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 the 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 period, firms/industries that are expected to suffer more in fundamentals, get mentioned more in legal stimulus bills, or have higher obligated funding amounts show higher individual stock returns when bad IJC news arrives. Our results suggest that investors form fiscal policy expectations.

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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 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 major stock index returns of around 30 basis points. Put differently, during this period, while Main Street *pains*, Wall Street *gains*, providing evidence of the "big disconnect" between the real economy and asset prices. While there is a growing literature on the dynamic aspect of return responses to macro announcement surprises, it seems difficult for existing theories to reconcile with our observation. For instance, Boyd, Hu, and Jagannathan (2005) predict that rising unemployment news should be bad news for stocks during economic contractions as it should signal bad future dividend growth; on the other hand, Elenev, Law, Song, and Yaron (2022) predict that rising unemployment news could be good news if lower interest rates are expected; however, the interest rate was already at its zero lower bound during most of 2020-2021, and most unconventional monetary policies were announced before April 1, 2020.[2] This puzzling "Main Street pain, Wall Street gain" phenomenon during COVID-19 calls for other explanations of time-varying stock return responses to macro shocks.

We start by establishing a few stylized facts about this phenomenon. It (a) appears only when bad IJC news arrives, (b) is stronger for Dow Jones indices than for the Nasdaq index, (c) prices mainly through the cash flow component of stock returns according to a VAR estimation, and (d) builds throughout the morning and peaks around noon. Using actual IJC news articles written on IJC announcement days that we manually collect from CNBC (2013-2021), we find that since 2020, mentions of fiscal policy (FP) significantly surpass those of monetary policy and are higher on bad IJC surprise days. In light of these observations, we propose *fiscal policy expectations* as a new mechanism in this paper.

In a low-interest-rate and crisis environment, when Main Street suffers more than expected (e.g., a larger IJC surprise), investors may expect more generous Federal Government support, *driving up* the expected future cash flow growth and the stock prices. We examine two testable predictions from this hypothesis, at the aggregate and cross-sectional levels. We first construct

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

[2] We summarize the timeline of Federal Reserve COVID-19 responses in Appendix Table A1.

and compare the abilities of several text-based and survey-based mechanism proxies to explain the dynamics of return responses to IJC surprises from 2013 to 2021. We find that FP mentions in IJC news articles significantly and positively explain return responses to IJC shocks, particularly on bad IJC days. In the cross section, we find that firms/industries that are *expected to receive more fiscal support* exhibit *higher* individual stock returns when bad IJC news arrives. While there is little to no literature on measuring fiscal policy expectations, we construct three novel cross-sections based on firm-level expected fundamental COVID-19 impact measures using job postings, industry mentions in actual stimulus bills, and obligated fiscal distributions to firms. Finally, 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.

We provide more details about each part next. We start by examining how stock prices respond to IJC surprises (or shocks) in the past decade, using daily, open-to-close, and high-frequency data. Initial Jobless Claims are announced every Thursday morning at 8:30 a.m. Eastern Time, and IJC surprises or shocks are defined as percent differences between actual and expected IJC numbers in this paper. While the "bad is bad" / "good is good" pricing remains true most of the time, we show that the relationship has grown weaker in recent years and even inverted, particularly from February 2020 to March 2021 (the end of our sample). This opposite effect is strongest on bad IJC days and among Dow Jones stocks, prices through the cash flow channel (according to a quasi Campbell and Vuolteenaho (2004) decomposition), and gradually builds throughout the day, as opposed to an acute response shortly after the announcement. To reconcile our empirical findings, we propose that a fiscal policy (FP) expectation channel may be more relevant in explaining dynamic return responses to bad IJC news in a persistent zero-lower-bound (ZLB) or low-interest-rate world, where the discount rate faces a constraint. The monetary policy (MP) expectation as discussed in Elenev, Law, Song, and Yaron (2022) may be a more relevant mechanism when the market is responding to good IJC news.

Our analysis faces an obvious measurement challenge: There is little to no literature on measuring FP expectations. As we are among the first to attempt a time series proxy at the aggregate level, we choose to conduct textual analysis to help us understand systematically what people discuss when IJC news comes out each Thursday. In this way we are able to construct relative topic mentions as our testable mechanisms: 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 (FP) and monetary policy (MP) 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, which continued to the end of the sample. Importantly, the increased mentions of FP mainly occur on bad IJC days, while the hump-shaped mentions of MP primarily arise from good IJC days, meaning that FP (MP) is more often discussed when the macro conditions are worse (better) than expected. 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.

At the aggregate level, our hypothesis predicts that fiscal (monetary) policy expectations should be an important determinant for return responses to bad (good) IJC shocks. We use two empirical frameworks to test our hypothesis at the aggregate level. 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 return coefficients of IJC shocks. Both tests show similar results, both qualitatively and quantitatively, and are robust to controlling for business cycle state variables such as uncertainty. Overall, we find that both FP and MP variables can significantly counteract the normal return responses to IJC shocks. 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 associated with return responses to good IJC shocks.

