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

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Abstract

When Initial Jobless Claims (IJC) are higher than expected, investors may expect more generous federal government support and drive up aggregate stock prices through the expected cash flow channel, leading to a novel "Main Street pain, Wall Street gain" phenomenon. This phenomenon emerges when news articles on IJC announcements mention fiscal policy keywords more. During the COVID-19 period, firms/industries that get mentioned more in actual legal stimulus bills, have higher obligated funding amounts, or are expected to suffer more in fundamentals show higher individual stock returns when bad IJC news arrives. Our results suggest that investors form fiscal policy expectations.

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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

Conventional wisdom and standard asset pricing theories suggest that bad (good) macro news should drive down (up) stock prices. However, using announcement and high-frequency data from February 2020 to March 2021, we observe that a one standard deviation (SD) increase in the initial jobless claims (IJC) surprise is associated with significant increases in daily open-to-close market index returns of around 30 basis points. In addition, this phenomenon is more pronounced when bad IJC news arrives (i.e., when the actual IJC is higher than expected), and appears to operate through the expected cash flow channel, given the evidence from stock return decomposition as well as normal behaviors in discount-rate sensitive assets.

The existing literature on the dynamic aspect of return responses to macro announcement surprises mostly focuses on the interest rate expectation mechanism (see e.g. Boyd, Hu, and Jagannathan (2005), Elenev, Law, Song, and Yaron (2022)). Rising unemployment news could be good news if lower interest rates are expected. However, during most of 2020-2021, the interest rate was already at its zero lower bound, most unconventional monetary policies were announced before April 1, 2020,[2] and the futures market did not move much with IJC news. This puzzling phenomenon during COVID-19 calls for other mechanisms of time-varying stock return responses to macro shocks.

We propose a "fiscal policy expectations" mechanism. 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* the expected future cash flow growth and the stock prices. The current fiscal policy literature (e.g., Croce, Kung, Nguyen, and Schmid (2012a), Croce, Nguyen, and Schmid (2012b), Gomes, Michaelides, and Polkovnichenko (2013), and Croce, Nguyen, and Raymond (2021)) focuses on the long-term equilibrium effects of FP on asset prices and economic variables; in our paper, we argue for the existence of an FP expectations mechanism, which gets capitalized at a much higher frequency.

We face empirical challenges in testing this hypothesis, as there are no futures market or surveys from which one can easily elicit high-frequency expectations. As a result, we test our hypothesis by

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

[2] We summarize day-by-day actions by the Federal Reserve in response to the COVID-19 crisis in Appendix Table A1.

examining two testable predictions at the aggregate and cross-sectional levels. First, we find that mentions of FP in IJC news articles significantly surpass those of monetary policy (MP) since 2020, and move more aggressively and higher on bad IJC surprise days. In a sample from 2013 to 2021, time-varying FP mentions as a new state variable are able to significantly and positively explain return responses to IJC shocks, particularly on bad IJC days. Second, we find that firms/industries that are expected to receive more fiscal support exhibit higher individual stock returns when bad IJC news arrives. We construct three novel cross-sections, based on industry mentions in actual stimulus bills, detailed obligated fiscal distributions to firms, and firm-level expected fundamental COVID-19 impacts. In the last part of the paper, we conceptualize and solve a long-run risk framework with a simple *fiscal* rule, and demonstrate its potential to explain this phenomenon in terms of the pricing channel and the source of the heterogeneity.

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. We motivate our research question by identifying several abnormal stock market responses to IJC surprises during a particular COVID period (February 2020 to March 2021, dropping outliers and overlaps with major macro and monetary policy announcements), using daily open-to-close or high-frequency data. In order to make the abnormality claim, we find a "normal" comparison to the COVID period, with a similar monetary policy environment (i.e., expansionary and zero-lower-bound), as a way to potentially control for the monetary policy mechanism. Our first stylized fact is that stock returns increase significantly with IJC shocks, while Fed Funds futures as well as several discount-rate-sensitive asset prices exhibit normal but statistically weak responses. The second is that the pricing channel likely works by affecting expected future cash flow growths; the effect is stronger for Dow Jones indices than for the Nasdaq index, for NCF than for NDR as filtered from a VAR framework, and for stocks than for discount-rate-sensitive assets. Third, this phenomenon holds particularly true when bad labor news arrives. Fourth, it builds throughout the morning and peaks around noon, as opposed to an immediate response post announcement, suggesting a counteracting force in place.

To investigate the mechanisms, we first turn to news articles from 2013 to 2021 and conduct textual analysis to help us understand systematically what people discuss when IJC news comes out each Thursday. We construct relative topic mentions as mechanism proxies to be linked to return responses: FP, MP, and business conditions. For instance, when words such as "aid," "extend," "benefit," "Congress," "lawmaker," and "federal government" appear in one article, the scenario typically reflects an ongoing fiscal discussion. On the other hand, words such as "Federal Reserve," "bank," and "inflation" should capture monetary policy discussions.

Mentions of fiscal policy and monetary policy in IJC news articles exhibit distinctive time-series patterns. MP mentions increased around 2017 and 2018 but then entered a decline that lasted until the end of the sample (March 2021), with a small bump around early 2020. FP mentions remained low until April 2020, when they dramatically increased and continued to do so through the end of the sample. Importantly, the increased mentions of FP mainly occur on bad IJC days, while the humped shape of aggregate MP mentions is primarily driven by good IJC day mentions. In other words, FP (MP) is more persistently discussed when macro conditions are worse (better) than expected during the paper sample period. Together with additional narrative evidence, we interpret higher FP (MP) mentions in our low-interest-rate sample as expansionary (contractionary) policy expectations; the MP interpretation can also be confirmed using data from the Survey of Professional Forecasters.

We use two empirical frameworks to test the aggregate testable prediction under our hypothesis. In the first empirical framework, we project rolling return-IJC responses to rolling topic mentions of FP and MP; in the second test, we use non-overlapping quarterly text-based state variables and quarterly survey-based expectation revisions of future interest rates (as an alternative proxy for the MP channel) to span the time variation in the return coefficients of IJC shocks. Both tests show similar results qualitatively and quantitatively and are robust to controlling for business cycle state variables such as uncertainty. During a period where FP (MP) mentions are one SD higher than average, return responses to a 0.1 unit increase in IJC shocks increase by 16-20 (11-13) basis points. However, the dynamics of return responses to bad IJC shocks are only significantly explained by FP mentions, lending support to the role of fiscal policy expectation in explaining the "Main Street pain, Wall Street gain" phenomenon. On the other hand, monetary policy expectation (from either text- or survey-based measures) is typically associated with return responses to good IJC shocks.

Under this fiscal policy expectation mechanism, when a bad IJC shock arrives, investors may expect an increase in the likelihood of an expansionary fiscal policy; this could affect expected aggregate economic growth through fiscal distributions to households and, most importantly for our analysis, to firms, from which we can obtain a cross section. As a result, to test our cross-sectional prediction under the hypothesis, we exploit the COVID-19 period for several reasons: one, the COVID-19 stimulus bills have received unprecedented public attention, as policymakers typically spend months debating them, which helps with effect salience; two, the pandemic has reached almost all industries, which helps us observe a wide heterogeneity of effects. To proxy for firm-level or industry-level fiscal policy expectations, we construct three novel cross-sections based on (1) industry mentions in actual stimulus bills, (2) firm-level obligated fiscal funding from the U.S. Government, according to the Treasury registry office, and (3) firm expected fundamental suffering. Results from these three cross-sections lend support to the *fiscal*-based interpretation.

First, investors may infer the likelihood of a particular industry or firm receiving more fiscal support from direct industry mentions in actual stimulus bills. We search industry mentions in the following four stimulus bills using industry keywords from the NAICS website, an exogenous source: The Coronavirus Aid, Relief, and Economic Security ("CARES") Act, the Consolidated Appropriations Act ("CAA"), the American Rescue Plan ("ARP") Act, and the Health and Economic Recovery Omnibus Emergency Solutions ("HEROES") Act. Industries mentioned more heavily in actual bills exhibit statistically higher return-IJC shock correlations, supporting our hypothesis. For instance, the healthcare industry receive a considerable amount of fiscal subsidy given the nature of the pandemic crisis, demonstrating 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. This evidence is the first indication of a fiscal side of the story, which motivates our second cross-section.

Second, we parse down and create a novel dataset that includes all details about both obligated (promised) and total actual amounts given to each company under each bill, as identified by a Disaster Emergency Fund Code (DEFC). The fiscal distributions are in the form of Paycheck Protection Program (PPP) or forgivable loans. We are able to identify 138 companies out of the S&P 500 in our government spending records. Companies 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%. Unsurprisingly, healthcare and air transportation are the industries receiving the greatest fiscal spending during the pandemic, consistent with our bill-mentioning study.

In our last cross-section evidence, we use a new dataset that indexes all internet job postings; we define changes in a firm's job postings from 2019 to April/May of 2020 as a forward-looking measure for expected COVID-19-induced losses. Firms with greater decreases in job postings exhibit a higher return-IJC shock correlation. Several popular Compustat variables (i.e., quarter-on-quarter or year-on-year changes in employment, revenue, and EPS) show robustness results. We also form a portfolio in which we long the "Most-Suffering" quintile and short the "Least-Suffering" quintile and find that the average daily portfolio returns from February 2020 to March 2021 are 10-13 basis points higher on bad IJC days, while the portfolio returns are significantly negative on good or non-IJC days.

In the last part of the paper, we solve a conceptual asset pricing framework in closed form, aiming to reconcile our empirical results, particularly on the pricing channel and sources of cross-sectional heterogeneity. This model builds on Bansal and Yaron (2004), but differs by introducing a simple fiscal policy rule. When a negative macro shock arrives, government spending is expected to go up, which could counteract the traditional negative effect on the price-dividend ratio through the expected growth state variable. In the cross-section, firms can experience different levels of fiscal pass-through to their expected growth, hence generating different return responses to the macro shock. Calibration using standard parameter choices demonstrates this model's ability to generate "bad is good" price responses.

Related literature

Our research contributes to the economics and finance literature in several ways. Macro announcements are paid tremendous and increasing attention in the past decades (Fisher, Martineau, and Sheng (2022)). Recent empirical evidence shows that macro announcements matter to the stock market (e.g., Gilbert (2011), Savor and Wilson (2013), Cieslak, Morse, and Vissing-Jorgensen (2019), Hirshleifer and Sheng (2021) 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), Boyd, Hu, and Jagannathan (2005), Andersen, Bollerslev, Diebold, and Vega (2007)) that typically predicts that business conditions reinforce macro shock pricing during contractionary times; these studies rely on a sample prior to 2000. More recent studies (Elenev, Law, Song, and Yaron (2022), Yang and Zhu (2021), and Caballero and Simsek (2021)) argue that time-varying return responses to macro news likely depend on monetary policy intervention expectations, which do not need to correlate with business cycles. Our empirical evidence calls for a new mechanism of time-varying stock return responses to macro surprises, which makes our research question relevant. While discount rate movements have been given the most focus in the literature, we propose investors' anticipations about fiscal policy as a source of variation in cash flow expectations. In addition, as Fisher, Martineau, and Sheng (2022) point out, most of the literature focuses on monthly macro variables; there is scant literature on weekly initial jobless claims announcements, whereas the public pays significant and often greater attention to IJC than Non-Farm Payrolls, and did so even before COVID-19.[3] We provide answers to their calls, and demonstrate weekly IJC's ability to drive both aggregate and cross-sectional responses.

Second, we complement the existing fiscal policy literature. There is an extensive literature on the macroeconomic effects of fiscal policy,[4] but there is scant research on its asset pricing effects. The few such studies (see Croce, Kung, Nguyen, and Schmid (2012a), Croce, Nguyen, and Schmid (2012b), Gomes, Michaelides, and Polkovnichenko (2013), Diercks and Waller (2017), and Croce, Nguyen, and Raymond (2021)) mostly focus on examining the long-term effects of tax policies and public deficits within an equilibrium framework. Recent empirical papers such as Baker, Bloom, Davis, and Sammon (2021) and Greenwood, Laarits, and Wurgler (2022) point out the rising importance of *actual* fiscal policy news in positive short-term stock market jumps. Our research argues that fiscal policy could already affect the capital market through investor expectation, which get capitalized at a high frequency. While we provide one particular driver that helps "sign" fiscal policy expectations, Bianchi, Cram, and Kung (2021) examine the effect of congressional tweets on the market, and Xu and You (2023) examine analyst expectations of actual procurement transactions using a longer sample from 2008-2022.

Third, the macroeconomics public finance literature has exploited spatial variation to examine the effects of fiscal policy on local macroeconomic variables, e.g., Nakamura and Steinsson (2014), Auerbach, Gorodnichenko, and Murphy (2020) Autor, Cho, Crane, Goldar, Lutz, Montes, Peterman, Ratner, Villar, and Yildirmaz (2022), and Auerbach, Gorodnichenko, Murphy, and McCrory (2022). Similarly, our paper uses the cross-firm variation in obligated amounts to examine heterogeneous asset price responses; we document that the stock prices of firms that are expected to receive more from the Paycheck Protection Program rally more when the market expects a more generous fiscal policy.

The remainder of the paper is organized as follows. Section 2 establishes the four stylized facts about the "Main Street pain, Wall Street gain" phenomenon using aggregate daily and high-frequency evidence. Section 3 investigates plausible mechanisms using textual analysis and forecaster survey data, while Section 4 tests our hypothesis in the cross section. Section 5 solves a conceptual asset

[3]We thank Charles Martineau for sharing with us the Macroannouncement Attention Indexes (MAI) dataset (Fisher, Martineau, and Sheng (2022)), extended till after COVID-19 for us.

[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), Bretscher, Hsu, and Tamoni (2020), Bhandari, Evans, Golosov, and Sargent (2021), Jiang (2021), Jiang, Lustig, Van Nieuwerburgh, and Xiaolan (2022), and many others.

pricing model with a simple fiscal rule. Section 6 offers concluding remarks.

2. Stylized Facts

In this section, we identify several abnormal price responses to initial jobless claims (IJC) surprises[5] during the COVID-19 period (February 2020 to March 2021) by studying a wide range of asset classes and using daily open-to-close or high-frequency data. Section 2.1 constructs our main IJC shocks, and Section 2.2 establishes the stylized facts.

2.1. IJC shock

We focus on initial jobless claims as our primary macro announcement shock for several reasons. First, among various macro announcements in the U.S., only IJC are released at a weekly frequency (08:30 a.m. Eastern Time every Thursday), and such timely releases offer more information for empirical identification. Second, economically, jobless numbers are "Main Street" variables, and should matter to the financial market and policymakers. In fact, the existing empirical literature typically finds that the financial market responds to labor news significantly (see, e.g., Aruoba, Diebold, and Scotti (2009), Kurov, Sancetta, Strasser, and Wolfe (2019), Elenev, Law, Song, and Yaron (2022), Diebold (2020), Fisher, Martineau, and Sheng (2022)).

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 (ending Saturday), 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 IJC announcement days that do not overlap with Federal Open Market Committee meetings (henceforth FOMC) and other major macro announcements. The top two plots in Appendix Figure A1 show the time series of our main IJC shock with and without identified statistical outliers[6] and days overlapping with the FOMC. It can be tested that our main IJC shock series is stationary and well-behaved.

Throughout Section 2, we use a "normal" comparison for the COVID-19 period, one with similar monetary policy by design (as a way to preliminarily control for the mechanism emphasized in Boyd,

[5] In this paper, we use "surprise," "shock," and "news" interchangeably.

[6] Boxplot outlier analysis using the $\times 2$ interquartile range rule suggests that 2021/3/19 (actual: 281K; expected: 200K; 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.

Hu, and Jagannathan (2005) and Elenev, Law, Song, and Yaron (2022)):

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*

A one standard deviation (SD) above average IJC shock in Period "Normal" corresponds to a 4.4% shock; that is, actual jobless claims are 4.4% higher than expected. On the other hand, a 1 SD above average IJC shock in Period "COVID" corresponds to a 10.6% shock (mean 1.9% + SD 8.7%). Mean, SD, and skewness of IJC shocks on bad IJC days (when actual jobless claims are higher than expected) are all higher than their counterpart statistics on good IJC days across all three periods. The COVID period includes 54 weeks after excluding the three aforementioned IJC outliers and the overlapping FOMC announcement days. Detailed statistics are reported in Appendix Table A2.[7]

2.2. Asset price responses: pricing channels, Treasury, asymmetry, and high-frequency evidence

We follow the literature and evaluate the responses of asset prices (denoted by y_t) to IJC shocks on announcement days; the statistical and economic magnitudes of β_1 are of interest:

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

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%. Such conventional "bad is bad, good is good" return responses to macro shocks disappear during the COVID-19 period that we study. Stock returns increase by about 31 basis points with a 10% IJC shock. In terms of economic magnitude in standard deviations, a one SD IJC shock corresponds to a 0.2 SD increase in daily open-to-close stock returns.[8]

We call this observation the *"Main Street pain, Wall Street gain"* phenomenon, and explore pricing channels, Treasury asset responses, asymmetry, and intradaily patterns below.

[7] The simple level difference $IJC_t - E_{t-\Delta}(IJC_t)$ is also an intuitive alternative choice (see, e.g., Balduzzi, Elton, and Green (2001), Kurov, Sancetta, Strasser, and Wolfe (2019), etc.); however, it is less suitable in our research given the obvious structural break in the level of initial claims during March and April of 2020, which can be seen in the second halves of Figure A1 and Table A2 in the appendix.

[8] It is commonly found 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.

Pricing channels. Following Campbell and Vuolteenaho (2004), we decompose the unexpected part of market returns into changes in expectations of future cash flow growth ("NCF," or cash flow news) and changes in expectations of the future discount rate ("NDR," or discount rate news):

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

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 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 $0.95^{1/252}$.[9] 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, 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 results 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.[10] Appendix B provides more details on the estimation procedure, our replication results for Campbell and Vuolteenaho (2004), and new results in the current sample period. For 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); 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 also increasing expected future cash flow growth. In our modern sample (1982/01-2021/04), we find that NDR (NCF) explains 31% (34%) of the total return variability, with a positive covariance between NDR and NCF. Results are robust using open-to-close or daily stock

[9] 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)).

[10] 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 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.

market returns. One useful takeaway, from the long-term time series perspective, is that pure cash flow innovations exhibit 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 daily stock returns can be explained by the increase in the expected future discount rate, as shown in Column NDR. In contrast, during the COVID-19 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 NCF. This is the first indication that the COVID-19 period mechanism might be different from the normal period mechanism.

Treasury assets. Columns (5)-(9) in Table 1 show how Treasury-related assets (long-term U.S. government bond returns, 10-year yields, Treasury implied volatility, and Fed Funds futures) respond to IJC shocks during normal and COVID periods. During the normal period, when a bad IJC shock arrives, we observe that long-term government bond prices (yields) increase (decrease) as stock prices generally decrease, which is consistent with the standard risk premium story. During the COVID period, the coefficient signs and economic magnitudes (in SDs) for long-term government bond prices and yields are consistent with those during the normal period, but they become statistically insignificant. The normal but weak discount-rate-sensitive asset responses to IJC shocks during this period are in stark contrast to the opposite and significant stock market responses to IJC shocks. If the reason why the COVID period's stock market responses were the opposite of normal ones was a dominating "monetary policy expectation" story (that dominated the standard risk premium story),[11] then one would have expected significant and even stronger responses among discount-rate-sensitive assets to start with, reinforcing the positive and negative coefficients in Columns (5) and (6), respectively. We do not find this. Also, we do not find significant responses in Fed Funds futures rates. Therefore, this result joins the Campbell-Vuolteenaho decomposition evidence above to indicate that the significant and opposite stock price responses during the COVID period are likely explained through a non-discount rate channel.

[11]When a bad (good) IJC shock arrives, investors could expect an easier (tighter) monetary policy in the future, which hence drives up (down) both stock and bond prices.

Asymmetry. Further decomposing the total stock return responses into bad and good IJC day responses, we find that the "Main Street pain, Wall Street gain" phenomenon during the COVID-19 period mostly occurs when the actual IJC number is higher or worse than expected. Table 2 shows that all statistically significant and positive coefficients come from bad IJC days (see Panel A). R^2s are also noticeably high compared to those typically found in macro announcement studies ($< 5\%$). A one SD increase in IJC shock corresponds to a 0.4 SD increase in stock prices, with the strongest effect in the Dow Jones Industrial and Transportation indices and the weakest effect in the Nasdaq 100. Another way to look at Table 2 is that it displays preliminary cross section evidence.[12] The joint facts that DJ indices respond more positively to IJC shocks and, as we know from the literature (e.g., Campbell and Vuolteenaho (2004)), value stocks are more sensitive to market cash flow news lends support to the cash flow pricing channel.

To directly visualize the asymmetry, Figure 1 depicts the data, with the returns and IJC shocks side by side in a time-series plot. Returns and IJC shocks tend to clearly move in the *same* direction on bad IJC days (i.e., the worse/higher the IJC shocks, the higher the stock returns), yielding a significant and positive relationship. On the other hand, they often move in an opposite direction on good IJC days. This "Main Street pain, Wall Street gain" phenomenon also does not seem to be driven by one or two particular date(s). In fact, from the top plot, the periods between April 2020 and November 2020 and after February 2021 exhibit rather strong positive comovement between IJC shocks and stock returns.

High-frequency evidence. We also trace out futures market reactions to IJC shocks using high-frequency data for closer identification. We follow the literature (e.g., Kurov, Sancetta, Strasser, and Wolfe (2019) and Elenev, Law, Song, and Yaron (2022)) and construct cumulative returns 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 announcement), and 3:30 p.m. (shortly before market close). Consistent with the literature, Table 3 first shows no pre-announcement drift for labor news during both the normal and COVID periods. During the normal period, Dow futures decrease significantly with IJC shocks beginning 5 minutes after the announcement; the effect remains statistically strong until noon. This effect is robust if we evaluate bad and good IJC days separately, and exhibits similar economic magnitude as well (-114.518*** and -111.963*, respectively). In the COVID period (see the

[12] For a more formal analysis, please see Section 4.4.1 in the Cross Section part of the paper.

right panel), Dow futures prices still decrease with IJC shocks at 8:35 a.m., but with a much smaller magnitude (-45.530), and eventually they increase with IJC shocks, with a significant and positive coefficient (356.293*). The coefficients during the COVID-19 period are significantly *higher* for all of our post-announcement time stamps than during the normal period. This evidence suggests the new mechanism plays a counteracting force against traditional channels.

Moreover, this counteracting mechanism is particularly strong on bad IJC days, resulting in a "bad is good" response. From Panel B of Table 3, unlike the acute "bad is bad" response during the normal period, which begins five minutes after the announcement, this "bad is good" response builds throughout the morning (421.878*) and persists into the afternoon (632.505**). On good IJC days, futures prices decrease with IJC shocks with a coefficient (-183.772*) that is economically and statistically close to its normal-period counterpart (-111.963*).

