on Main Street households – lends supportive evidence to the existence of the "Main Street pain, Wall Street gain" phenomenon.

Besides employment, manufacturing, and consumption-related macro announcements, we also check return responses to other traditional macro variables that, for instance, enter the Taylor rule – CPI changes and industrial production growth. Both should be quite informative about conventional monetary policy. Although the correlation coefficients are all statistically insignificant and economically less clear, these two variables seem to draw an opposite effect from what the "Main Street pain, Wall Street gain" phenomenon would predict: Bad news about the economy can decrease stock returns, given the positive coefficients.

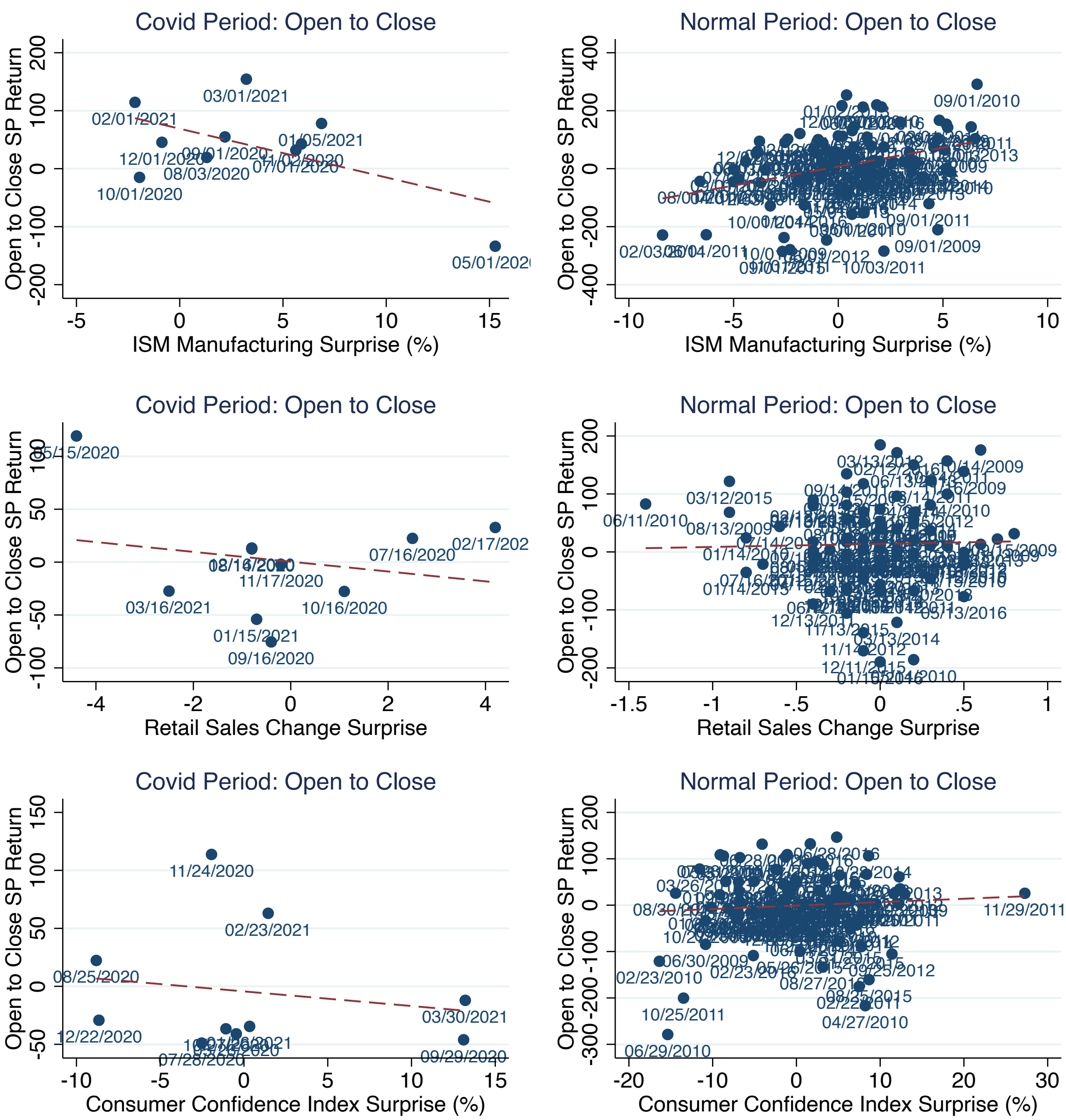


Figure OE2: Manufacturing and consumption/consumer news and daily open-to-close returns.

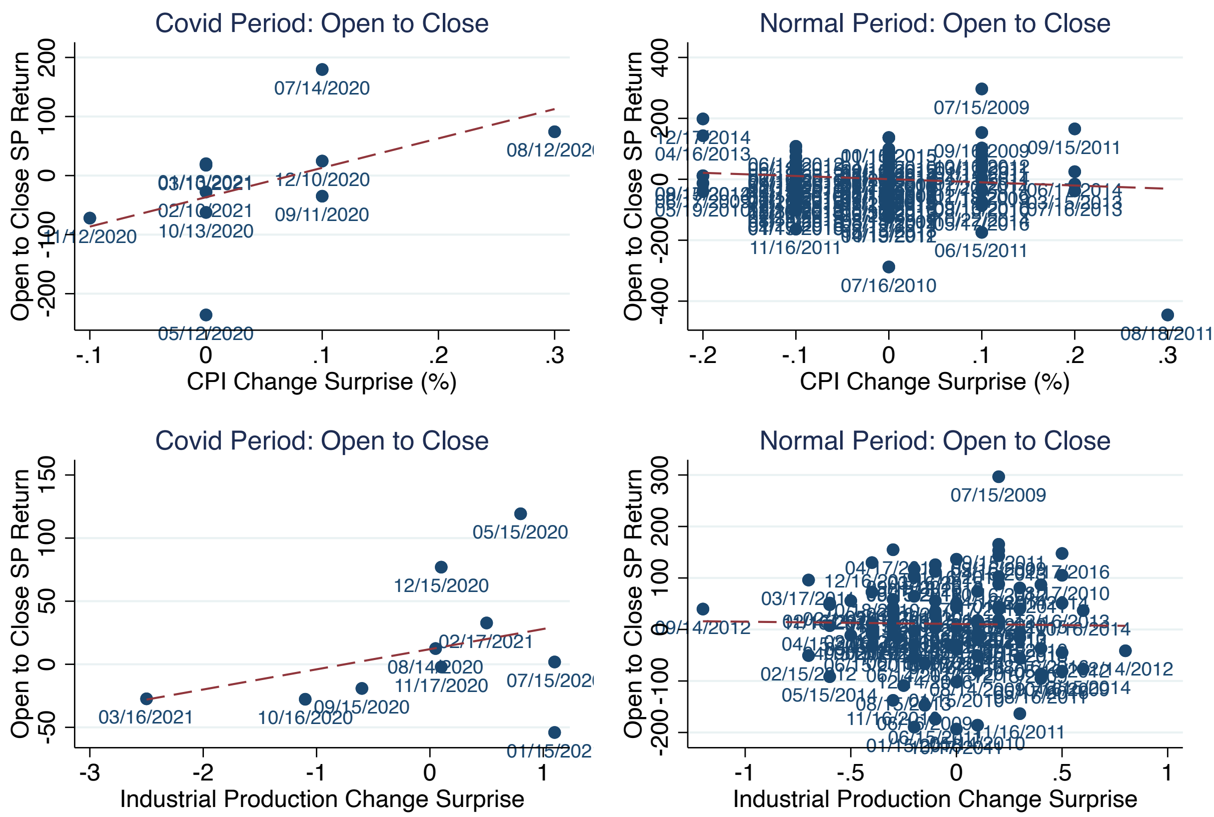


Figure OE3: Other economy news and daily open-to-close returns.