Our hypothesis in the cross section predicts that firms/industries that are expected to receive more fiscal support should 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. The COVID-19 crisis renders an ideal context to test our hypothesis: one, the COVID stimulus bills have received unprecedented public attention, as policymakers typically spend months debating them, which helps with effect salience; and two, the pandemic has reached almost all industries, which helps us observe a wide spectrum of effects. As in the aggregate study, an empirical challenge arises: how can we measure firm-level or industry-level fiscal policy expectation? We collect various data sources and utilize *three* cross-sectional sorting strategies. We find that a stronger "Main Street pain, Wall Street gain" effect (or a higher correlation between individual returns and IJC shocks) during COVID occurs in (1) firms that are expected to suffer more during the early COVID period, (2) industries that are mentioned more in actual bills, and (3) firms that are promised more fiscal funding from the U.S. government. These three cross-sections jointly support the *fiscal*-based interpretation.

Here are a few highlights of our three cross-sectional studies. First, we use a novel dataset that indexes all internet job postings and define changes in a firm's job postings from 2019 to April/May of 2020 as a forward-looking measure for its expected COVID-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 value-weighted portfolio in which we long the "Most-Suffering" quintile and short the "Least-Suffering" quintile and evaluate its performance from February 2020 to March 2021. We find that the average daily portfolio returns are positive only on bad IJC days, ranging from 10 to 13 basis points, while the portfolio returns are significantly negative on good- or non-IJC days.

Second, investors may also infer the likelihood of a particular industry/firm receiving more fiscal support from direct industry mentions in actual bills. This motivates our second cross-sectional exercise. We search industry mentions in the following four stimulus bills using industry keywords from an exogenous source (the NAICS website): 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 generally exhibit higher return-IJC shock correlations, supporting our hypothesis. For instance, health care industries 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.

In our last cross-sectional evidence, we use obligated fiscal distribution to each firm from the government. We obtain and examine both obligated (promised) and total actual amounts given to each company identified by a Disaster Emergency Fund Code (DEFC); importantly, we focus on the Paycheck Protection Program (PPP), which accounted for the majority of fiscal spending intended to directly support a company's payroll to facilitate their recovery. Companies that are promised large direct emergency payments (i.e., >3 million) exhibit an average return-IJC correlation of 0.174, while the correlation is only 0.118 for companies with no or minimal fiscal transfers. Unsurprisingly, healthcare and air transportation are the industries receiving the greatest fiscal spending during the pandemic, consistent with our bill-mentioning study.

The paper concludes with two additional analyses. In the external validation analysis using seven mainstream *monthly* macro announcement surprises, we find that the "Main Street pain, Wall Street gain" phenomenon appears particularly strong when we use those macro variables that paint a health report of the Main Street households: non-farm payrolls, unemployment rate, manufacturing, and retail sales. Next, we solve a conceptual asset pricing framework in closed form 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 from it 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, different firms can experience different levels of fiscal pass-through to their expected growth. Calibration using standard parameter choices demonstrates this model's ability to generate "bad is good" price responses.

Our research contributes to the economics and finance literature in several ways. First, 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 the macro shock pricing during contractionary time; these studies usually rely on a sample prior to 2000. More recent studies (Elenev, Law, Song, and Yaron (2022), Yang and Zhu (Forthcoming), 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.

As a theoretical contribution, our paper points out that, in a persistent zero-lower-bound, low-interest-rate modern economy, neither existing explanation seems to dovetail with the "Main Street pain, Wall Street gain" phenomenon observed during the COVID-19 period (February 2020 to March 2021). One could argue that this phenomenon may still be explained by unconventional monetary policy (UMP) expectations, but three other facts appear to push against it. When we construct the MP topic mentioning state variable, UMP should already be picked up, as the MP keyword list includes terms such as "Federal Reserve" and "monetary policy." Moreover, it appears that most UMP programs were announced and communicated to the market before April 2020 (see Appendix Table A1), whereas the "Main Street pain, Wall Street gain" phenomenon is more pronounced starting from May 2020 to the end of the sample in early 2021. Additionally, Treasury portfolios (long-term bond returns, long-term yields, and Treasury implied volatility) and highly-leveraged firms in the cross section do not move much on IJC days, which suggest stable expectations of both level and fluctuations of the discount rate. In general, our evidence calls for a new mechanism of time-varying stock return responses to macro surprises, which makes our research question more relevant.

We fill this knowledge gap by proposing and examining a new theoretical channel: *fiscal policy expectations*. Then, both our theory and empirical evidence suggest that monetary policy expectations matter more in explaining time-varying return responses to good news. Our evidence on the *asymmetric* effects of both fiscal policy and monetary policy lends immediate support to predictions made in Caballero and Simsek (2021) that have not been formally tested.[3] Therefore, one implication that applies beyond our sample period is that investors

[3]From their Section 6: "*While we do not explicitly model fiscal policy, our analysis of the price impact of news suggests that fiscal policy is likely to complement monetary policy when the output gap is significantly negative... fiscal policy increases asset prices and the extent of overshooting — an outcome that the central bank desires but cannot achieve due to the discount rate constraint.*" In other words, fiscal policy may play a more (less)

appear to pay attention to and form expectations of fiscal policy — particularly under *bad* real economic conditions and when monetary policy exhausts its tools. In fact, Leeper, Walker, and Yang (2010) have long suggested that "anticipated fiscal adjustments" should have real growth implications, and our work uses patterns in asset prices and lends support to their theory.