Finally, while decomposing NCF and NDR at such a high frequency is empirically challenging, we directly examine two futures markets that should be more sensitive to discount rate news (see Appendix Table A3): 30-day Fed Fund futures, and 10-year Treasury note futures. It is comforting to see that results are consistent with the daily evidence in Table 1. During the normal period (left panel), the long-term Treasury note futures prices increase significantly with a bad IJC shock 5 minutes after the announcement time, while the short-term futures prices do not. This is consistent with the standard risk premium channel of macro shocks. During the COVID period, interest rate futures prices also increase with IJC shocks, with a similar economic magnitude in SD terms compared to that of the normal period. All high-frequency data are obtained from Tick Data.

Summary In this section, we use a period-by-period framework to document a new "Main Street pain, Wall Street gain" phenomenon that appears during the COVID-19 period:

1. Stock returns significantly increase with IJC shocks, while Fed Funds futures as well as several discount-rate-sensitive asset prices exhibit normal but statistically weak responses.
2. The pricing channel is likely through affecting expected future cash flow growths, given that the effect is stronger for Dow Jones indices than for the Nasdaq index, for NCF than for NDR as filtered from a VAR framework, and for stocks than for discount-rate-sensitive assets.
3. This phenomenon appears mostly when bad labor news arrives.
4. It builds throughout the morning and peaks around noon, as opposed to the typical immediate response after the announcement.

An array of robustness tests using E-mini S&P futures, alternative IJC shocks, and a sample without April 9, 2020 (an unscheduled Federal Reserve announcement day) are shown in Appendix Tables A4, A5, and A6, respectively. Appendix Section E.1 provides robustness evidence on the phenomenon using monthly announcements of unemployment rates and non-farm payrolls, two other often-studied labor variables (see recent work as Fisher, Martineau, and Sheng (2022).

3. Mechanism: Textual Analysis

Evidence from the previous section seems to call for a new pricing channel for macro news, one which is strong enough to overturn the conventional wisdom of "bad is bad" and likely passes through by affecting expected future market cash flows. Our hypothesis is that, 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*, driving up expected future cash flow growth and aggregate stock return responses. This hypothesis has the potential to jointly explain the four stylized facts described above, especially as fiscal spending is typically expected to behave like a "put" (asymmetry) and value stocks are more sensitive to cash flow news (pricing channel).

While, unlike monetary policy expectations, there is no (readily available) futures market that trades on fiscal policy expectations nor a longitudinal survey that tracks public views of fiscal policy, we point out that our hypothesis has two testable predictions and we focus on testing them in the remainder of the paper.

1. At the aggregate level, time-varying fiscal policy (FP) expectations should explain time-varying return responses to IJC shocks, particularly on bad IJC days. We test the aggregate prediction using primarily newspaper data and textual analysis from 2013 to 2021. We start by providing first evidence on what people talk about on IJC announcement days in Section 3.1, and then link it to asset returns.

2. 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 test the cross-section prediction using firm-level data from the Treasury registry office, the actual stimulus bill, and firm fundamentals data in Section 4.

3.1. Textual analysis: What do people talk about on IJC days?

We focus on CNBC's IJC news articles, which are written and published each Thursday to describe and interpret that morning's IJC announcement. This text source is suitable for our research for several reasons. Unlike other news sources such as WSJ or Bloomberg, CNBC has a clear designated website for Initial Jobless Claims announcements, https://www.cnbc.com/jobless-claims/. A team of CNBC economists writes one article for each Thursday's IJC announcement and revises it throughout the morning; they occasionally will repost Reuters IJC articles as well. This consistent and reliable source of IJC-focused news articles helps with empirical identification, as it already filters away "noisy" articles that may mention "initial jobless claims" but do not focus on interpreting the IJC announcement. Moreover, CNBC is a major business news broadcaster with a wide network of investors, reporters, and commentators; it is fair to say that normal traders watch CNBC daily or frequently. To the best of our knowledge, we are among the first to parse and examine this website in a systematic way.

We use Python and then manually verify CNBC IJC news articles on announcement days for as far back as is available online; news on CNBC's website is not directly downloadable from well-known news aggregators (e.g., RavenPack, LexisNexis, Factiva). There are 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.

We are able to identify 366 IJC articles from the CNBC website through March 18, 2021, the end of our sample. Figure 2 shows the distribution over time. In the top plot, it is noticeable that we can identify only a few articles from before 2013 from their website, while the number becomes quite stable afterwards. This limits the start year of our aggregate analysis to 2013. The bottom plot shows a stable split between bad and good IJC announcements per 60-week rolling window.

Topics. We consider 5 topics that either matter directly to our theory or act as methodology validation: Fiscal policy (FP), monetary policy (MP), economic uncertainty (UNC), Coronavirus-related (COVID), and normal words that appear in describing IJC (NORMAL). Appendix C provides detailed bags of keywords.

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. Therefore, 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. Here are a few examples of FP mentions on *bad* IJC days during the COVID-19 period when actual jobless numbers are worse than expected:[13]

1. August 20, 2020: *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: *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: *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.*

The second important topic we trace out is monetary policy, which is a mechanism that the literature already discusses. The words we choose are fairly standard and general, such as "central

[13]From 1 to 3: https://www.cnbc.com/2020/08/20/weekly-jobless-claims.html; https://www.cnbc.com/2020/12/17/weekly-jobless-claims.html; https://www.cnbc.com/2021/02/18/us-jobless-claims-.html; https://www.reuters.com/business/us-weekly-jobless-claims-rise-labor-market-recovery-stalls-2021-02-18/

bank," "inflation," and "Federal Reserve," as well as Federal Reserve Chairpersons' last names, etc. The third topic is economic uncertainty, and we follow Baker, Bloom, and Davis (2016). Note that we do not use the existing EPU index because we are interested in mentions of economic uncertainty specifically in IJC news articles published on announcement days, for identification purposes. The fourth topic, for validation reasons, is coronavirus-related, as one should expect the topic's mentions to increase dramatically after January 2020. The fifth topic includes normal IJC terms, such as "initial," "jobless," "claim," "unemployment," "Thursday" and so on, and we expect mentions of this topic will remain stable and high over time.

Topic mentioning scores. To retrieve the relative importance of our various bags of words in IJC news articles on announcement days, 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.

Findings. Given that each IJC article is relatively short (average=327 words), we construct topic mentions metrics using a rolling group of weeks. For illustration purposes, Figure 3 considers 60-week rolling windows and shows the rolling topic mentions, normalized by the "Normal-IJC" mentions from the same rolling window. The first observation, serving more as a validation, is the time variation in the "Coronavirus" topic, which, as expected, starts off as irrelevant but increases by 10 times during 2020-2021.[14]

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 increase around 2017 and 2018 but then decline, 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). It is noteworthy that MP is in fact well attended to during 2020-2021; what's different here is that we are interested in what

[14]Earlier values are not exactly at zero because some of the words in this topic, such as "virus," do occur before 2020.

the media discusses specifically on IJC announcement days, which should provide cleaner insights relevant to our identification. 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.

The mentions of economic uncertainty 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 reaches peaks around the Brexit referendum in 2016, the China-U.S. trade war in 2018-2019, the COVID-19 peak in early 2020, and then the U.S. election in late 2020.

Figure 4 complements Figure 3 by constructing "bad" ("good") topic mentions metrics using articles on bad (good) IJC days from the same 60-week rolling window. For interpretation purposes, we normalize a topic's mentions using its value during the first 60-week window, so that "1.5" means that the bad day mentions of a particular topic increase by 50% compared to the beginning of the sample. We discuss two important observations. In the upper left plot of Figure 4, FP mentions grow more aggressively on bad IJC days, and are mainly responsible for explaining the upward FP pattern from Figure 3. 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 (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.

Importantly, these empirical observations, taken together with the narrative above, suggest that higher FP mentions during our sample period potentially indicate higher expansionary policy expectations; higher MP mentions may indicate higher contractionary policy expectations, e.g., through higher interest rates. In addition, among what can be validated further, we find that MP mentions on good IJC days during a quarter increase significantly with the quarterly revisions in interest rate expectations (source: SPF) at a correlation of 0.46***.[15]

To summarize, the construction and potential interpretations of our evidence on FP and MP mentions allow us to test our aggregate-level hypothesis. We consider two different empirical frame-

[15]That is, when MP mentions on good IJC days within a quarter are higher, forecasters typically also anticipate future interest rates to increase from surveys.

works in Sections 3.2 and 3.3. Figure C1 in the appendix provides a jackknife exercise that replicates Figure 4 by dropping one FP or MP keyword (and its derivatives) and recalculating the topic mentioning scores. The tight bandwidth, constructed using minimum and maximum values, indicates potentially low measurement uncertainty.

3.2. Mechanism evidence using rolling windows

We project time-varying return responses to IJC shocks on time-varying topic mentions. Table 4 uses an 80 IJC day rolling window to construct return responses to IJC shocks, good and bad, and topic mentioning scores. Similarly, Panel A (Panel B) in Table 5 uses rolling windows of 40 bad (good) IJC days to construct bad IJC day (good IJC day) return responses and topic mentioning scores. Given the text data availability, the sample starts around 2014 and continues to March 2021. Newey-West standard errors are reported in parentheses. Right-hand-side variables are standardized for interpretation purposes.

We find that the dynamics of return responses to IJC shocks are significantly explained by both FP and MP mentioning variables. Positive loadings in Table 4 mean that both are counteracting forces to the normal pattern (i.e., stock returns should decrease with IJC shocks). During a period in which FP mentions are one SD higher than average, return responses to a 0.1 unit increase in IJC shocks can *increase* by 16-20 basis points. 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.

Panel A of Table 5 shows consistently significant and positive coefficients for FP, not MP, demonstrating that the dynamics of return responses to bad IJC shocks are mostly associated with the dynamics of fiscal policy expectations. When fiscal policy expectations are one SD higher than average, a 0.1 increase in IJC shocks can lead to a 26-34 basis point increase in stock returns, with a stronger response in the Dow Jones 65 index. In Panel B, monetary policy mentions explain more variation in return responses to good IJC shocks than fiscal policy does. This evidence supports Elenev, Law, Song, and Yaron (2022): when monetary policy is expected to tighten, stock prices can decrease even though the IJC numbers are better than expected.

We conduct a series of robustness tests and produce some graphical evidence as well. The first three robustness tests are shown in Tables 4 and 5, considering alternative left-hand-side variables (economic magnitude and the Dow Jones 65's open-to-close return responses) and an additional control variable of uncertainty. Table A8 in the appendix includes three more tests. Robustness test (4) drops 4/9/2021 given the additional Federal Reserve action on that day; test (5) uses a 60-day rolling window when examining all IJC days; test (6) uses 30-day rolling windows instead of 40-day rolling windows when examining bad/good IJC days. Figure A2 exhibits SD changes in unexpected S&P 500 returns, discount rate news (NDR), and cash flow news (NCF) given a +1 SD IJC shock (i.e., bad shock) in the top plot and given a -1 SD IJC shock (i.e., good shock) in the bottom plot. The patterns of the unexpected S&P 500 return (black solid line) and NCF (red dashed line) responses to bad IJC shocks and the FP mentions discussed earlier are noticeably similar. This graphic evidence in turn also supports the close relationship between the cash flow pricing channel of the fiscal policy expectation mechanism that we propose in this paper; the NCF-IJC shock relation is also stronger in the bad IJC plot. In the bottom plot, NDR responses to good IJC shocks (blue dotted line) also move closely with the MP mentions.

3.3. Mechanism evidence using non-overlapping data

We next test our hypothesis by constructing non-overlapping quarterly state variables and using them to directly interact with IJC shocks. The specification is as follows:

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

where t and τ denote daily and quarterly frequency, respectively, y is stock returns (in basis points) on 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 consider bad (good) IJC days within the quarter and obtain quarterly "bad" ("good") topic mentions measures. Next, we follow Elenev, Law, Song, and Yaron (2022) 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). Due to the availability of news files, as explained in Section 3.1, the regression sample runs from January 2013 to March 2021.

The quarterly time-series patterns of these textual-based state variables appear less continuous by design but largely follow the rolling patterns. FP and MP mentions are statistically uncorrelated, regardless of bad or good IJC days. 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 4). In fact, the good IJC day MP mentions and $\Delta Tbill3m$ are significant and positively correlated at 0.46***, which supports the idea that more MP mentions can be interpreted as higher expectations of contractionary MP. The evidence mentioned above is shown in Figure A3.

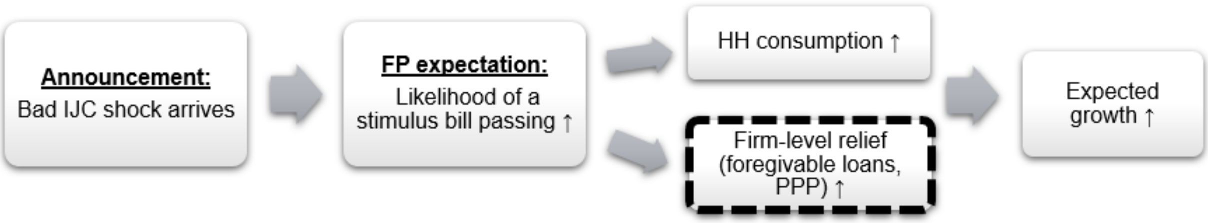
Table 6 reports the regression results of Equation (3) and examines the relative importance of multiple state variables; the interaction coefficients are of interest.[16] First, on bad IJC announcement days, when fiscal policy mentions are one SD higher than the average, stock returns could significantly *increase* by around 26 basis points with a 10% IJC shock, given the significant and positive interaction estimates (258.381*** using the S&P 500 and 257.325** using the Dow Jones 65). This magnitude is quite consistent with Table 5, although they use different methodologies. The MP mentions or the expectation revisions about the future interest rate ($\Delta Tbill3m$) 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. Instead, on announcement days when monetary policy mentions are one SD higher than the average, stock returns significantly decrease by 19-30 basis points with a -10% IJC shock, given the positive interaction term. This evidence lends support to the monetary policy expectation story, counteracting the "good is good" conventional pattern. When we include $\Delta Tbill3m$, replacing MP, in the last column of Table 6, we find consistent results. When the interest rate is expected to increase by 0.09 percent annually (which corresponds to about one SD of $\Delta Tbill3m$), stock returns significantly decrease by 50-67 basis points with a -10% IJC shock, given the positive interaction term (671.552** using the Dow Jones 65 in Table 6). Both results are robust to including uncertainty.

4. Mechanism: Cross-Sectional Evidence

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 we examine, a *stimulus bill passing* – to increase, which could affect the expected aggregate economic growth through fiscal distributions to households (HH) and to firms. As it is challenging to design a households cross-sectional analysis, we focus on firms/industries, as outlined in this diagram:

[16] We relegate univariate results to Table A9 in the appendix.



Therefore, our hypothesis predicts that firms/industries that are *expected* to receive more fiscal support will exhibit higher individual stock returns when bad IJC shocks appear, hence a stronger "Main Street pain, Wall Street gain" phenomenon in their respective stock price responses.

There are two empirical challenges when designing our cross-sectional analysis. One, the passing of fiscal policy and budget allocations – unlike monetary policy – typically results from a long period of congressional debates and vetting, which adds complications to dynamic sorting strategies. Therefore, we test this hypothesis using a static period from February 2020 to March 2021 (dropping outlier IJC shocks and macro and monetary policy overlaps as before); during this period, the fiscal stimulus bills received unprecedented public attention and should be sufficiently economically relevant to almost all industries and firms for us to observe *heterogeneous* individual stock return responses.

Two, we face a challenge similar to one encountered in the aggregate study: it is close to empirically impossible to measure fiscal policy expectations at the firm level or industry level, given the lack of futures markets and longitudinal survey platforms. We even looked at the betting market (such as Kashi and Polymarket), and found no reliable tokens to be used for our research. Therefore, we create three micro-level data sets that could reflect cross-sectional differences in fiscal policy expectations. A stronger "Main Street pain, Wall Street gain" effect (or a higher correlation or beta between individual returns and IJC shocks) during COVID-19 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 during the COVID-19.

Sections 4.1, 4.2 and 4.3 present evidence using these three cross-sectional measures, and Section 4.4 presents two extending discussions. We primarily consider the firm universe of the S&P 500, consistent with our aggregate analysis. All cross-sectional tests robustly support our hypothesis.

4.1. Cross-sectional evidence 1: Industry mentions in actual bills

Investors may infer the likelihood of a particular industry/firm receiving more fiscal support than others from relative industry mentions in actual bills. We therefore search industry mentions in the following stimulus bills. Of these, the three COVID-related stimulus bills were signed into law: (1) The Coronavirus Aid, Relief, and Economic Security ("**CARES**") Act was initially introduced in the U.S. Congress 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, passed the Senate as the CARES Act on March 25, 2020, and was signed into law by President Donald Trump on March 27, 2020. (2) The Consolidated Appropriations Act, 2021 ("**CAA**") was a spending bill introduced as H.R. 133 for the fiscal year ending September 30, 2021; it was the product of months of congressional deliberations. It passed Congress on December 21, 2020 and was signed into law by President Donald Trump on December 27, 2020. (3) The American Rescue Plan ("**ARP**") Act was introduced in the U.S. Congress 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. In addition, (4) the Health and Economic Recovery Omnibus Emergency Solutions ("**HEROES**") Act was introduced in the U.S. Congress on May 12, 2020 as H.R. 6800 and passed the House on May 15, 2020; it did not pass the Senate in the next 6 months, and Congress passed the CAA instead in December 2020.

We use final versions of these bills (source: Congress.gov) to conduct textual analysis, and we consider one bill at a time. As an exogenous source for industry keywords, for each 2-digit NAICS industry, we put together words from the 6-digit NAICS website (except for stop words).[17] We then search for and calculate simple industry mentions in one actual bill at a time. Three 2-digit NAICS industries cannot be found in the S&P500 firm pool that we study, and three other industries have fewer than 5 firms.[18] We therefore focus on the remaining 14 industries, which have $\geq$5 firms in the S&P500 firm pool. Finally, to construct industry-level return-IJC correlations, we calculate individual return-IJC correlations and then calculate the simple industry average.

Figure 5 plots industry mentions in the CARES Act on the x-axis (higher=more mentions) against industry return correlations with IJC shocks on the y-axis (i.e., higher=stronger "Main Street pain, Wall Street gain" effect).[19] We document a significant and positive relationship between industry

[17]For instance, the keywords for "21 Mining" are obtained from this website: `https://www.naics.com/six-digit-naics/?v=2017&code=21`.

[18]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.

[19]To make stock return responses to IJC shocks comparable across industries/firms, we look at SD changes in

mentions and industry return-IJC correlation during COVID-19. The fitted line yields a correlation coefficient of 0.44 (SE=0.24), which is a surprisingly strong result given that this comes from only 14 data points and a simple textual analysis. Evidence using the other three bills can be found in Appendix Figure A4.

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=0.016). Other non-crisis-related industries with frequent mentions in the CARES Act also exhibit higher "Main Street pain, Wall Street gain" behavior when bad IJC shocks arrive. One example is the transportation industry. 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. Similarly, the transportation industry shows an industry return-IJC correlation of 0.186 (p=0.092), which is higher than the S&P500 average (0.141).

4.2. Cross-sectional evidence 2: Promised COVID-19 related spending

The previous cross-sectional evidence is a first indication for the role of fiscal policy expectations in shaping cross-industry differences in return responses to IJC shocks. In our second cross section, we construct and examine a new dataset that has COVID-19-related fiscal spending promised and actually distributed to each firm. Intuitively, investors would expect certain firms to receive more fiscal support if they are *promised* to receive more.

Specifically, we parse down and identify both promised and total actual "award" amounts (i.e., an award according to the database means forgiven grant paid) to each company during the COVID-19 period, if any, using detailed information from the entire website https://www.usaspending.gov/. This database contains the full details of each award, including recipient names and addresses, recipient parent names and addresses (if available), obligated amounts (promised awards), total gross outlay (actual awards paid out), award purpose, and other contract information. This database enables us to identify, at least under these COVID-19 headline bills, the forgiven beneficiaries of COVID-19-related fiscal stimulus packages. Appendix D provides more description of our data source and collection process. Given our research objective, we are interested in *all* COVID-19 spending using the Disaster Emergency Fund Codes and also a clear subset category,the Paycheck Protection

individual open-to-close stock returns given a one SD IJC shock; econometrically, this is equivalent to the correlation between individual stock returns and IJC shocks, denoted by $Corr^i$ in text below.

Program (PPP, Disaster Emergency Fund Codes = O or P). To the best of our knowledge, this is one of the first efforts linking this firm-level covid-awards and PPP data to stock market data in the literature.[20]

Some awards are quite sizable and indicative of government support toward firms in the form of cash flow. For instance, after the COVID-19 crisis began in the U.S., American Airlines received 6 billion dollars on April 21, 2020[21] as part of the payroll support program in the Coronavirus Aid, Relief, and Economic Security (CARES) Act, enacted on March 27, 2020. This act established the PSP1 to provide a total of up to $25 billion for passenger air carriers. Also, this initial spending continues to predict future support; for example, American Airlines received another 3.3 billion dollars in support,[22] authorized under Subtitle A of Title IV of the Consolidated Appropriations Act, 2021 (PSP Extension Law). Also, United HealthCare Services, Inc received provider relief funds as a healthcare service provider under the Paycheck Protection Program and Health Care Enhancement Act.[23] The company further received a 161 billion dollar direct payment from the government to address the pandemic crisis.[24] These transactions are not trivial payments to allow small business entities to keep their employees but rather awards to large companies for specific purposes, e.g., transportation and healthcare. They are often distributed to subsidiaries.

In the S&P 500 universe, we are able to identify 138 companies in our government spending records.[25] COVID-19-related funding is highly skewed: out of the 138 companies in the S&P 500 universe, 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.[26] As COVID-19 funding was delivered in staggered phases as dictated by the multiple government acts, we also observe negative numbers in the data. This means that the government revoked the funding or

[20]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.

[21]See the USAspending link: https://www.usaspending.gov/award/ASST_NON_ACWS0060_2001/.

[22]See the USAspending link: https://www.usaspending.gov/award/ASST_NON_ATSE0233_2001/.

[23]See the USAspending link: https://www.usaspending.gov/award/ASST_NON_PRF20200001_7526/.

[24]See the USAspending link: https://www.usaspending.gov/award/ASST_NON_PRF20200001_7526/.

[25]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.

[26]The top 5 COVID-19-spending four-digit NAICS industries are Scheduled Air Transportation; Drugs and Druggists' Sundries Merchant Wholesalers; Couriers and Express Delivery Services; Medical and Diagnostic Laboratories, and Pharmaceutical and Medicine Manufacturing.

reduced the award amount. As a result, when calculating the obligated or total actual amounts, we consider both "All" (positive+negative amounts on records) and "Positive" (positive amounts only). We then construct and examine three firm-level fiscal support proxies: the log of the obligated amount across all COVID-19 spending types, the log of the obligated amount from the Paycheck Protection Program only, and the log of the actual total gross outlays.

In Column (1) of Table 7, top panel, 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)-(7), we show that this result is robust using (a) positive amount items only, (b) PPP items only, or (c) actual outlays. Figure 6 displays the data. In the top panel, we group the S&P 500 companies into four brackets by obligated PPP funding and plot average return-IJC correlations. The stock return-IJC shock correlation is on average 13.2% for the non-recipient companies, according to the leftmost dot. As the obligated PPP amount increases, stock return-IJC shock correlations steadily increase. The top bracket, in which the log of PPP funding is above 15 (or above 3.3 million dollars), hits an average of 18.5% in return-IJC correlation. For a robustness check, we find the award dollar amount received by each of 138 companies and divide this by their 2019 revenue (to control for size); we then order the companies by this percentage and create percentile ranks for them as a new RHS variable. In the bottom panel of Figure 6, we estimate local regressions to fit the non-linear relationship between the correlation and percentile rank of the PPP award ratio. The return-IJC correlation mainly increases when the rank is among the top 40%, roughly the 55 firms with the largest PPP award ratios.

We conduct two more robustness tests, relegated to Appendix Figure A5. First, we examine the cross-sectional results on bad IJC days only and find consistent patterns (with slightly higher coefficients, as expected). Second, we use the return-IJC beta and find that the positive relationship between promised fiscal outlays and return responses to IJC shocks remains statistically significant.

4.3. Cross-sectional evidence 3: Firm COVID-19 impact measures

More broadly speaking, firms that are expected to be more affected by COVID-19 could receive more government support. Both realized and expected impact likely would enter active policy debates, and hence are meaningful to our research. Therefore, we use *four* measures to capture to what extent a firm has been and will likely continue to be negatively affected by COVID-19.

Our first measure uses a novel dataset provided by LinkUp, a data aggregator that indexes job listings directly from employer websites (typically an employer's applicant tracking system in real-time). LinkUp provides us monthly job posting data classified using 6-digit NAICS codes. We group the job posting data into 4-digit NAICS codes, and construct our first "COVID-19 impact" measure using changes in the number of job postings from a code's 2019 average to its 2020 April-May average. One advantage of this measure is its forward-looking and foresighted nature; firms cut their job listings 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.[27] 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 in July 2021 and trace all matched PERMNOs (the CRSP identifier) through our COVID-19 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-19 impact measures, the lower (more negative) a measure is, the more a firm is negatively impacted by COVID-19. 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-19. The 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 shown in Appendix Table A10.

Table 8 reports the regression results (N=498) by projecting firm-level return-IJC correlations onto firm-level COVID-19 impact proxies. In the first two rows, the average return-IJC correlation is significant and positive at 0.141 (or 14.1%); the average return-bad IJC correlation is around

[27] "2020Q2" ("2019Q2") refers to 10-Q numbers reported in 2020 (2019) July, August, or September from Compustat.

0.176, whereas the average return-good IJC correlation remains negative at -0.075.[28] Results using all-IJC correlations (see the first column) show significant and negative coefficients across all of our measures. That is, firms that are expected to suffer or actually suffered more (i.e., lower RHS variables) exhibit higher return-IJC correlations. To make sense of the coefficients, a one SD below average job posting change (-39%-21%=-60%; see Table A10) 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. Further decomposition in the next two columns confirms that this negative coefficient mostly comes from bad IJC days. For financial variables, a quintile (20%) drop in the "suffering" rank corresponds to around a 1.2%-1.6% increase in the correlation.

This main result is also displayed as negative slopes in Figure 7, where we split firms uniformly into 20 bins (represented as 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-19 damage in the right/top 20 percent. Companies with more severe COVID-19 damage are the firms that drive the cross-sectional "Main Street pain, Wall Street gain" phenomenon.

4.4. Two extending discussions

4.4.1. Cash flow sensitivity: Additional evidence from portfolio sorting

We also examine our hypothesis using portfolio sorting techniques. We sort our 498 stocks into 5 quintile bins based on the aforementioned COVID-19 impact measures, and form a portfolio that longs the most-suffering bin and shorts the least-suffering bin with value weights and daily open-to-close individual stock returns. We then evaluate its performance on bad and good IJC announcement days, as well as any other days without IJC announcements, from February 2020 to March 2021 (without 03/19, 03/26, 04/02/2020, and 04/09/2020, as before).

Consistent with our hypothesis, Figure 8 shows that, using any of our COVID-19 impact measures, average daily open-to-close portfolio returns on bad IJC days are positive and higher than those on good or non-IJC days. The bad-IJC daily average return ranges from 10 to 13 basis points, with our main forward-looking measure (changes in online job postings from 2019 to April/May of 2020) giving the largest portfolio return compared to financial measures (revenue or EPS changes). The

[28]It is worth mentioning that, econometrically, the sum of the two correlations from bad IJC days and from good IJC days does not need to add up to that of all IJC days.

average good or non-IJC days returns are often negative with statistical significance, meaning that firms that are more negatively impacted by COVID-19 underperform on days with good or no IJC announcements. Figure A6 in the appendix shows robustness test results using equal weights or using alternative COVID-19 impact proxies.

Lastly, we form portfolios based on several reported firm characteristics and risk proxies pre-COVID (as of the end of 2019); of these, some characteristics have been found 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.

Figure 9 shows that small and value firms and firms with cash shortages outperform when IJC numbers are worse than expected, according to the solid bars. This finding echoes the cash flow pricing channel of fiscal policy expectations, as small and value firms typically exhibit high sensitivity to market cash flow news. When bad labor numbers come out, such firms are expected to have stronger future cash flow growth (in the context of COVID-19, a stronger recovery), as investors anticipate more generous government support. On the other hand, such highly cash-sensitive firms perform worse on good IJC days (shaded bars) or non-announcement days (hollow bars) than on bad IJC days, which is as expected. Highly cash-sensitive firms are more severely impacted by COVID-19; according to our textual analysis evidence, there are fewer FP mentions – which we interpret as lower expectations of FP – on good IJC days; as a result, consistent with our mechanism, highly cash-sensitive firms show lower average returns on non-bad IJC days.

We also sort on firms' pre-COVID leverage or riskiness conditions, where leverage is defined as (long-term debt+short-term debt)/shareholder equity.[29] 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 channel that we document above. When good IJC news comes out, investors may expect monetary policy to tighten, which would be proportionally worse news for highly-leveraged firms. As a result, this MP mechanism does indeed predict highly-leveraged firms' stock prices to be lower, resulting in a positive low-minus-high leverage portfolio return. However, what is more relevant to this paper is whether leverage could be an alternative channel for the "Main Street pain, Wall Street gain" phenomenon. We find weak evidence, as the low-minus-high leverage portfolio shows close to zero and insignificant returns on both bad and non-IJC days.

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

4.4.2. Discussion: Who gets what?

These three cross-sections (bill mentioning, obligated and actual fiscal support, expected COVID-19 damage), that we uniquely constructed or collected from various data sources allow us not only to draw a conclusion with a potential *fiscal*-related interpretation but also to provide collective answers in an ongoing debate: During COVID-19, who gets what? Our cross-section datasets provide insight into this question.

Figure 10 compares stock market presence, expected COVID-19 damage, bill mentions, and obligated fiscal support at the industry level. We first 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-19 impact, subfigure (b) shows that the majority of the industries align with the speculation that industries are mentioned more 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, illustrated in different colors in subfigure (b), stand out. Healthcare industries are among the most mentioned ones due to the nature of the crisis, but their job postings changes do not place them among the most negatively affected firms. The finance and insurance industries are also more frequently mentioned, as we find their keywords when a bill discusses the financial market, banking, and monetary vehicles for households and companies, as well as government intervention programs, such as benefits for workers, promoting economic security, pensions, and housing provision as part of the stimulus actions; the high frequency of mentions of finance is expected. The mining industry experienced severe COVID-19 impacts; given our calculation, an 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 in the other three bills. Robustness results are shown in Figure A7 in the appendix.

The two bottom plots of Figure 10 compare bill mentions and fiscal support, proxied by the fraction of firms in an industry that receive > \$0 fiscal support, shown in subfigure (c), and promised PPP outlays, shown in subfigure (d). Both plots show statistically significant and strongly positive trends, with above 0.6 correlation coefficients. Manufacturing is the only industry that seems to draw a disconnect between its mentions in the actual bills and its received fiscal support.

5. A Conceptual Asset Pricing Framework with a Fiscal Rule

In this section, we provide a conceptual asset pricing framework to reconcile our empirical results, focusing on the pricing channels and cross-sectional heterogeneity. This model builds on Bansal and Yaron (2004) (henceforth, BY2004) but differs from it by introducing a simple fiscal policy rule. We derive the model in closed form.

5.1. Setup

In this general framework, agents derive utility from the macroeconomic condition, G, and overall gross returns, R, with the Epstein and Zin (1989) and Weil (1989) recursive preferences. We focus on deriving the price-dividend ratio and write down the logarithm of the intertemporal marginal rate of substitution (IMRS),

$$m_{t+1} = \theta \log \beta - \frac{\theta}{\psi} g_{t+1} + (\theta - 1) r_{m,t+1}, \tag{4}$$

where g_{t+1} is a real growth rate from period t to $t+1$ and $r_{m,t+1}$ is the observable log return on the market portfolio or the log return on the aggregate dividend claims. The parameters follow the conventional assumptions: $0 < \beta < 1$ is the time discount factor; $\theta \equiv \frac{1-\gamma}{1-\frac{1}{\psi}}$, with $\gamma \geq 0$ being the risk aversion parameter and $\psi \geq 0$ the intertemporal elasticity of substitution (IES) parameter; as discussed in Bansal and Yaron (2004), Epstein-Zin preferences imply that the agents may have preferences for early resolution of uncertainty, which is when $\gamma > \frac{1}{\psi}$, and together with $\gamma > 1$ and $\psi > 1$, θ will be negative.

The modelling of the expected growth process differs from the general consumption-based literature by introducing a fiscal policy expected growth variable, FP_t, to the economy. The government is expected to use its expenditure components to react to changes in output growth; hence, FP_t generally reacts negatively to output growth shocks, and also contains an exogenous, zero-mean white noise disturbance. This fiscal policy follows Pappa (2009), among many others. In this model, we shut down the monetary policy rule for simplicity. The modeling of dividend growth follows the general dynamic process with time-varying expected growth and real growth comovement.

5.2. Dynamic processes

The dynamics of log real growth from period t to $t+1$ (g_{t+1}), growth uncertainty (v_{t+1}), expected growth (x_{t+1}), expected fiscal spending growth (FP_{t+1}), and log dividend growth from period t to

$t+1$ (Δd_{t+1}) are given as follows, respectively:

$$g_{t+1} = \mu_g + x_t + \sqrt{v_t}\varepsilon_{g,t+1}, \tag{5}$$

$$v_{t+1} = \mu_v + \rho_v v_t + \sigma_v \varepsilon_{v,t+1}, \tag{6}$$

$$\boxed{\text{[Long-run risk]}}\ x_{t+1} = \rho_x x_t + \sigma_{xg}\sqrt{v_t}\varepsilon_{g,t+1} + \underbrace{\sigma_{xFP}}_{>0} FP_{t+1} + \sigma_x \varepsilon_{x,t+1}, \tag{7}$$

$$\boxed{\text{[Expected fiscal spending growth]}}\ FP_{t+1} = \underbrace{\sigma_{FPg}}_{<0}\sqrt{v_t}\varepsilon_{g,t+1} + \sigma_{FP}\varepsilon_{FP,t+1}, \tag{8}$$

$$\Delta d_{t+1} = \mu_d + \rho_{dx} x_t + \sigma_{dg}\sqrt{v_t}\varepsilon_{g,t+1} + \sigma_d \varepsilon_{d,t+1}, \tag{9}$$

$$\varepsilon_{g,t+1}, \varepsilon_{v,t+1}, \varepsilon_{x,t+1}, \varepsilon_{FP,t+1}, \varepsilon_{d,t+1} \sim i.i.d\ \text{N(0,1)}.$$

The time-varying conditional variance of output growth is expressed as $v_t = Var_t[g_{t+1}]$. The expected growth process, or the "long-run risk" variable, loads on real growth shock $\varepsilon_{g,t+1}$, (expected) fiscal policy, and an exogenous shock $\varepsilon_{x,t+1}$. Fiscal policy in this economy has four features. (1) The output growth coefficient of the fiscal rule in our context σ_{FPg} is negative, as the fiscal rule is expected to correct the underlying economic condition. (2) The pass-through from the fiscal rule to the expected growth of the economy, σ_{xFP}, is strictly positive, and for simplicity we model σ_{xFP} as a free parameter. (3) Additional heteroskedasticity is also introduced into the economy through FP_{t+1}, in order to realistically capture the fact that an easing or expansionary FP is likely more aggressive when large negative growth shocks are realized. (4) We allow the fiscal rule to contain a discretionary shock, $\varepsilon_{FP,t+1}$. Finally, the dividend growth process (Δd_{t+1}) loads on the real growth shock and an uncorrelated homoskedastic shock (for simplicity).

Besides the introduction of the fiscal rule, our model differs from the BY2004 framework as it now allows for comovement between expected growth state variable x_{t+1} and real shocks $\varepsilon_{g,t+1}$. Dividend growth also now realistically loads on real shocks. This point has been closely discussed in Xu (2021).

All shocks mentioned above ($\varepsilon_{g,t+1}, \varepsilon_{v,t+1}, \varepsilon_{x,t+1}, \varepsilon_{FP,t+1}$, and $\varepsilon_{d,t+1}$) are uncorrelated Gaussian shocks. All σ parameters, or shock loading coefficients, are expected to be positive, except for σ_{FPg} as motivated above.

5.3. Price-dividend ratio

We derive asset prices using the SDF mentioned in Equation (4) and the standard asset pricing condition $E_t[M_{t+1}R_{i,t+1}] = 1$ for any asset $R_{i,t+1}$ (log return $r_{i,t+1}$) including the market return $R_{m,t+1}$ (log market return $r_{m,t+1}$). Given all shocks in the system are conditionally normal, the

Euler equation can be rewritten as follow:

$$E_t\left[\exp\left(\theta\log\beta-\frac{\theta}{\psi}g_{t+1}+(\theta-1)r_{m,t+1}+r_{i,t+1}\right)\right]=1\Leftrightarrow \tag{10}$$

$$E_t\left(\theta\log\beta-\frac{\theta}{\psi}g_{t+1}+(\theta-1)r_{m,t+1}+r_{i,t+1}\right)+\frac{1}{2}V_t\left(\theta\log\beta-\frac{\theta}{\psi}g_{t+1}+(\theta-1)r_{m,t+1}+r_{i,t+1}\right)=0. \tag{11}$$

The relevant state variables in solving for the equilibrium price-dividend ratio are x_t and v_t. We follow Bansal and Yaron (2004)'s approximate solution method (in order to derive a closed-form solution) and conjecture the logarithm of the price-dividend ratio, $z_t = A_0 + A_1x_t + A_2v_t$. We substitute this conjecture into the log market return equation, $r_{m,t+1} = \Delta d_{t+1} + k_0 + k_1z_{t+1} - z_t$, and then to the Euler equation equivalent expression in Equation (11). As the Euler condition must hold for all values of the state variables, it follows that all terms involving x_t and v_t must satisfy these two conditions, respectively:

$$-\frac{\theta}{\psi}+\theta\left[\rho_{dx}+k_1A_1\rho_x-A_1\right]=0, \tag{12}$$

$$\theta(k_1A_2\rho_v-A_2)+\frac{1}{2}\left[-\frac{\theta}{\psi}+\theta\sigma_{dg}+\theta\, k_1A_1\left(\sigma_{xg}+\sigma_{xFP}\sigma_{FPg}\right)\right]^2=0. \tag{13}$$

The highlighted part is where the fiscal rule enters the model, and we discuss the pricing implications in following paragraphs.

Here are the solutions and interpretations under typical BY2004 parameter assumptions (according to their Table IV: $\rho_{dx}=3$, $\psi=1.5$, $\gamma=7.5$ (hence $\theta=-19.5$), $k_1=0.95$, $\rho_x=0.979$, $\rho_v=0.987$, $\sigma_{dg}=4.5$, $\sigma_{xg}=0.044$):

$$A_1=\frac{\rho_{dx}-\frac{1}{\psi}}{1-k_1\rho_x}=33.3576>0. \tag{14}$$

A positive A_1 means that the intertemporal substitution effect dominates the wealth effect, and therefore when expected growth increases, agents buy more risky assets, pushing up the asset prices. The solution for A_2 for all parameter choices of σ_{xFP} and σ_{FPg} is negative:

$$A_2=\theta\frac{\frac{1}{2}\left[-\frac{1}{\psi}+\sigma_{dg}+\, k_1A_1\left(\sigma_{xg}+\sigma_{xFP}\sigma_{FPg}\right)\right]^2}{1-k_1\rho_v}<0. \tag{15}$$

A negative A_2 means that a rise in growth volatility lowers the price-dividend ratio, and a more permanent volatility process (i.e., higher ρ_v) yields a stronger volatility compensation demanded, further lowering the price-dividend ratio.

To be more specific, the price-dividend ratio decreases as the risk premium demanded increases. In this framework, the *sources* of the demanded volatility compensation are dividend risk, long-run risk, and the new fiscal policy risk, which counteracts with the previous two channels, given the negative σ_{xFP}. Intuitively, when bad shocks arrive, the risk premium increases; when there is a fiscal policy expectation in place, it could precisely offset the risk premium effect by introducing a counteracting effect through the expected growth channel x.

Lastly, A_0 is implicitly defined in closed form.

5.4. The equity risk premium and contemporaneous log market returns

Next, we derive the equity risk premium and contemporaneous log market returns, and discuss how fiscal policy enters the equilibrium price (which is highlighted for reading convenience). Given the no-arbitrage condition and that log stock return is quasi-linear with multinormal shock assumptions, the equity risk premium can be solved as follows:

$$
\begin{aligned}
E_t\left(r_{m,t+1} - rf_t\right) + \frac{1}{2}V_t(r_{m,t+1}) &= -Cov_t(m_{t+1}, r_{m,t+1}) \\
&= \underbrace{\left[\frac{\theta}{\psi}\left(\sigma_{dg} + k_1 A_1(\sigma_{xg} + \sigma_{xFP}\sigma_{FPg})\right) + (1-\theta)\left(\sigma_{dg} + k_1 A_1(\sigma_{xg} + \sigma_{xFP}\sigma_{FPg})\right)^2\right]}_{\equiv B_{erp}(\sigma_{FPg})} v_t \\
&\quad + (1-\theta)\left[\sigma_d^2 + (k_1 A_1 \sigma_x)^2 + (k_1 A_1 \sigma_{xFP}\sigma_{FP})^2 + (k_1 A_2 \sigma_v)^2\right].
\end{aligned} \tag{16}
$$

We apply first-order Taylor approximations to the log stock return from $t-1$ to t, as our paper focuses on contemporaneous changes, and hence the log market return process can be written as:

$$
\begin{aligned}
r_{m,t} &= \Delta d_t + k_1 z_t - z_{t-1} + k_0, \\
&= constant + \left[\rho_{dx} + k_1 A_1 \rho_x - A_1\right] x_{t-1} + \left[k_1 A_2 \rho_v - A_2\right] v_{t-1} \\
&\quad + \underbrace{\left[\sigma_{dg} + k_1 A_1\left(\sigma_{xg} + \sigma_{xFP}\sigma_{FPg}\right)\right]}_{\equiv B_r(\sigma_{FPg})\ ①} \sqrt{v_{t-1}}\varepsilon_{g,t} \\
&\quad + \sigma_d \varepsilon_{d,t} + k_1 A_1 \sigma_x \varepsilon_{x,t} + \underbrace{k_1 A_1 \sigma_{xFP}\sigma_{FP}}_{③} \varepsilon_{FP,t} + \underbrace{k_1 A_2 \sigma_v}_{②} \varepsilon_{v,t}.
\end{aligned} \tag{17}
$$

Next, we focus on how fiscal policy expectations play a role in the equilibrium log market return. In a world without the fiscal rule, when bad output news $\varepsilon_{g,t}$ arrives (which is probably also accompanied with positive $\varepsilon_{v,t}$), an increasing risk premium and lower expected future growth lead to decreases in asset prices. The fiscal rule enters the pricing in three ways at the equilibrium:

- ***The expected cash flow channel.*** "①" in Equation (17) demonstrates that fiscal policy could counteract the conventional positive relationship between expected growth (x_t) and the price-dividend ratio (z_t), given $\sigma_{xFP}\sigma_{FPg} < 0$ and $\sigma_{xg} > 0$. As a result, fiscal policy could alter the sign of return loadings on macro news, potentially resulting in a "bad is good" scenario as we observe in the empirical evidence. The effect should increase monotonically with the magnitude of σ_{FPg}.

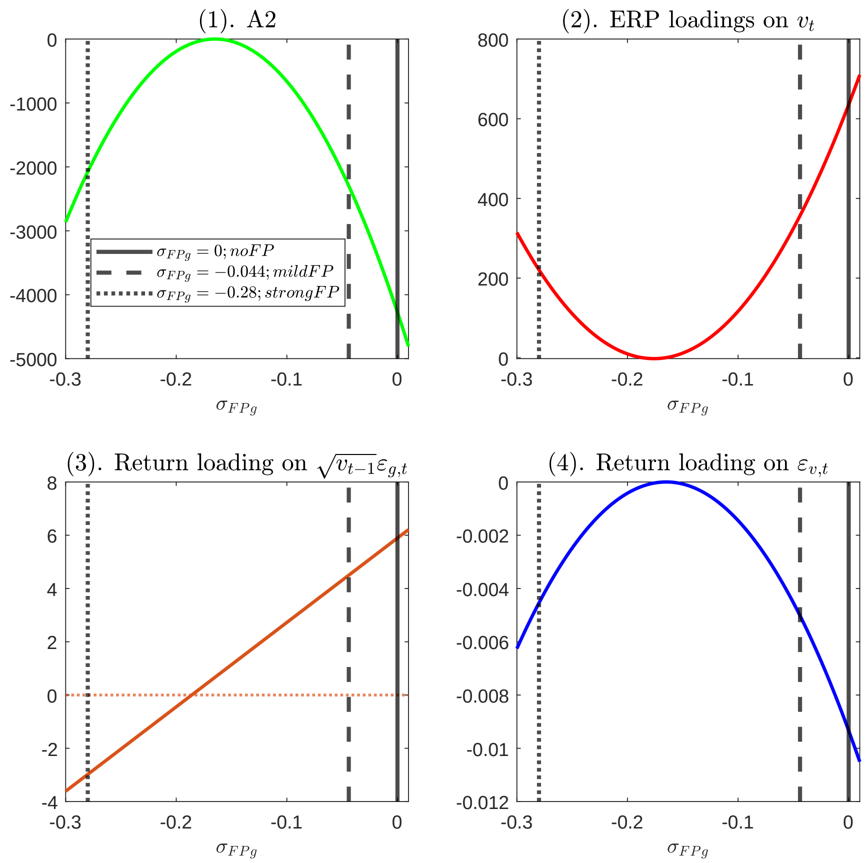
- ***The risk premium channel.*** "②" in Equation (17) demonstrates changes in market prices coming from the risk premium, and the closed-form solution above shows that A_2 is a non-linear function of σ_{FPg}. From Equation (16), fiscal policy could have a non-linear effect on the market compensation for stochastic volatility risk via the long-run risk channel. To understand this risk premium channel better, we simulate the relation between $B_{erp}(\sigma_{FPg})$ and σ_{FPg} using Bansal and Yaron (2004) parameter choices; we discuss more in Section 5.5 below. Overall, the market compensation for bearing volatility risk is always positive, given realistic parameter choices. The relation initially decreases when there is a mild fiscal rule (when σ_{FPg} moves from 0 to a small negative number), precisely due to the counteracting effect in the expected growth channel; however, it eventually increases when there is a very strong fiscal rule (when σ_{FPg} becomes very negative), as the fiscal policy introduces large increases in expected growth and agents demand compensation for the increasing volatility.
- ***Discretionary fiscal shock.*** "③" in Equation (17) shows a discretionary fiscal policy shock that is orthogonal to the fiscal rule in response to the changing macro condition. Given the parameter signs, an unexpected government spending shock drives up stock prices given the higher expected cash flows.

5.5. Calibration

We calibrate the solution using parameters from Bansal and Yaron (2004) and assume the overall market-level pass-through of the fiscal rule to expected growth (σ_{xFP}) is 1. When $\sigma_{FPg} = 0$, there is no fiscal policy rule; when $\sigma_{FPg} = -0.044$, this completely cancels out the standard expected growth loading on macro shock ($\sigma_{xg} = 0.044$), dubbed "mild FP"; when $\sigma_{FPg} = -0.28$, it represents a region where the fiscal rule not only dominates the expected growth loading on macro shock (σ_{xg}) but also the dividend growth loading on macro shock (σ_{dg}), dubbed "strong FP."[30]

Plot (1) in this section shows that price decreases with volatility, as A_2 is always negative given a wide spectrum of σ_{FPg}. Starting from $\sigma_{FPg} = 0$ to its left, the fiscal rule starts to counteract with the volatility risk in the expected growth channel, leading to a smaller A_2 (in magnitude), a lower equity risk premium loading on v_t (as in Plot (2)), and a smaller return loading on volatility shock (as in Plot (4)). As the fiscal rule becomes more aggressive, the "strong FP" case arises, which is likely to closely represent what happened during the COVID-19 crisis – bad macro news may trigger fiscal policy to respond so that the expected growth increases. The magnitudes of A_2, the equity risk

[30]In other words, σ_{FPg} such that $\sigma_{dg} + k_1 A_1(\sigma_{xg} + \sigma_{xFP}\sigma_{FPg}) < 0$.



premium loading on volatility, and return loading on volatility shock rebound through the higher risk compensation demanded given the high fluctuation fiscal policy may introduce to the economy. This rationalizes the **risk premium** channel, the second channel described in Section 5.4. The COVID-19 implication is that the market compensation for stochastic volatility risk increases when a bad macro shock arrives, hence driving down asset prices.

Next, Plot (3) depicts the effect of fiscal policy expectations through the **expected growth** channel, the first channel described in Section 5.4. The initial mild counteracting is intuitive. The COVID-19 scenario is likely represented towards the left/lower end of the spectrum; the implication is that returns could load negatively on the macro shock, as the fiscal rule could precisely offset dividend growth and changes in price-dividend ratio that are driven by changing expected growth.

In summary, when σ_{FPg} is negative enough to change the sign of $B_r(\sigma_{FPg})$ from positive (the "bad is bad" scenario) to negative (the "bad is good" scenario), we should look at the left lower corner of Plot (1). The risk premium increases as σ_{FPg} becomes more active (more negative) precisely because the fiscal rule introduces volatility risk and agents dislike uncertainty. If the risk premium channel dominates, prices should go down when a bad macro shock arrives; however, this is not what we observe in the data during the period of interest. To rationalize the empirical evidence that we document in this paper, the expected growth channel is likely the dominant channel.

It is noteworthy that this model focuses on the pricing channel and assumes fiscal policy expectations with an exogenous dynamic process. We leave more precise modeling of expectations and high-frequency macro announcement dynamics to future research.

5.6. Cross-sectional implications

Our model also has implications for the cross-section. Suppose firm-level expected growth and dividend growth processes are as follows:

$$x^i_{t+1} = \rho^i_x x_t + \sigma^i_{xg}\sqrt{v_t}\varepsilon_{g,t+1} + \sigma^i_{xFP} FP_{t+1} + \sigma^i_x \varepsilon^i_{x,t+1}, \tag{18}$$

$$\Delta d^i_{t+1} = \mu^i_d + \rho^i_{dx} x^i_t + \sigma^i_{dg}\sqrt{v_t}\varepsilon_{g,t+1} + \sigma^i_d \varepsilon^i_{d,t+1}. \tag{19}$$

For our paper, we focus on one particular heterogeneity source: there may be firm-level σ^i_{xFP}, capturing potentially different levels of pass-through of the expected fiscal rule. Following the intuition in Equation (17), it can be easily shown that firms with higher sensitivity to the fiscal rule should exhibit a higher chance of offsetting the standard dividend growth and long-run risk effects of macro news on their stock prices, resulting in a less positive or more negative coefficient in response to macro news.

6. Conclusion

Our paper starts with a surprising observation during the COVID-19 period (2020/02-2021/03): a one standard deviation increase in initial jobless claims (IJC) leads to significantly higher daily major stock index returns of around 30 basis points. This phenomenon (a) appears only when bad news arrives, (b) is stronger for the Dow Jones indices than for the Nasdaq index, (c) prices through the cash flow channel, and (d) builds throughout the morning. Meanwhile, actual IJC news articles in the COVID-19 period show an unprecedented increase in the mentioning of fiscal policy (FP), and this increase is particularly large on bad IJC days. In light of these observations, we propose fiscal policy expectations as the new mechanism in this paper and test our hypothesis both in time series and cross section. In a low interest rate, crisis economy, when Main Street suffers (e.g., the actual IJC number is worse than expected), investors may expect more generous federal government support through fiscal policy, driving up the expected future cash flow growth and aggregate stock return responses. In the cross-section, firms/industries 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. In an external validation exercise across seven mainstream, macro variables announced monthly, we find strong evidence of this phenomenon on labor, manufacturing, and consumption/consumer macro announcement days, and weak evidence among macro variables that are conventionally understood as inputs to the Taylor rule, such as inflation and real growth variables. Adding to our aggregate and cross-firm evidence reported in this paper, this cross-macro variable evidence potentially offers another angle for bringing out the fiscal policy mechanism.

Our paper is among the first to document that investors appear to incorporate fiscal policy expectations into asset pricing, and one particular driver is labor news. Future research should examine the macroeconomic effects and welfare effects of fiscal policy expectations. The fact that people have formed expectations about what we call a "government put" may feed back to the macro economy (e.g., inflation hikes and the Great Resignation) through consumption behaviors, labor options, and borrowing decisions. Moreover, the "Main Street pain, Wall Street gain" phenomenon we document is another example of the "big disconnect" between the real economy and financial markets. While the COVID-19 crisis triggered an unprecedented adverse shock to the labor market, investors' anticipation of fiscal stimulus benefited shareholders. In dollar terms, from February 2020 to March 2021 (the end of our sample), 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. Our work implies that the distributional effect of fiscal policy could also transmit through this "government put" expectation, which gets capitalized at a high frequency. An optimal fiscal stimulus should consider *fiscal policy expectations* for the fairness and overall welfare effects of public policies.

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Table 1: Pricing channels.

This table decomposes the unexpected part of log market returns (or market news) into changes in expectations of future cash flow growth ("NCF", or cash flow news) and changes in expectations of future discount rate ("NDR", or discount rate news). **Periods:** For motivation, we consider two non-overlapping, post-Global Financial Crisis sample periods; the periods are selected based on their zero-lower-bound (ZLB) monetary policy. **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 IJC_t 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 of survey forecasts submitted until shortly before the announcement at time $t-\Delta$. Both actual and expected claims are obtained from Bloomberg. Summary statistics using $IJC_t - E_{t-\Delta}(IJC_t)$ are reported in Appendix Table A2. We exclude identified IJC outlier days (3/19/2020, 3/26/2020, and 4/2/2020). **LHS:** (1) "S&P500" denotes the daily open-to-close log returns (unit: basis points; source: DataStream). Then, we include (2) unexpected returns, (3) NCF, and (4) NDR, all in unit of basis points; the detailed construction method is described in Appendix B. In short, we estimate monthly parameter estimates of the Campbell and Vuolteenaho (2004) framework using monthly data from the past 30 years (1982-2021), and then we impute daily measures using daily data and these parameters. By design, NCF minus NDR yields the total unexpected return. (5) "Gov Bond Return" denotes the daily log bond returns using the long-term Government bond index (unit: basis points; source: DataStream). (6) "Chgs in 10-yr Yield" denotes the first differences in the 10-year Treasury Yield (unit: annual percents; source: DataStream). (7) "Chgs in Treasury IV" denotes the first differences in the Treasury implied volatility (unit: annual percents; source: CBOE). (8, 9) "Chgs in long-term or short-term Fed Funds futures rates" denotes the changes in daily Fed Funds futures rates (unit: annual percents; source: DataStream). **Reporting:** "IJC shock coeff." reports the regression coefficients with robust standard errors and R-squared displayed in 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)	(9)
	S&P500	**Unexpected Return**	**NCF**	**NDR**	**Gov Bond Return**	**Chgs in 10-yr Yield**	**Chgs in Treasury IV**	**Chgs in long-term Fed Funds**	**Chgs in short-term Futures Rates**
Panel A. **"Normal" zero-lower-bound period: 2009/07-2016/12**									
IJC shock coeff.	-97.163	-86.736	-3.993	**82.743***	**174.551*****	**-0.207*****	-1.786	**-0.083*****	0.003
(SE)	(107.303)	(106.271)	(79.224)	**(48.330)**	**(52.324)**	**(0.060)**	(1.813)	**(0.032)**	(0.010)
SD chngs per 1SD shock	-0.042	-0.037	-0.002	**0.037**	**0.168**	**-0.167**	-0.137	**-0.136**	0.019
R2%	0.18%	0.15%	0.00%	**0.55%**	**2.81%**	**2.78%**	1.36%	**1.86%**	0.04%
Panel B. **"Covid" zero-lower-bound period: 2020/02-2021/03**									
IJC shock coeff.	**307.916***	299.961	**298.903****	-1.058	60.588	-0.087	-2.182	-0.024	0.029
(SE)	**(186.945)**	(186.761)	**(133.464)**	(103.733)	(61.521)	(0.066)	(2.342)	(0.020)	(0.022)
SD chngs per 1SD shock	**0.197**	0.192	**0.197**	-0.001	0.132	-0.177	-0.121	-0.112	0.103
R2%	**3.90%**	3.68%	**7.56%**	0.00%	1.75%	3.13%	1.46%	1.25%	1.06%

Table 2: Asymmetry and assets.

This table focuses on the COVID Period (2020/02 to 2021/03, the end of our sample) and provides further evidence on the source and asymmetry of the "Main Street pain, Wall Street gain" phenomenon. 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%.

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

	S&P500	**Unexpected Return**	**NCF**	**NDR**	**Nasdaq100**	**DowJones65**	**DowJones30 Indus.**	**DowJones20 Transp.**	**DowJones15 Util.**
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
R2%	**15.97%**	**15.68%**	**17.40%**	1.97%	7.56%	**15.33%**	**14.97%**	**10.31%**	5.32%

Panel B. Sample: Good IJC days (actual jobless claims are lower than expected; 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
R2%	0.48%	0.48%	0.13%	0.67%	0.00%	1.99%	2.54%	1.07%	1.75%

Table 3: High-frequency evidence using E-mini Dow futures prices.

This table provides the intradaily return responses of E-mini Dow futures prices on IJC shocks. Intradaily 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.	-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

Table 4: Relationship between return responses and topic mentions from rolling windows: All IJC days.

This table examines the relationship between return responses to IJC shocks and topic mentions using rolling windows of 80 IJC days. Three return responses are considered – rolling S&P 500 return coefficient, rolling S&P 500 economic magnitude (SD changes in returns given a 1 SD IJC shock), and rolling Dow Jones 65 return coefficient. Each topic mentions variable (fiscal policy (FP), monetary policy (MP), and uncertainty (UNC); see Section 3.1 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. Appendix Table A8 provides more robustness tests. ***, p-value <1%; **, <5%; *, <10%.

	(1)	(2)	(3)	(4)
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**
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 5: Relationship between return responses and topic mentions from rolling windows: Asymmetry.

This table examines the relationship between return responses to IJC shocks and topic mentions using rolling windows of 40 bad IJC days in Panel A and 40 good IJC days in Panel B. Three return responses are considered – rolling S&P 500 return coefficient, rolling S&P 500 economic magnitude (SD changes in returns given a 1 SD IJC shock), and rolling Dow Jones 65 return coefficient. Each topic mentions variable (fiscal policy (FP), monetary policy (MP), uncertainty (UNC); see Section 3.1 for 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. Appendix Table A8 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 6: Mechanism evidence using non-overlapping state variables.

This table reports the following regression results:

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

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). Time series of all quarterly state variables are shown in Figure A3; due to news file availability, our sample runs from 2013Q1 to 2021Q1. Univariate regression results are shown in Appendix Table A9. We drop quarters when textual UNC mentions are missing. ***, 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**
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 7: Cross-section evidence: COVID-19 stimulus spending at the firm level.

This table regresses the individual return-IJC shock correlation on the COVID-19 relief funding promised or provided by the U.S. government, at the firm level. (Note that this correlation is statistically equivalent to “SD changes in returns given 1 SD IJC shock.”) In Panels A and B, we use the log of the COVID-funding dollar amount and a measure that controls for size and skewness, respectively:

$$\text{Panel A: } Corr^i = \beta_0 + \beta_1 log(1 + Covid\_Funding^i) + \epsilon^i;$$

$$\text{Panel B: } Corr^i = \beta_0 + \beta_1 Rank\left(\frac{Covid\_Funding^i}{2019Revenue^i}\right) + \epsilon^i.$$

Columns (1) and (2) use the *obligated* amount (i.e., promised awards) of all COVID-19 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. ***, 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) All	(2) Positive	(3) All	(4) Positive	(5) All	(6) Positive
	Panel A: Dependent Variable: $log(1 + Covid\_Funding^i)$					
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)
Obs	498	498	498	498	498	498
	Panel B: Dependent Variable: $Rank(\frac{Covid\_Funding^i}{2019Revenue^i})$					
Coefficient β_1	3.661*	3.715**	4.242**	4.281**	4.586**	4.398**
(SE)	(1.867)	(1.867)	(1.865)	(1.864)	(1.916)	(1.906)
Obs	498	498	498	498	498	498

Table 8: Cross-section evidence: COVID-19 impact measures at the firm level.

This table uses economic magnitude (SD changes in returns given a 1 SD IJC shock, or, equivalently, return-IJC shock correlation) as our main return response DV so that it can be used to compare across firms; the sample uses IJC announcement days from February 2020 to March 2021 (excluding 03/19, 03/26, 04/02, and 04/09/2020, as motivated in the paper); 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. For (1), the online job posting data 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 Appendix Table A10. Standard errors are reported in parentheses; ***, p-value <1%; **, <5%; *, <10%.

	Dependent Variable:	**SD changes in individual stock returns given 1 SD IJC shock**		
	DV calculation sample:	**All-IJC**	**Bad-IJC**	**Good-IJC**
	DV Mean:	0.141	0.176	-0.075
	DV SD:	0.114	0.153	0.155
		b_{All}	b_{Bad}	b_{Good}
1 (Main Measure)	Job Postings Change; 2019 Average-2020 April&May Average , 4-digit NAICS	**-0.089*** (0.023)**	**-0.115*** (0.032)**	0.028 (0.037)
2	Employment Change; FY 2019-2020	**-0.060*** (0.017)**	**-0.053** (0.024)**	**0.102*** (0.024)**
3	Revenue Change; 2019Q2-2020Q2	**-0.081*** (0.018)**	**-0.062*** (0.024)**	**0.102*** (0.024)**
4	EPS Change; 2019Q2-2020Q2	**-0.080*** (0.017)**	**-0.070*** (0.024)**	0.018 (0.023)
5	Revenue Change FY2019-2020	**-0.105*** (0.017)**	**-0.071*** (0.024)**	**0.088*** (0.024)**
6	EPS Change FY 2019-2020	**-0.056** (0.018)**	-0.037 (0.025)	0.044 (0.023)

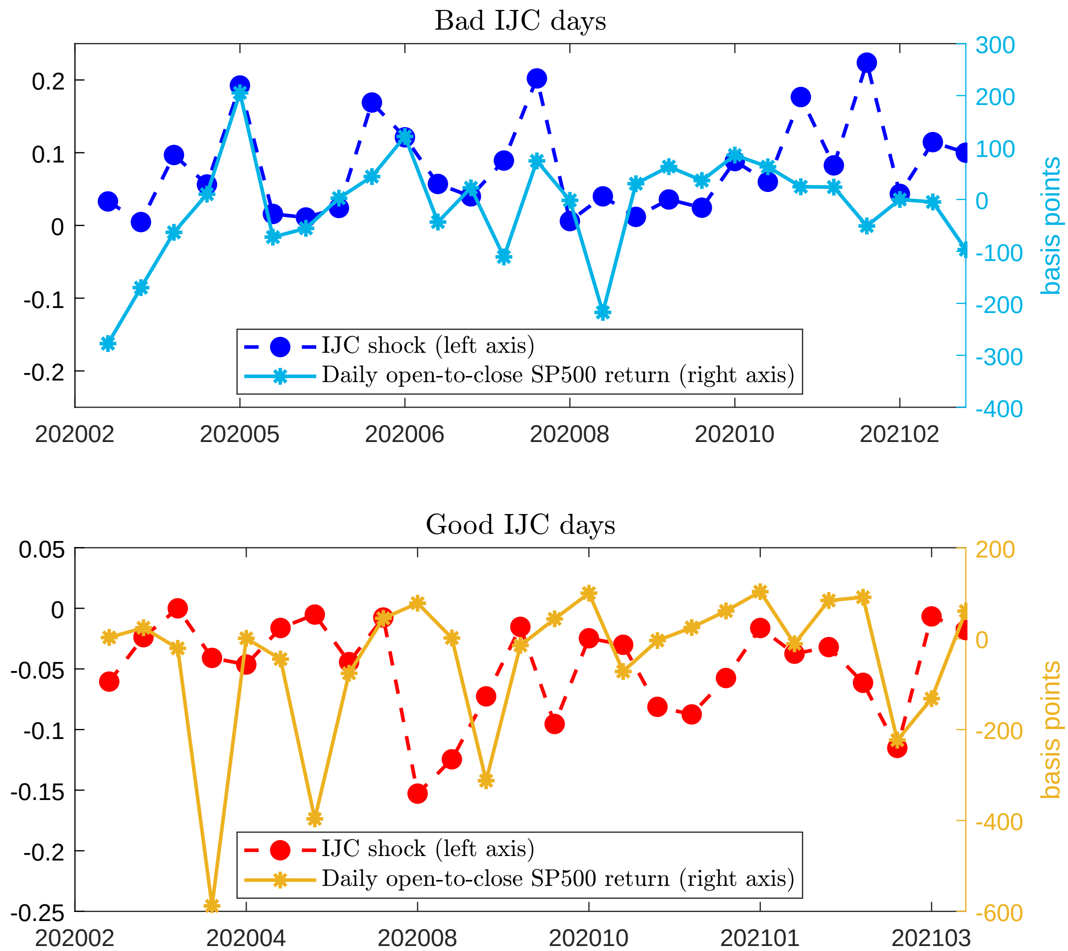


Figure 1: Relation between daily open-to-close S&P500 returns and IJC shocks during the COVID Period of interest (2020/02-2021/03), excluding IJC shock outliers (2020/3/19, 3/26, 4/2), FOMC days, and other major Federal Reserve announcements (2020/4/9).

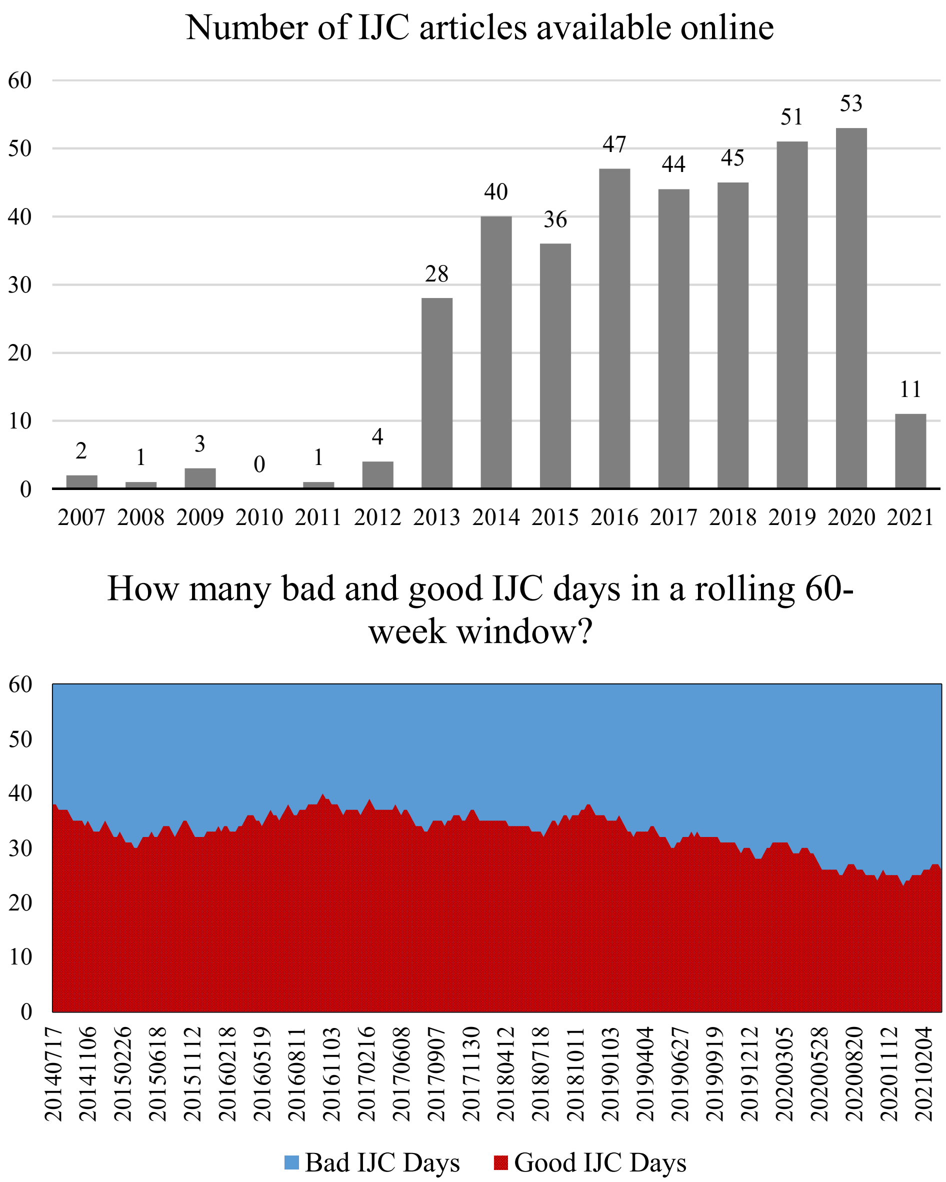


Figure 2: Summary of CNBC jobless claim articles through the IJC announcement date on 2021/3/18 (the end of our sample).

The data collection process is described in Section 3.1 and additional description is available in Appendix C. 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/.

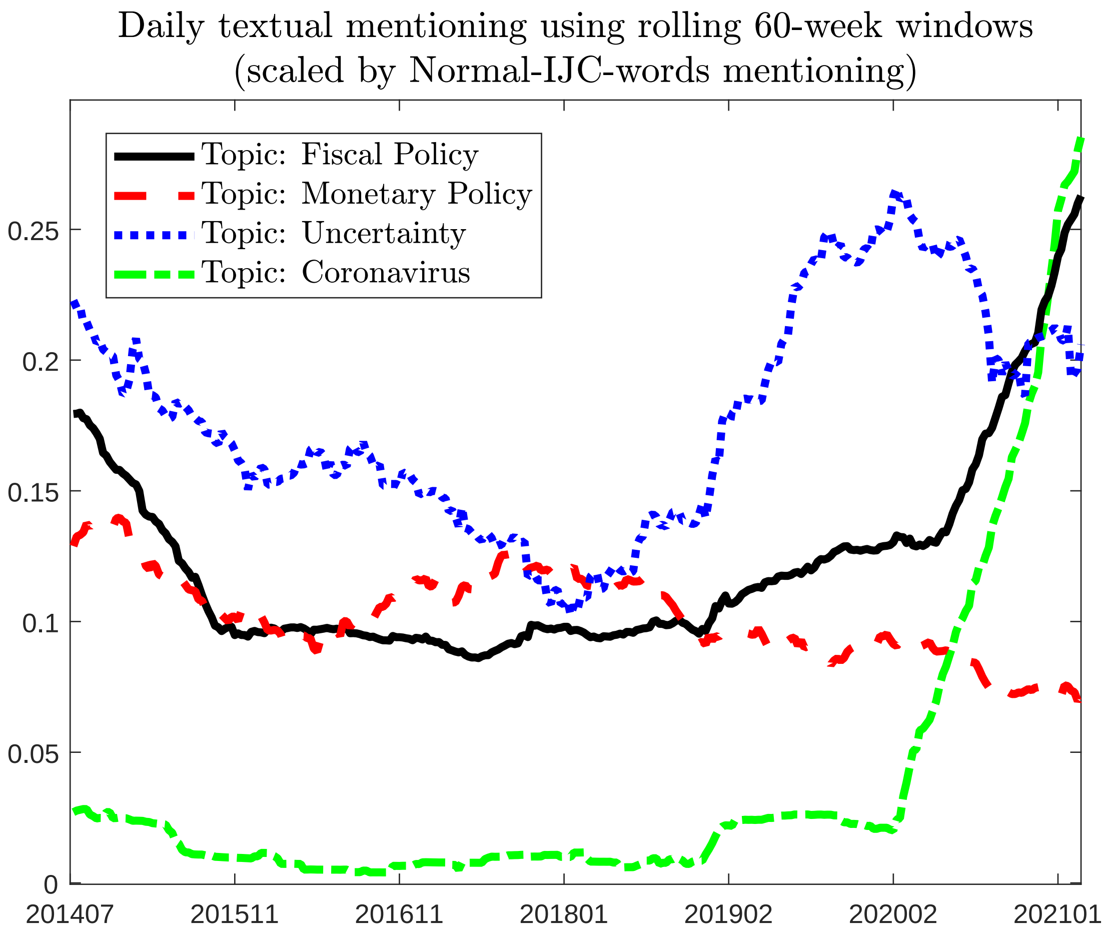


Figure 3: What do people talk about on IJC announcement days?

This figure shows the topic mentions obtained from rolling 60-week windows, where the four topic mentions are scaled by the mentions of normal IJC words (see Section 3.1 and Appendix C for more details). The "0.2" in the y-axis means that this topic's keywords are mentioned 20 times per 100 normal IJC words. The datestamp always refers to the last day of the rolling window.

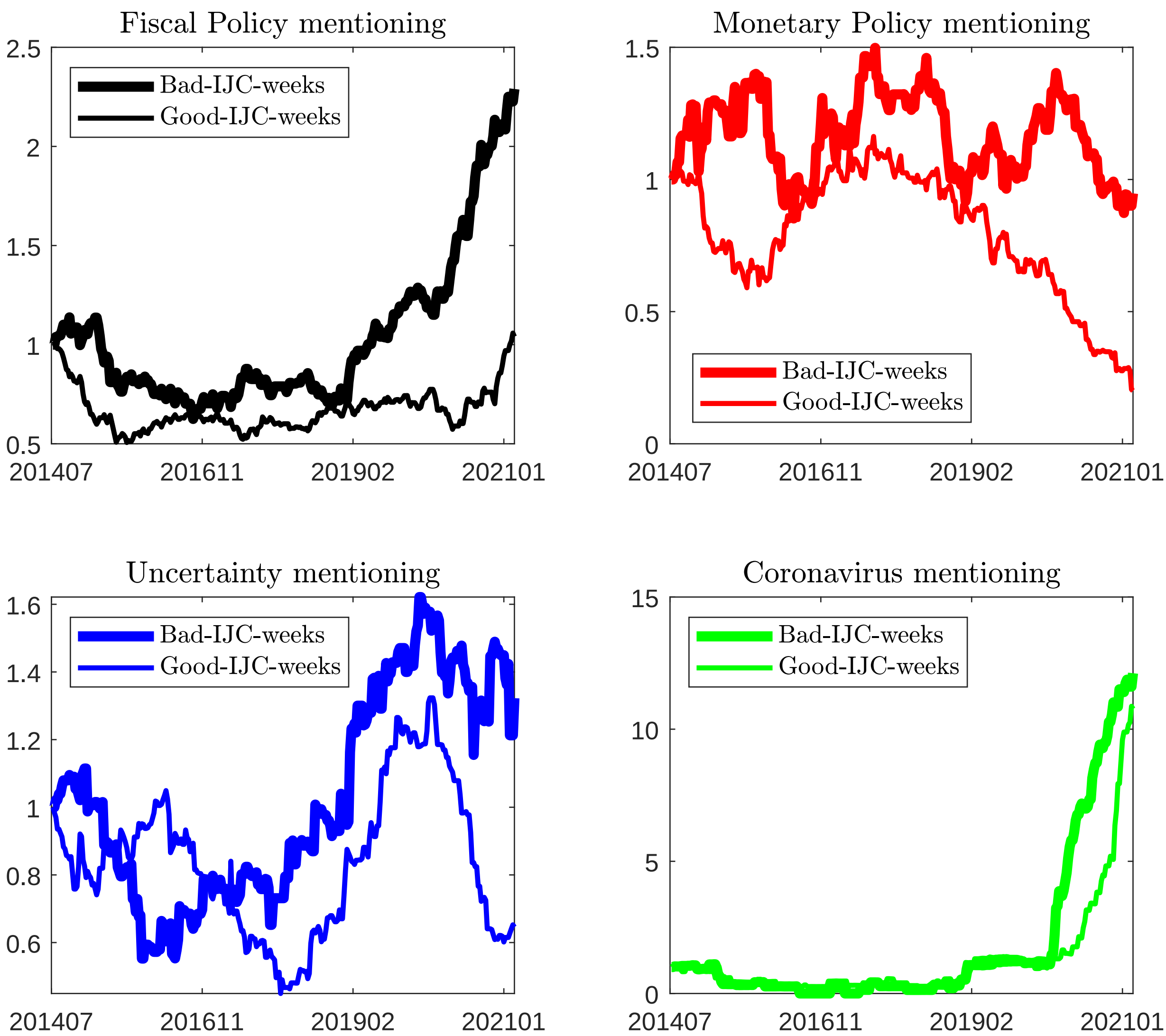


Figure 4: What do people talk about on bad and good IJC announcement days?

This table complements Figure 3 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, as in Table A7. The "1.5" means that mentions of this topic during (e.g.) bad days are 50% higher than at the beginning of the sample. The datestamp always refers to the last day of the rolling window.

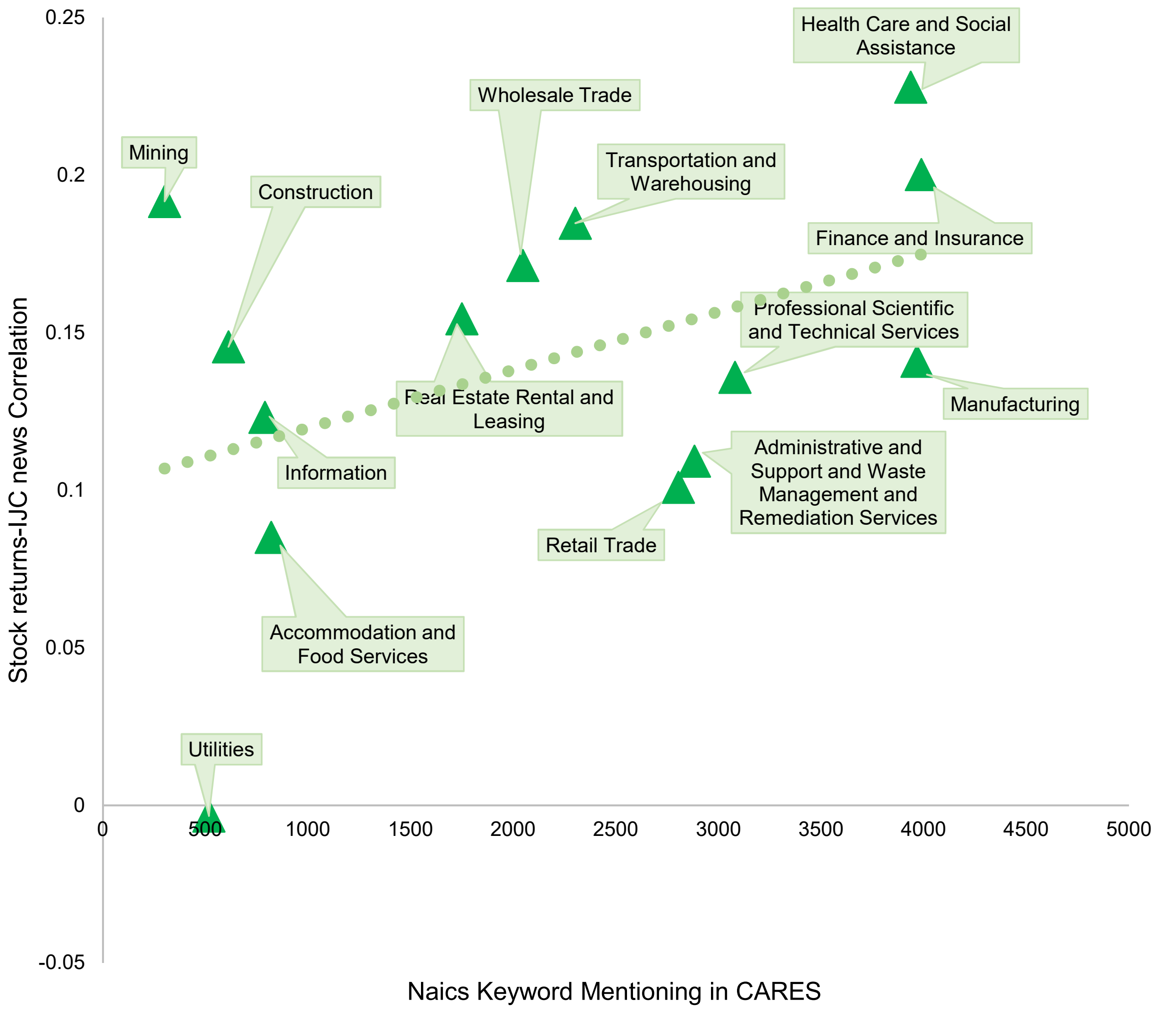


Figure 5: Cross-section evidence: Industry bill mentions and return-IJC correlations.

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. **Construct 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 are therefore excluded from this cross-sectional analysis. **Construct 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 U.S. Congress 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, 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 A4, 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).

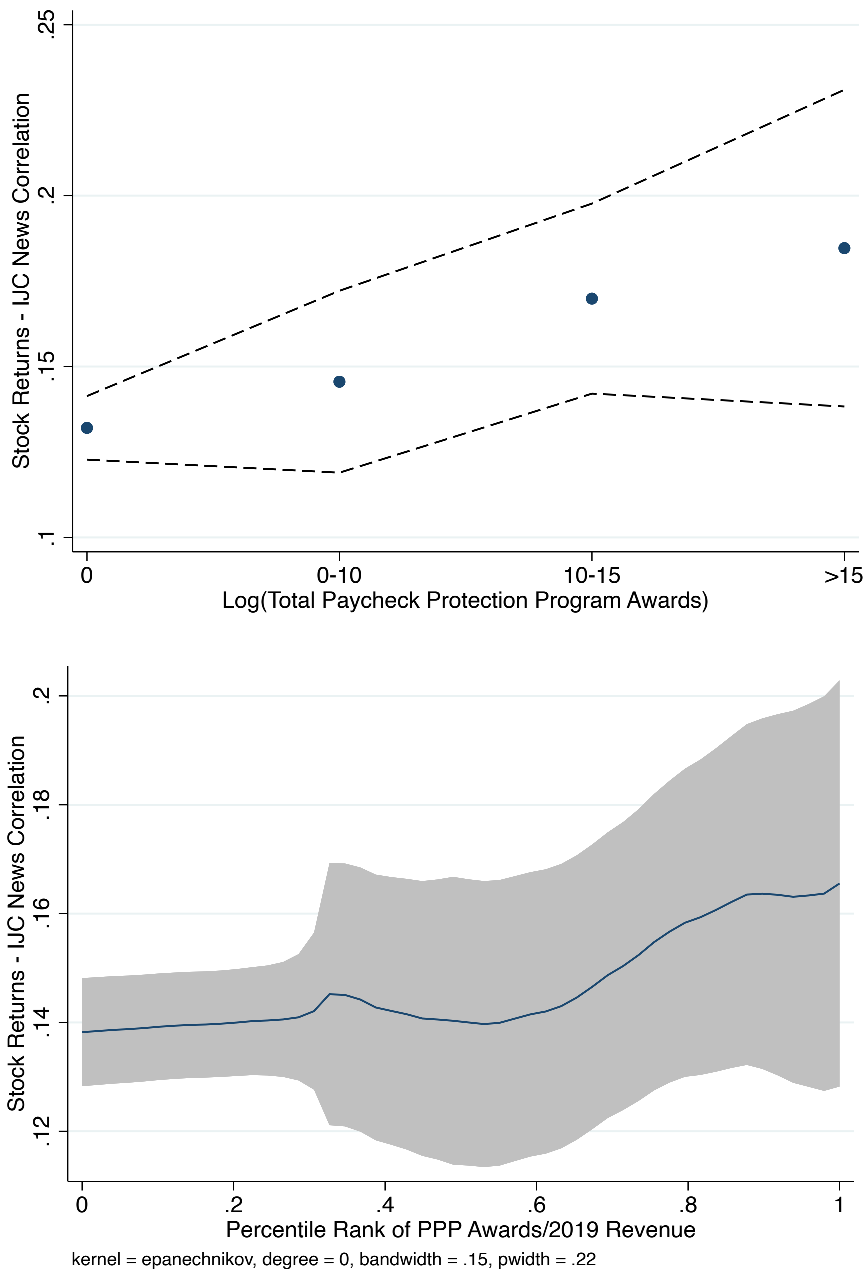


Figure 6: Cross-section evidence: Obligated Paycheck Protection Program awards and return-IJC correlations.

This figure depicts the relationship between return-IJC correlations and COVID-related funding awards. The top panel shows the average return-IJC shock correlations of four groups of firms sorted by their obligated paycheck protection program (PPP) award amounts: 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. The bottom panel plots the nonlinear relationship between the correlation and percentile rank of the PPP award scaled by 2019 revenue with kernel-weighted local polynomial smoothing. The company sample contains 498 companies in S&P 500.

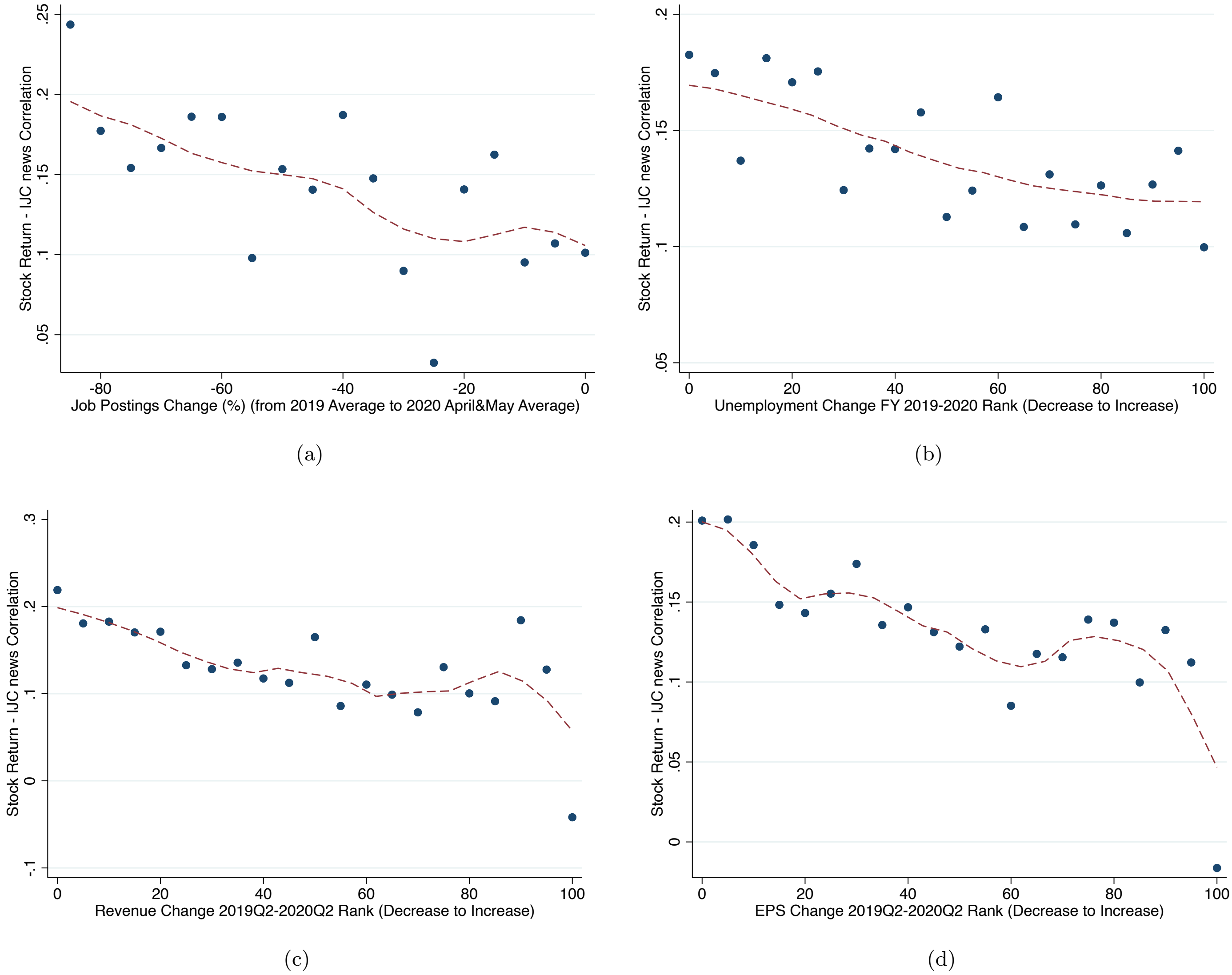


Figure 7: Cross-section evidence: COVID-19 damage and return-IJC correlations.

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). 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., moving more towards 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 "-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 as shown in Appendix Table A10.

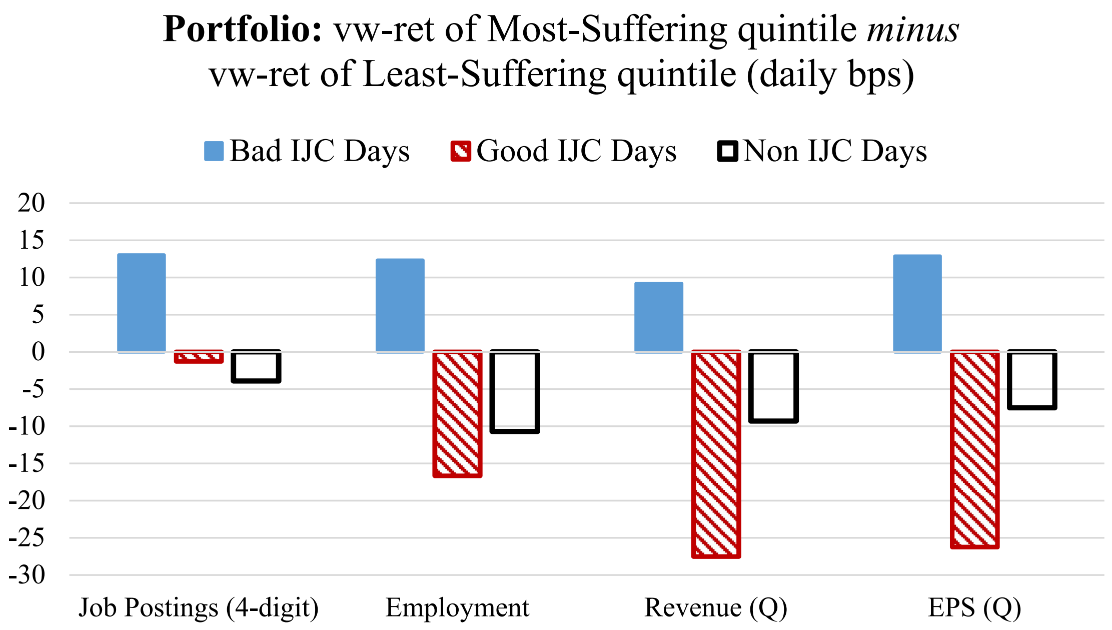


Figure 8: Investment strategy.

Step 1: We sort S&P500 firms into 5 bins based on our four main "firm COVID impact" measures as in Figure 7 and Table 8: (1) changes in the number of all-internet job postings (LinkUp; authors' calculation), (2) employment changes from FY 2019 to FY 2020 (Compustat), (3) revenue changes from 2019Q2 to 2020Q2 (Compustat), (4) EPS changes from 2019Q2 to 2020Q2 (Compustat). Step 2: We call the 1st (5th) quintile the "Most-Suffering" ("Least-Suffering") quintile and obtain value-weighted daily open-to-close returns for each quintile bin. Step 3: The portfolio takes the return difference between the Most-Suffering and the Least-Suffering quintile bins. Step 4: Within each quintile, 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, using alternative COVID impact proxies, and including these four dates are shown in Figure A6 in the appendix.

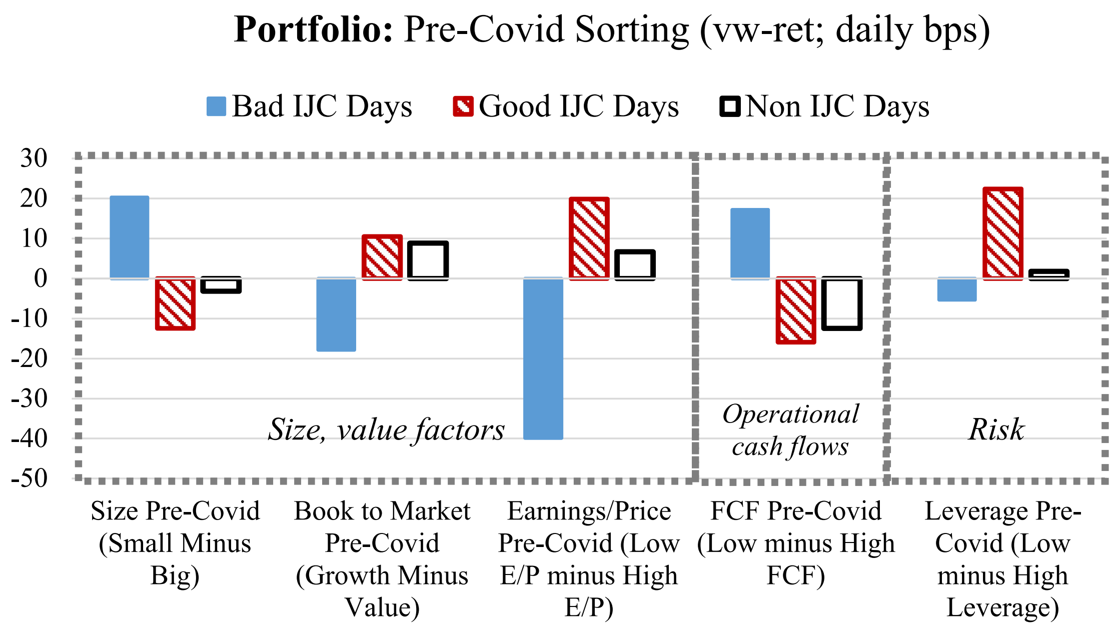
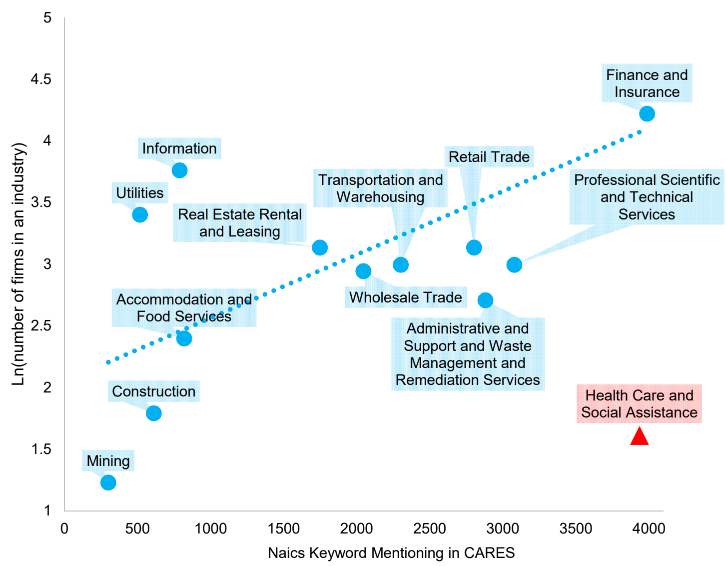
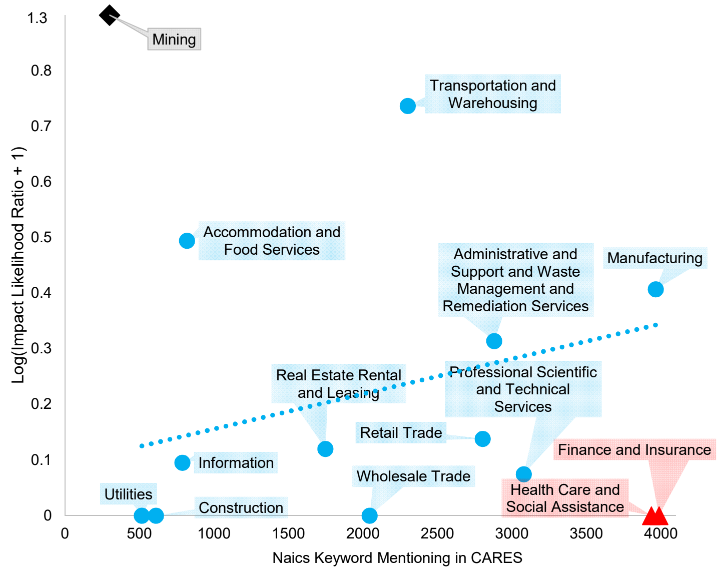


Figure 9: Standard firm characteristics.

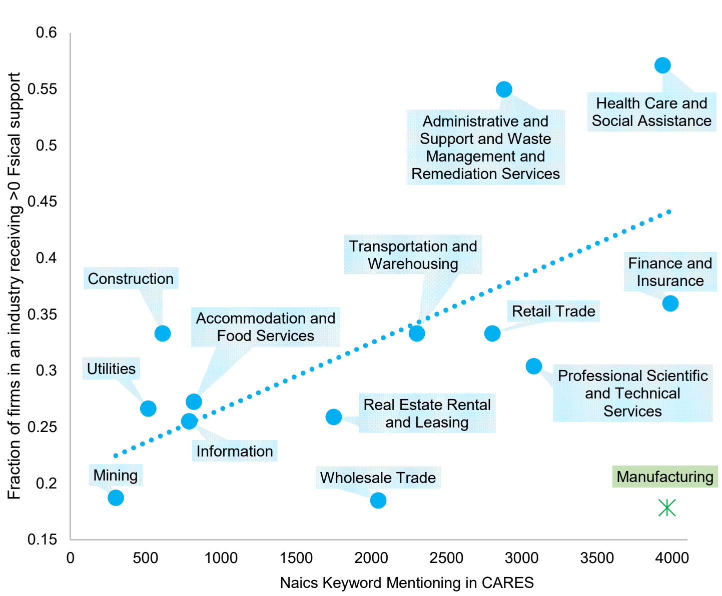
We sort S&P500 firms into 5 bins based on firms' end-of-2019 characteristics: (1) standard size and value factor (B/M, E/P); (2) free cash flows (FCF=operating cash flow (OANCF)-gross capital expenditures (CAPX)); (3) risk (leverage=(long-term debt+short-term debt)/share holder equity). The portfolio takes the return difference between the lowest (lowest-size, lowest-BM, lowest-EP, lowest-FCF, lowest-leverage) and the highest quintile bins. See other figure details in Figure 8.



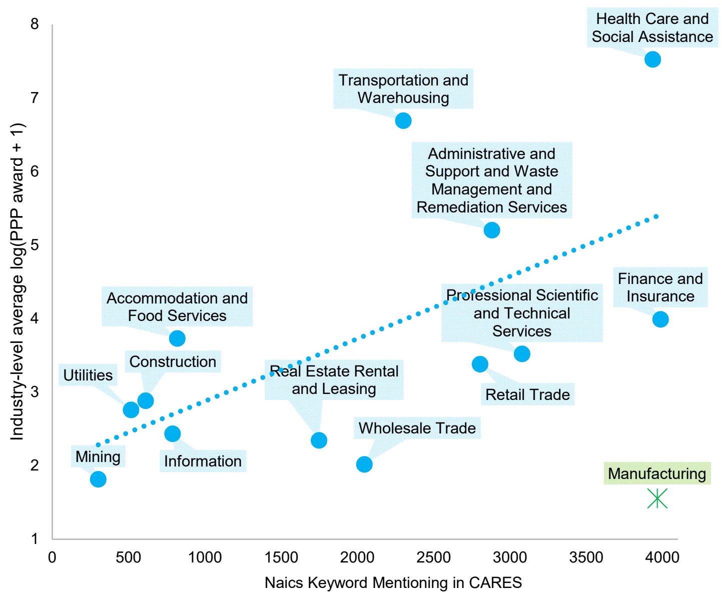
(a) y-axis: Industry presence in S&P500 (our 491 firm pool)



(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 10: Comparison across three cross-sectional dimensions at the industry level: Who get what?

This figure compares an industry's bill mentions with (a) its presence in the stock market, (b) its expected COVID-19 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-19 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.

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A. Additional Tables and Figures

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 accounces 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
	(continue next page)

		(continue previous page)
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: 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 A3: High-frequency evidence using interest rate futures prices.

This table complements Table 3 and tests whether the main bad IJC day results appear in discount-rate-related asset prices (interest rate futures prices). Panel A uses first differences in the 30-day Fed Fund futures (ticker symbol ZQ), as the index is directly related to the inverse of the expected Fed Funds rate; Panel B uses log changes in the 10-year Treasury note futures prices (ticker symbol ZN). In both panels, the higher the futures prices, the lower the rate or yields in expectations. All contracts are traded on the Chicago Mercantile Exchange (CME), and the merge with our IJC data requires adjusting the time zones. High-frequency futures data are from Tick Data. See other table details in Table 3. ***, 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. 30-day Fed Fund Futures price (LHS: first-differences×100); Bad IJC days								
IJC shock coeff.	0.057	-0.251	0.255	0.206	0.011	0.011	-1.302	-2.808
(SE)	(0.259)	(0.196)	(0.410)	(0.479)	(0.451)	(0.451)	(2.189)	(3.326)
SD chngs per 1SD shock	0.018	-0.068	0.045	0.032	0.005	0.005	-0.130	-0.187
Closeness (Covid-normal)?					-0.09	0.53	-0.70	-0.90
Panel B. 10-year Treasury Note Futures price (LHS: returns in basis points); Bad IJC days								
IJC shock coeff.	9.928	58.874**	50.651	103.110	7.338	9.611	49.452	19.164
(SE)	(12.628)	(28.938)	(54.313)	(68.489)	(11.704)	(12.704)	(33.426)	(35.277)
SD chngs per 1SD shock	0.049	0.147	0.065	0.102	0.123	0.139	0.226	0.082
Closeness (Covid-normal)?					-0.15	-1.56	-0.02	-1.09

Table A4: High-frequency evidence using E-mini S&P 500 futures prices.

This table complements Table 3 and provides the intradaily return responses of E-mini S&P 500 futures on IJC shocks. Intradaily 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 the close, 3:30 p.m. ET. The left four columns display results using the Normal Period, which is a generally normal period in which the rate was largely at the zero lower bound (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 coefficient and the Normal coefficient, with bold t-stats indicating one-sided 10% significance. High-frequency futures data are from Tick Data. See other notation details in Table 3.

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 A5: 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 Table A2 for the 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 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**
	R2%	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
	R2%	**2.59%**	**14.85%**	**3.97%**	3.25%	**5.28%**	0.19%

Table A6: 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
R2%	**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
R2%	0.48%	0.13%	0.67%	0.48%	0.00%	1.99%	2.54%	1.07%	1.75%

Table A7: What do people talk about on IJC announcement days?

This table complements Figure 4 and provides exact relative topic mentions values in six non-overlapping subsamples from 2013-2021. Each subsample has (around) 60 weeks; block "All days" uses all 60 weeks to compute topic mentions, and block "Bad days" ("Good days") uses bad (good) IJC days within the same 60-week subsample. **Panel A** reports text mentions relative to the first subsample in 2013-2014. Five topics are considered; standard errors are reported in parentheses, and the closeness test examines whether this value equals 1 (***, p-value <1%; **, <5%; *, <10%). Note that Figure 4 provides a continuously rolling version of bad and good relative mentions. **Panel B** provides the t statistics on whether the relative mentions of a given topic on bad days is the same as that topic's mentions on good days (i.e., the higher the t, the higher relative mentioning on bad days; 2.28** in row "Fiscal policy" means that 2.013*** from bad IJC days is significantly higher than 1.242 from good IJC days). **Text data:** The original news articles are manually obtained from `www.cnbc.com/jobless-claims/`; see details of textual analysis in Section 3 and Appendix C.

	(1)	(2)	(3)	(4)	(5)	(6)
Start Date (exclude)	20130110	20141023	20160505	20170817	20181206	20200130
End Date (include)	20141023	20160505	20170817	20181206	20200130	20210318
Panel A. Relative mentioning and closeness to beginning of the sample (2013-14)						
All days: Fiscal policy	1	0.710	0.707	0.728	0.974	**1.568*** **
(SE)		(0.211)	(0.211)	(0.208)	(0.231)	**(0.198)**
All days: Monetary policy	1	0.824	1.158	0.873	0.859	**0.510*** **
(SE)		(0.271)	(0.288)	(0.266)	(0.213)	**(0.165)**
All days: Uncertainty	1	0.930	0.815	0.821	1.499	0.979
(SE)		(0.569)	(0.424)	(0.503)	(0.748)	(0.600)
All days: Coronavirus-related	1	**0.222*** **	**0.472** **	**0.365** **	0.949	**10.125*** **
(SE)		**(0.222)**	**(0.239)**	**(0.284)**	(0.685)	**(1.791)**
All days: Normal IJC	1	1.175	1.275	1.210	1.217	0.961
(SE)		(0.200)	(0.222)	(0.199)	(0.195)	(0.150)
Bad days: Fiscal policy	1	0.671	0.772	**0.631* **	1.081	**2.013*** **
(SE)		(0.216)	(0.238)	**(0.204)**	(0.278)	**(0.300)**
Bad days:Monetary policy	1	0.886	1.196	0.816	1.022	0.773
(SE)		(0.299)	(0.350)	(0.302)	(0.266)	(0.281)
Bad days:Uncertainty	1	0.529	0.752	0.849	1.452	1.207
(SE)		(0.324)	(0.461)	(0.520)	(0.642)	(0.739)
Bad days:Coronavirus-related	1	**0.257*** **	**0.130*** **	**0.284** **	1.151	**11.548*** **
(SE)		**(0.257)**	**(0.130)**	**(0.284)**	(0.831)	**(2.593)**
Bad days:Normal	1	1.156	1.329	1.181	1.375*	1.248
(SE)		(0.193)	(0.235)	(0.198)	(0.221)	(0.198)
Good days: Fiscal policy	1	0.717	**0.636* **	0.793	0.873	1.242
(SE)		(0.215)	**(0.192)**	(0.217)	(0.207)	(0.156)
Good days: Monetary policy	1	0.783	1.065	0.936	0.707	**0.204*** **
(SE)		(0.290)	(0.290)	(0.273)	(0.216)	**(0.116)**
Good days: Uncertainty	1	1.187	0.677	0.781	1.402	0.763
(SE)		(0.727)	(0.414)	(0.478)	(0.859)	(0.467)
Good days: Coronavirus-related	1	**0.259*** **	**0.400* **	0.443	0.986	**10.727*** **
(SE)		**(0.259)**	(0.311)	(0.345)	(0.713)	**(1.850)**
Good days: Normal IJC	1	1.168	1.174	1.197	1.073	**0.741** **
(SE)		(0.202)	(0.202)	(0.196)	(0.172)	(0.114)
Panel B. Closeness between relative mentions during bad and good IJC days						
Fiscal policy	-	-0.15	0.44	-0.54	0.60	**2.28** **
Monetary policy	-	0.25	0.29	-0.29	0.92	1.87
Uncertainty	-	-0.83	0.12	0.10	0.05	0.51
Coronavirus	-	-0.01	-0.80	-0.36	0.15	0.26

Table A8: Robustness evidence for Tables 4 and 5: The relationship between return responses and topic mentions from rolling windows.

This table complements Tables 4 and 5 and shows 3 more robustness results, namely Robustness (4)-(6). To summarize:

- Robustness (1), (2), and (3) are already reported in Tables 4 and 5: using economic magnitude (in standard deviation rather than in 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 (not just drop the rolling window sample that ends with 2020/4/9). 2020/4/9 is a date with a series of new Federal Reserve announcements regarding CARES 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 4.
- 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 5.

See other table details in Table 5. ***, 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	
R2 Ordinary	61.2%	63.1%	56.3%	57.5%	54.4%	63.9%	48.0%
R2 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	
R2 Ordinary	57.5%	57.5%	57.5%	57.5%	57.5%	57.5%	57.5%	57.5%
R2 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 A9: Robustness evidence for Table 6: Mechanism and quarterly state variables.

This table reports the following regression results:

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

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). Time series of all quarterly state variables are shown in Figure A3; due to news file availability, sample runs from 2013Q1 to 2021Q1. ***, p-value <1%; **, <5%; *, <10%.

	Panel A. Bad IJC days					Panel B. Good IJC days				
▶ **Quarterly state variable (standardized):**	**FP**	**MP**	**UNC**	$\boldsymbol{\Delta Tbill3m}$	$\boldsymbol{\Delta Recess}$	**FP**	**MP**	**UNC**	$\boldsymbol{\Delta Tbill3m}$	$\boldsymbol{\Delta Recess}$
▶ *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 A10: 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 A11: Cumulative and average daily capital gains in the US 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 is 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 A2 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)

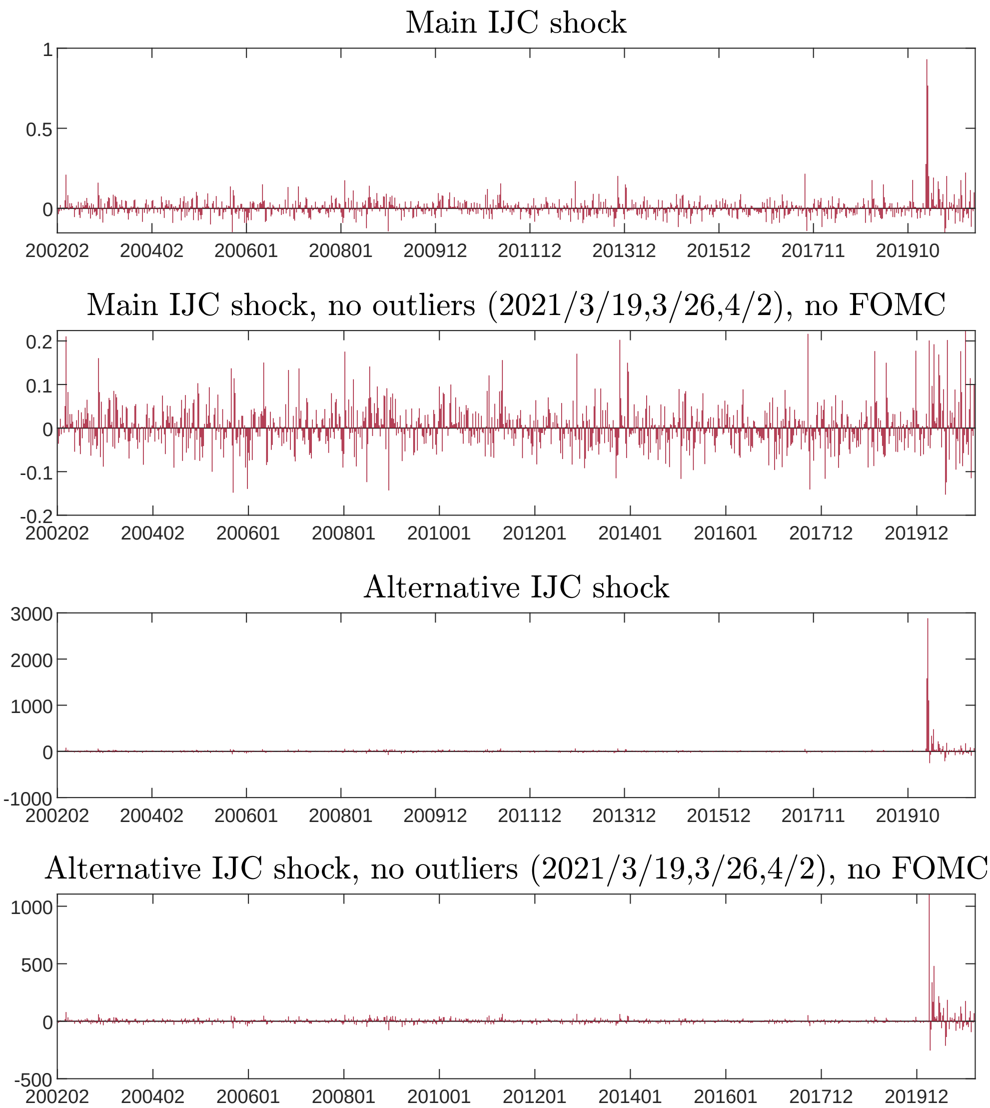


Figure A1: Time series of main IJC shocks ($\frac{IJC_t - E_{t-\Delta}(IJC_t)}{E_{t-\Delta}(IJC_t)}$) and alternative IJC shocks ($IJC_t - E_{t-\Delta}(IJC_t)$), with or without the identified outliers and FOMC days.

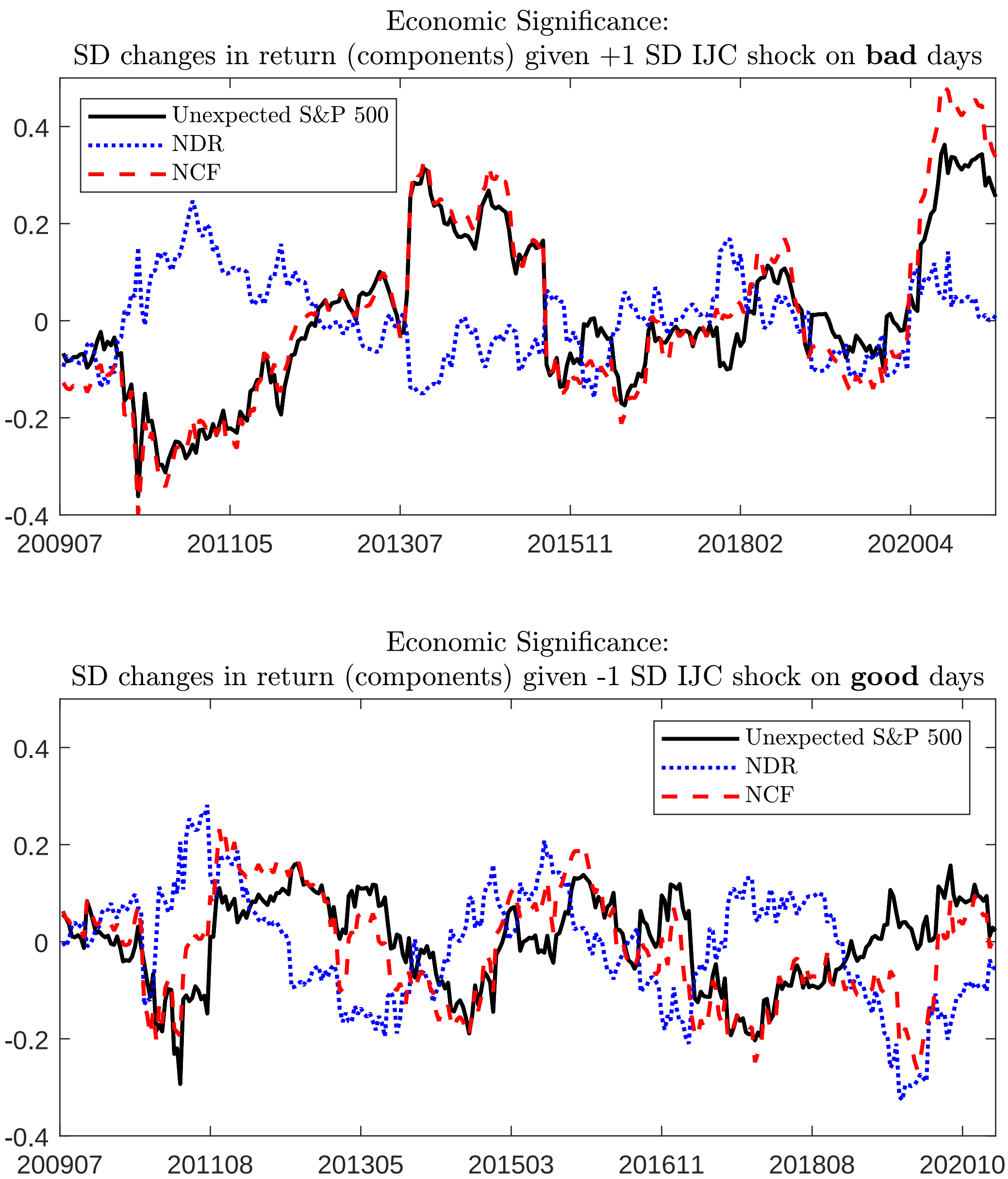


Figure A2: Time variation in return responses to IJC shocks on bad and good IJC days: NCF and NDR.

This figure focuses on the economic magnitude of return responses (SD changes in returns given a 1 SD shock), obtained from a rolling window of 40 bad or 40 good IJC weeks, which is consistent Table 5. The datestamp always refers to the last day of the rolling window. Top plot: if "bad is bad," risky asset returns should *decrease* given a +1 SD IJC shock (jobless claims are higher/worse than expected). Bottom plot: if "good is good," risky asset returns should *increase* given a -1 SD IJC shock (jobless claims are lower/better than expected).

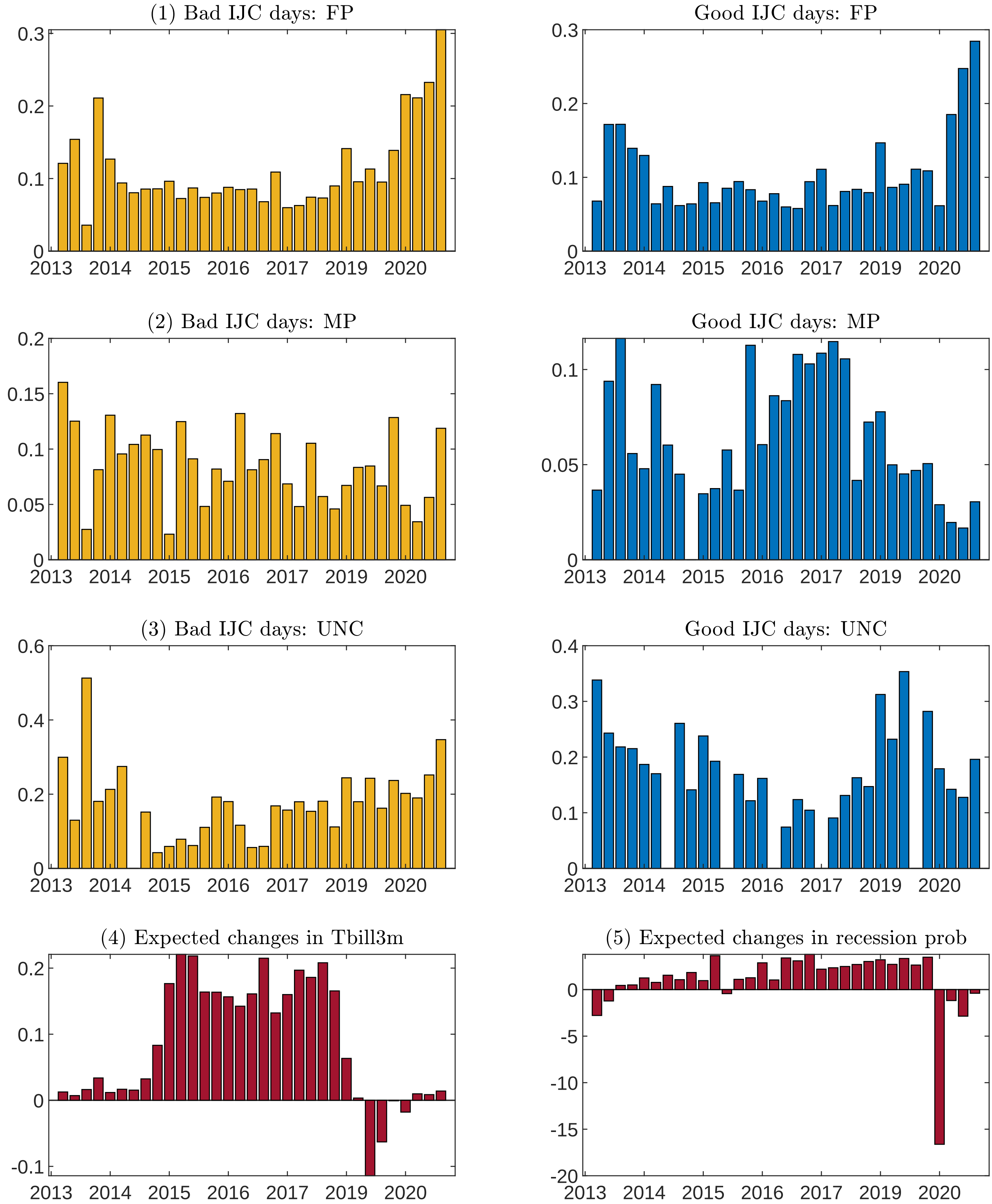
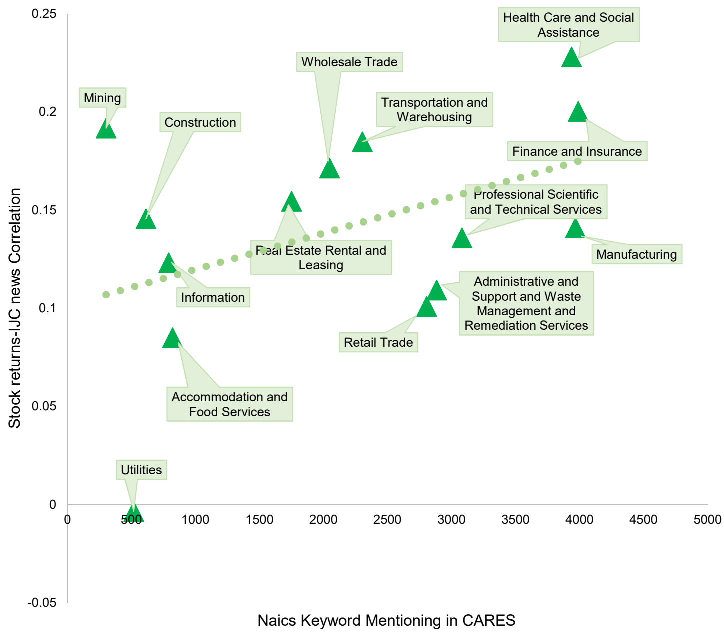
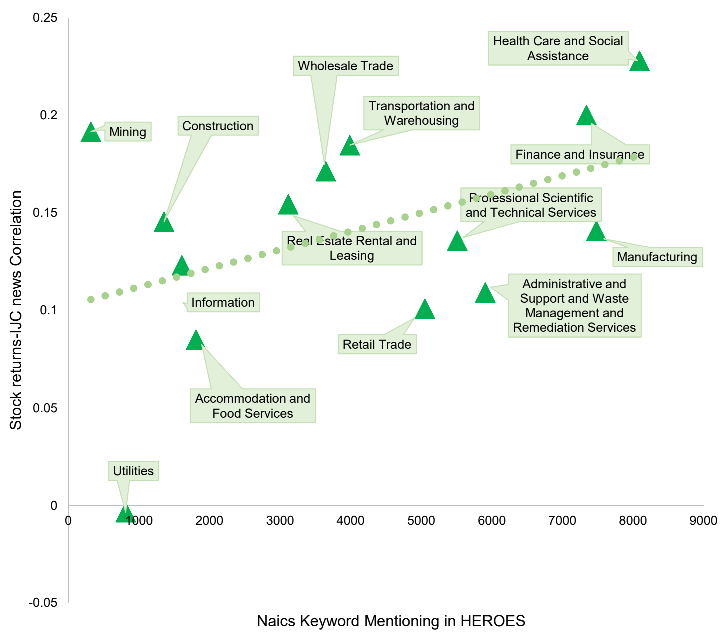


Figure A3: Quarterly state variables.

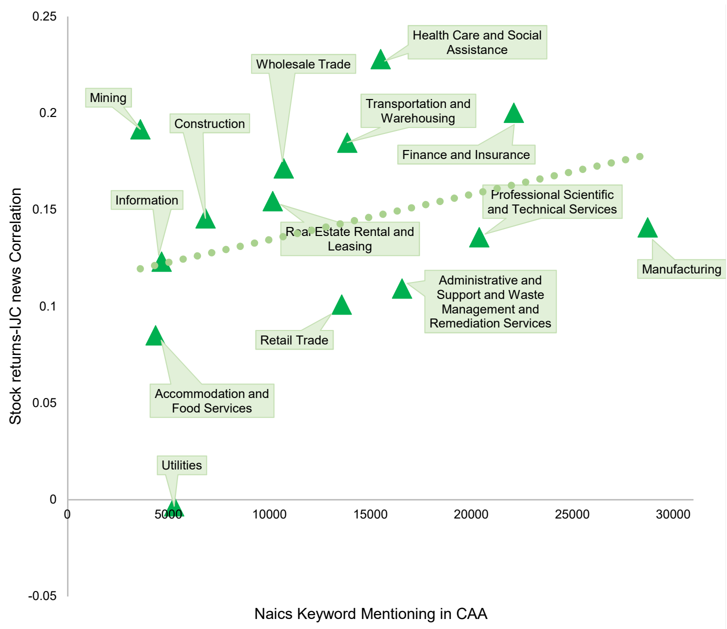
This figure depicts our non-overlapping quarterly topic mentions state variables, scaled by the score of normal IJC words in (1)-(3) and expected changes in T-bill rates and recession probability in (4)-(5). Sources are CNBC and author calculation for the top six plots and the Survey of Professional Forecasters for the bottom two plots (last row).



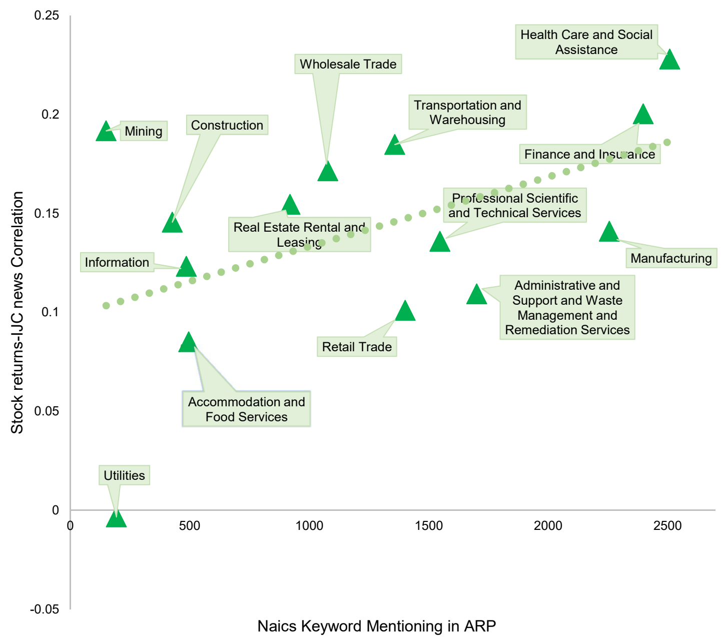
(a) x-axis: Industry mentions in the CARES Act



(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 A4: Robustness evidence for Figure 5: Industry mentions in actual bills.

This figure extends Figure 5 by 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 the U.S. Congress 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, 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) HEROES was introduced in the U.S. Congress on May 12, 2020 as H.R. 6800; it passed the House on May 15, 2020. (c) 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) ARP was introduced in the U.S. Congress 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.

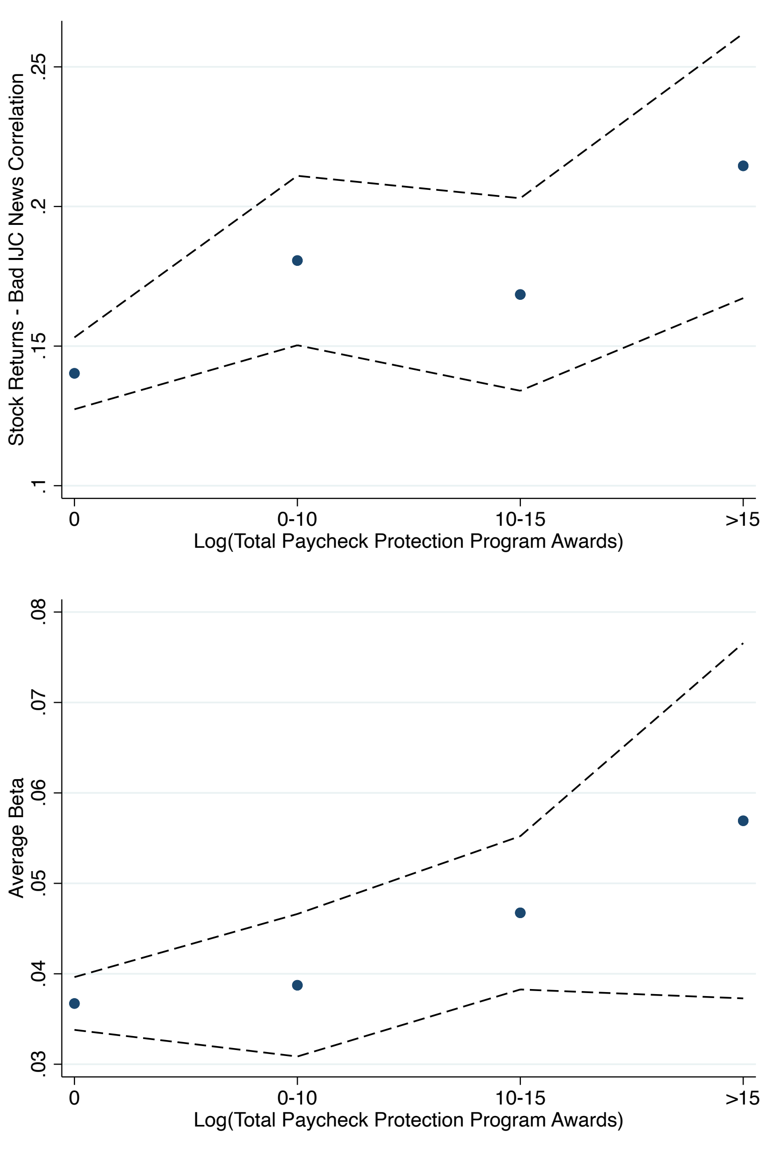


Figure A5: Robustness evidence for Figure 6: (top) Stock return correlation with bad IJC shocks; (bottom) Stock return sensitivity to IJC shocks or IJC betas.

The top panel of this figure depicts the average return-bad IJC shock correlations of four groups of firms sorted by their obligated Paycheck Protection Program award amounts: No COVID-19 related funding (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. The bottom panel depicts the average return-IJC beta. The company sample contains the 498 companies from the S&P 500.

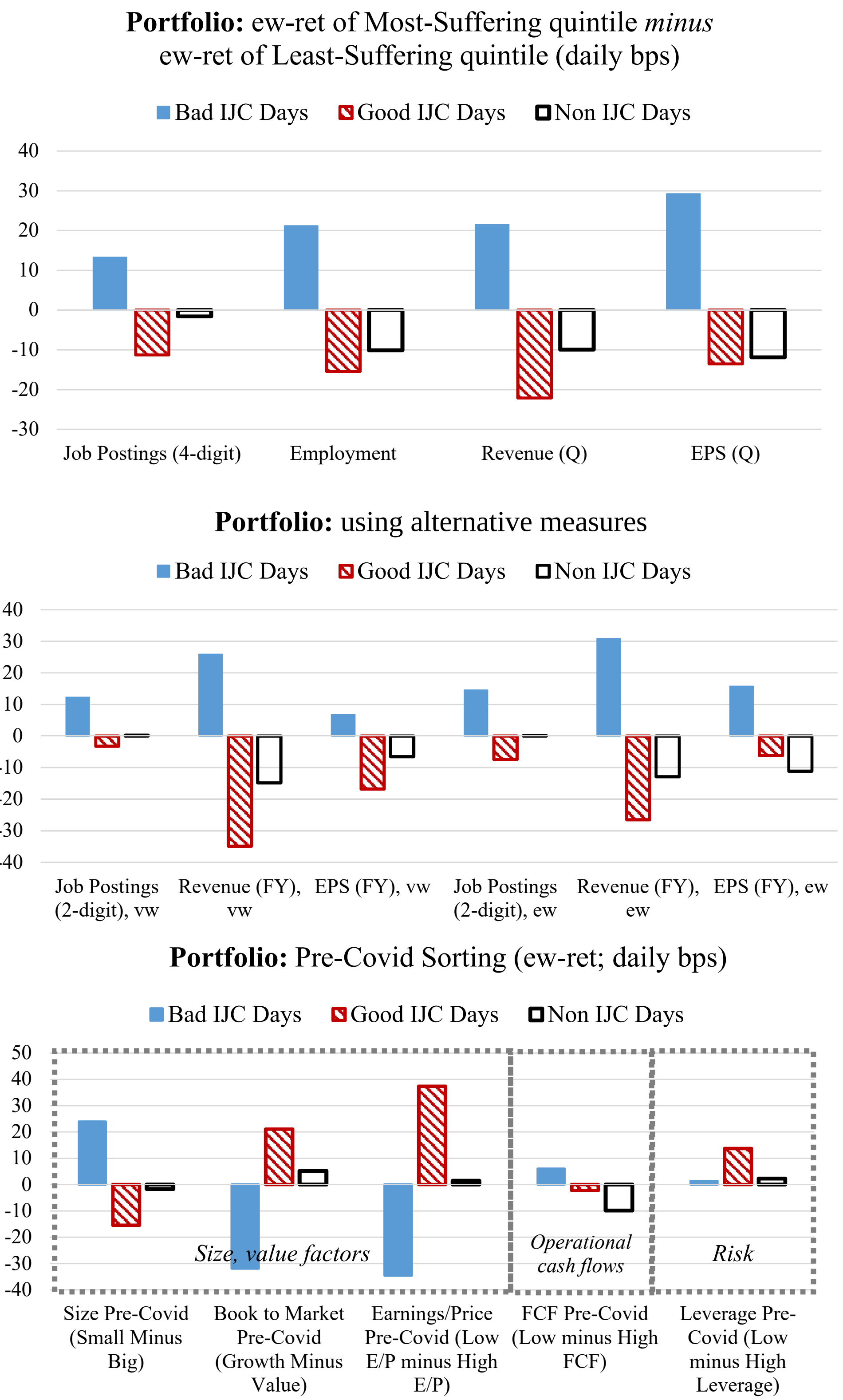
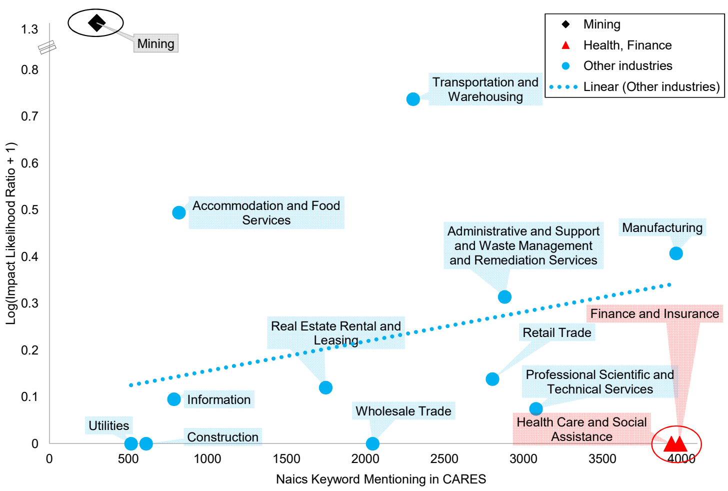
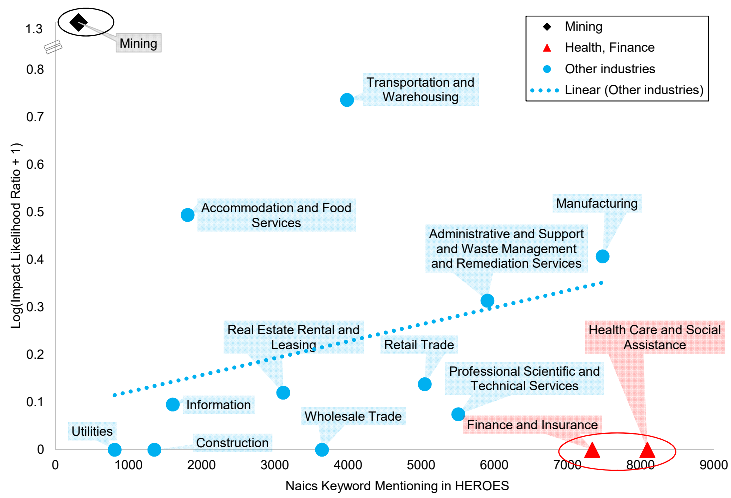


Figure A6: Robustness evidence for Figures 8 and 9: Portfolio returns.

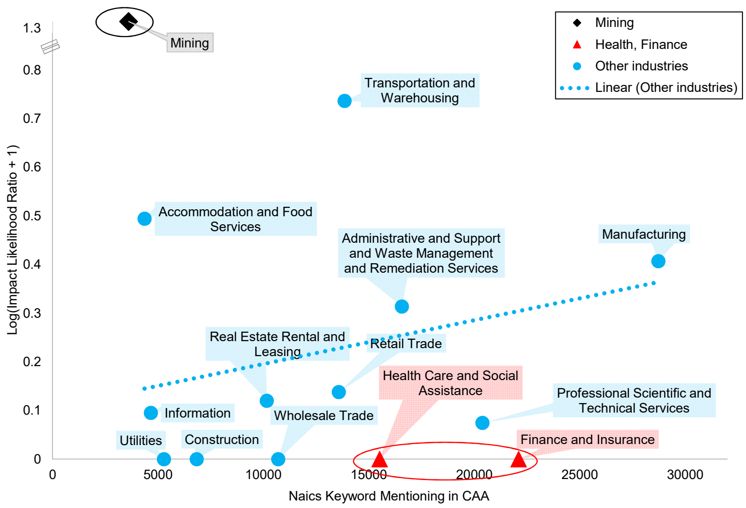
The first two plots provide robustness results for Figure 8 using equal weights (plot 1) and cautiously using a less accurate alternative COVID-19 impact measure at the firm level (plot 2). The third plot complements Figure 9 using equal weights. See other details in Figures 8 and 9.



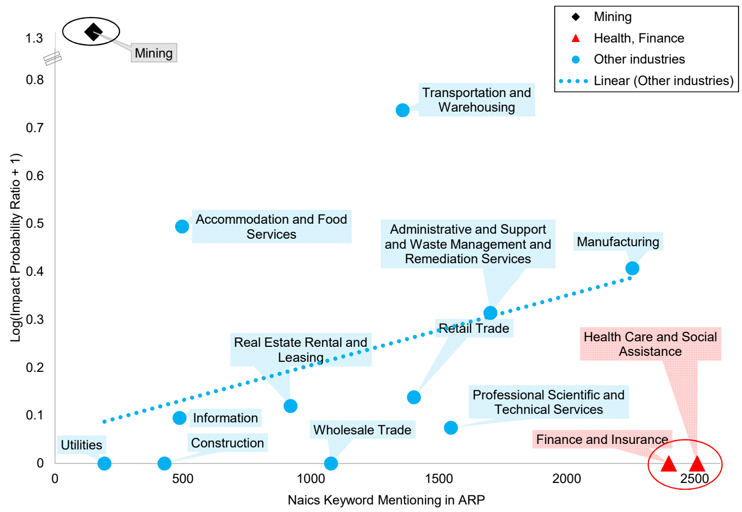
(a) x-axis: Industry mentions in the CARES Act



(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 A7: Robustness evidence for Figure 10: Industry mentions in actual bills.

B. 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 until 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 B1. Estimation results using monthly data are provided in Table B2. Figure B1 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 and then use the parameters 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 B3. 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 B1: 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 B2: 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_t^e	TY_t	PE_t	VS_t	$R^2(\%)$	$Fstat$
r_{t+1}^e	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_t^e	TY_t	PE_t	VS_t	$R^2(\%)$	$Fstat$
r_{t+1}^e	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_t^e	TY_t	PE_t	VS_t	$R^2(\%)$	$Fstat$
r_{t+1}^e	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	$r_t^{e,oc}$	TY_t	PE_t	VS_t	$R^2(\%)$	$Fstat$
$r_{t+1}^{e,oc}$	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 B1: 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 B2.

Table B3: 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%.

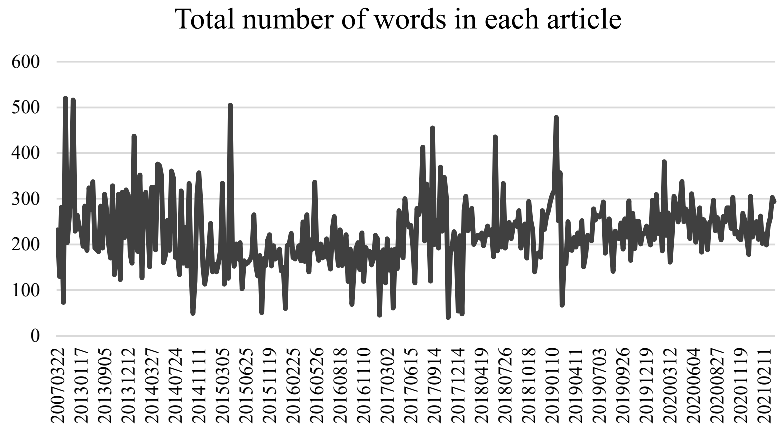
	Sample 1			Sample 2		
	NCF	NDR	NCF,NDR	NCF	NDR	NCF,NDR
Std/Corr	0.02412	0.05298	0.13237	0.02571	0.04340	-0.12449
	(0.00095)	(0.00244)	(0.06036)	(0.00101)	(0.00174)	(0.05281)
Var/Cov	0.00058	0.00281	0.00017	0.00066	0.00188	-0.00014
	(0.00005)	(0.00025)	(0.00008)	(0.00005)	(0.00015)	(0.00006)
r^e shock 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%

C. Details on Textual Analysis

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

In order to prepare a list of all articles on CNBC about weekly jobless claims, the first step is to download initial jobless claims announcement dates, and we obtain them from a tabulated version from Bloomberg that provides both actual and survey medians. Once all 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 in the same search box, and then identify the articles. Here we often come across dates with multiple articles which have the same keywords, i.e., jobless claims articles for the same dates; some are entirely related to the stock market, futures market, etc., but we make sure that we select only those articles that are categorized under the *US Economy* or *Economy* headers. The reason is that we need to read 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 reads the links to be scraped from the Excel sheet prepared from the search process. BeautifulSoup is a Python library for pulling data out of HTML and XML files.



C.2. Texts by topic

Table C1 summarizes the keywords for each of the five topics; their variants are also considered in the search (see details above). 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 C1 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, for instance,"bad" uses all weeks within the same 60-week interval that correspond to bad IJC announcements. As in Figure 4, 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 top four plots in Figure C1) and the 95% confidence intervals (see bottom four plots in Figure C1) are tight relative to the overall fluctuations.

C.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 lower-case 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 then 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 the matrix 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 C1: 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				

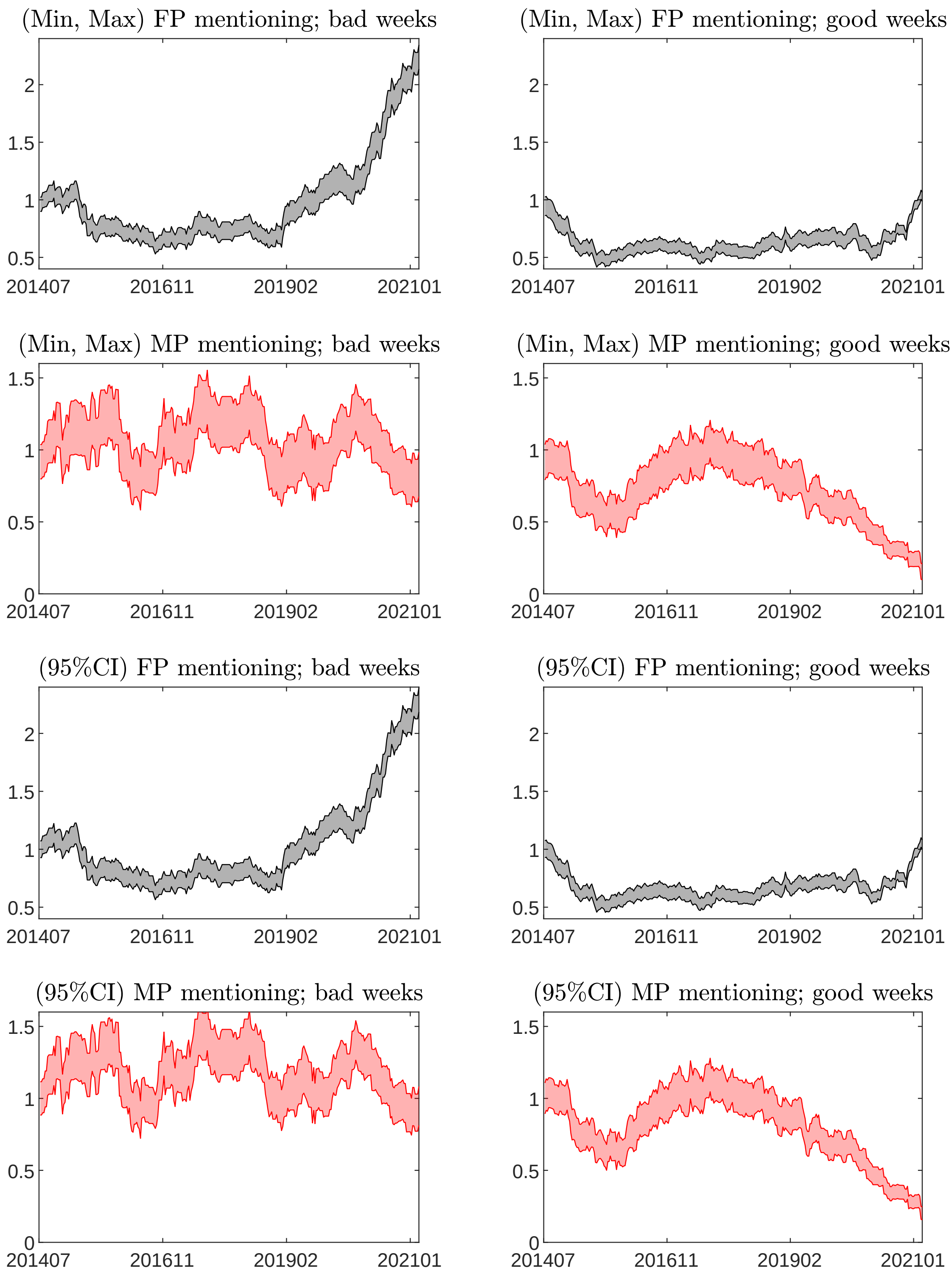


Figure C1: Jackknife exercise of the scaled rolling topic mention values. This table complements Figure 4 in the main text and provides measurement uncertainty. In this plot, we drop one keyword at a time and recalculate the bad and good rolling topic mentions scores using all bad and good IJC announcement 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.

D. COVID-19-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-19-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; 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-19-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); 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 the manual verification, we identify 11,018 records for 1670 Compustat companies matched with recipient (parent) names in COVID-19 spending records at the time of writing in FY 2020. Table D1 presents the summary statistics.

Table D1: Summary of COVID-19-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

E. Relationship Between Monthly Macro Announcement Surprises and Daily Open-to-close Returns

In our analysis in Section 2, the advantage of focusing on *weekly* initial jobless claims announcements is twofold, as we discussed in the main text. 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. Two, 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 E.1. This external validation then also potentially offers a unique cross-macro variable perspective that can help us further test our mechanism hypothesis (Section 3), 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 E.2. For this monthly variable analysis, we drop macro data corresponding to March 2020 (abnormal underestimates of the impact of COVID-19 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.

E.1. Monthly unemployment macro variables

The two top plots of Figure E1 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 the 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 significantly different from its Normal Period counterpart. Table E2 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 COVID-19 is significant and positive (0.793***), which is a strong result given that there are only 11 data points after taking out days with other, 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 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-19 can cause higher stock returns; an equality test is also rejected.

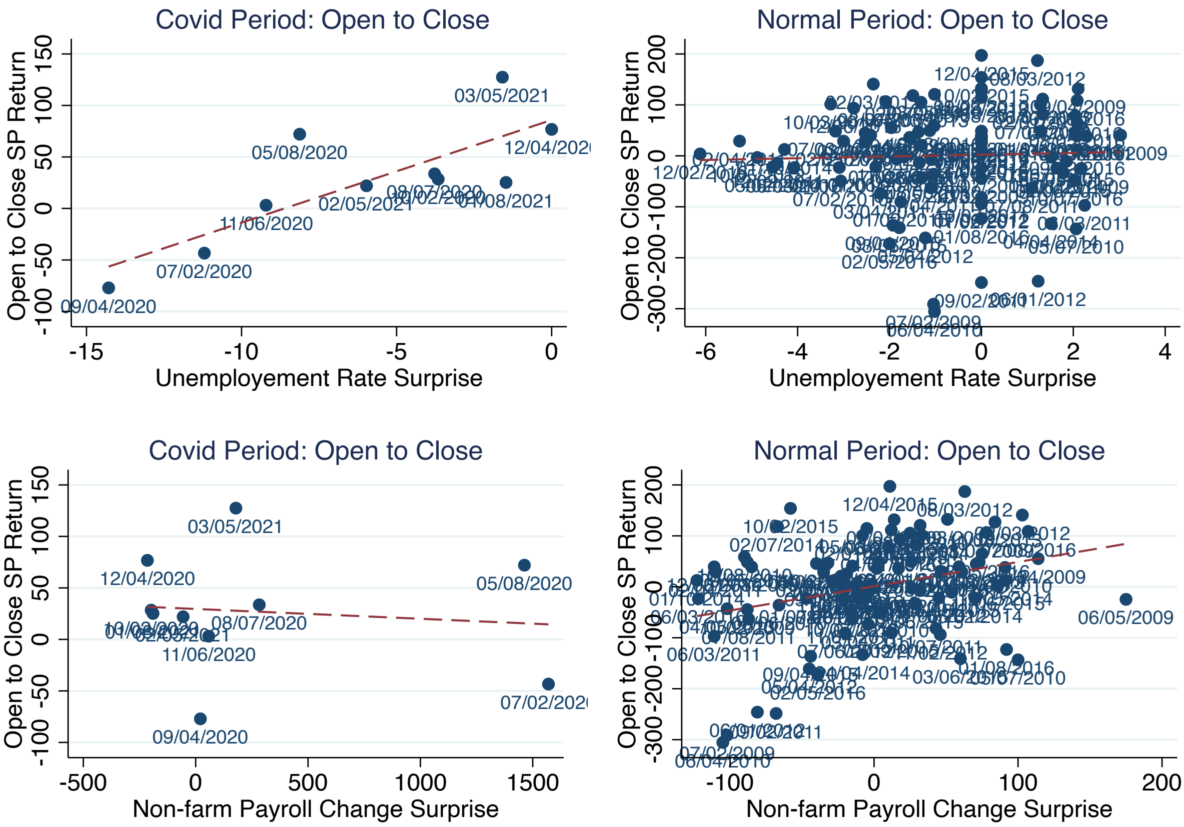


Figure E1: Unemployment news and daily open-to-close returns

E.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 E2, 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.

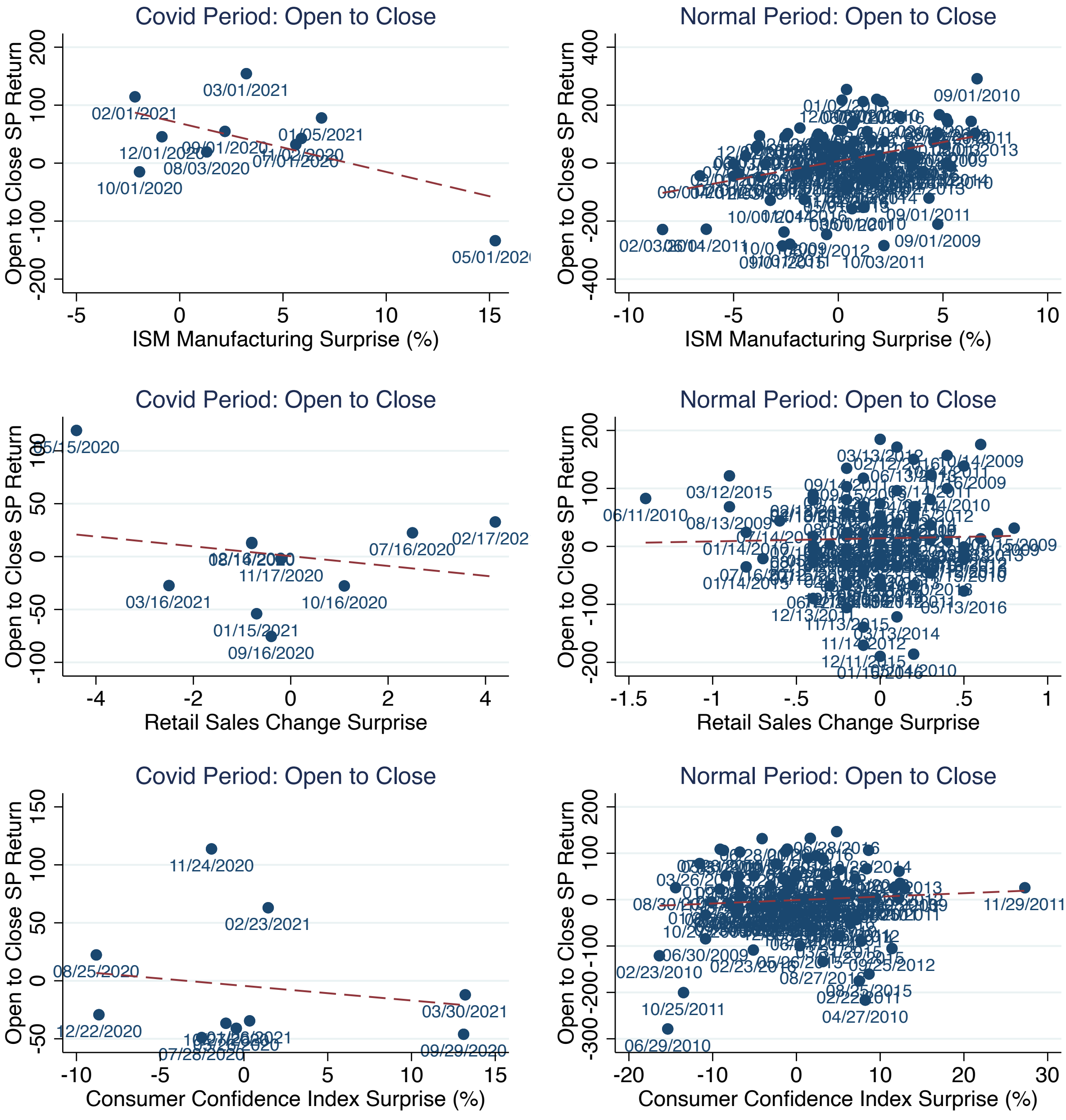


Figure E2: Manufacturing and consumption/consumer news and daily open-to-close returns

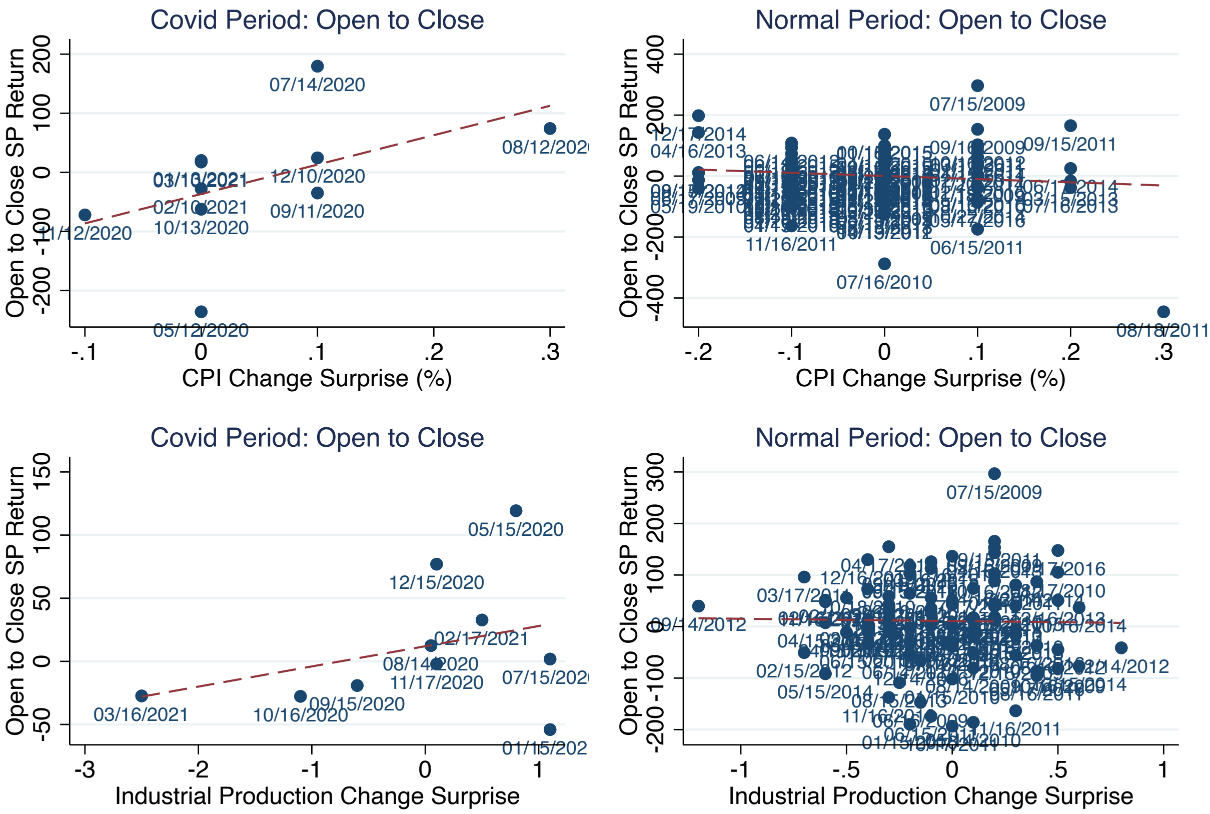


Figure E3: Other economy news and daily open-to-close returns

Table E2: 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	