Second, while there is an extensive literature on the macroeconomic effects of fiscal policy (see, e.g., Goulder and Summers (1989), Easterly and Rebelo (1993), Perotti (1999), Mankiw (2000), Akitoby and Stratmann (2008), Auerbach and Gorodnichenko (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), etc.), there is scant literature focusing on the relationship between fiscal policy and the stock market. The few existing papers examine the long-term effects of tax policies and public deficits on stock prices within an equilibrium framework (see recent related work in Croce, Kung, Nguyen, and Schmid (2012a), Croce, Nguyen, and Schmid (2012b), Gomes, Michaelides, and Polkovnichenko (2013), Diercks and Waller (2017), Croce, Nguyen, and Raymond (2021)). Yet a few recent empirical papers have suggested the rising importance of fiscal policy in positive short-term stock market jumps (see Baker, Bloom, Davis, and Sammon (2021) and Greenwood, Laarits, and Wurgler (2022)), which aligns with one of our big-picture takeaways despite our different research questions and approaches.

While there are no high-frequency survey measures or closely related futures markets, we provide a novel approach that uses macro (IJC) announcements to *sign* and capture fiscal spending expectations and their effects in stock prices, both in the time series and cross section. This micro approach is among the first to quantify such expectations, and has the potential to be easily expanded to capturing other policy expectations in future studies. Our paper hence closely follows the call in Goldstein, Koijen, and Mueller (2021) (pp.5146, *Review of Financial Studies COVID-19 special issue*), "Understanding the short- and long-run effectiveness of such fiscal policy interventions ... is an important question for future research."

Third, the Macroeconomics Public Finance literature have 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 the heterogeneous asset price responses; we document that stock prices of firms that are expected to receive more Paycheck Protection Program rally more when the market speculates 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

important role in explaining return responses to macro news on bad (good) days.

high-frequency evidence. Section 3 investigates plausible mechanisms using textual analysis and professional survey data, while Section 4 tests our hypothesis in the cross section. The paper concludes with two additional analyses: Sections 5 presents external validations, and Section 6 solves a conceptual asset pricing model with a simple fiscal rule to reconcile our empirical results (particularly on pricing channels and cross-sectional results). Section 7 offers concluding remarks.

2. Stylized Facts: Stock Return Responses to Labor News in the Recent Decade

We start by examining how stock prices respond to initial jobless claims (IJC) surprises[4] over the past decade, using daily, open-to-close, and high-frequency data. Section 2.1 constructs and discusses IJC shocks. Section 2.2 establishes several stylized facts at the stock market aggregate level and discusses pricing channels, asymmetry, and implications from high-frequency evidence.

2.1. IJC shock

We focus on initial jobless claims as our primary macro announcement shocks for several reasons. First, economically, jobless numbers closely reflect how "Main Street" is doing and should matter to policymakers. Second, the existing empirical literature has found that labor news in particular could induce stronger financial market reactions than other macro news (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 (2021)). Third, among various macro announcements in the U.S., only IJC is released at a weekly frequency (08:30 a.m. Eastern Time every Thursday), and such timely releases offer more information for empirical identification. We provide external validation for our main finding using seven mainstream monthly macro announcements in Section 5.

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 actual initial claims from last week (ending Saturday) that are released by the Employment and Training Administration (ETA) this week t, 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. For demonstration purposes, in this section we group the past decade into three

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

non-overlapping periods following the Global Financial Crisis, based on (a) general business conditions and (b) monetary policy, which can be motivated from existing theories (e.g., Boyd, Hu, and Jagannathan (2005) and Elenev, Law, Song, and Yaron (2022)):

Period 1	*2009/07-2016/12*		*Expansionary-Zero lower bound*
Period 2	*2017/01-2020/01*		*Contractionary-Low interest rate*
Period 3	*2020/02-2021/03*	*COVID-19*	*Expansionary-Zero lower bound*

The top two plots in Appendix Figure A1 show the time series of our main IJC shock with and without identified statistical outliers[5] and days overlapping with the FOMC. It can be seen that, although initial claims reach an unprecedented level during Period 3, "COVID-19," their IJC shocks exhibit similar distributions as those during the other two periods do. A one standard deviation (SD) IJC shock above average in Period 1, later referred to as "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 IJC shock above average in Period 3 "COVID-19" 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. Detailed statistics are reported in Appendix Table A2.[6]

2.2. Stock return responses: Pricing channels, asymmetry, and high-frequency evidence

We first examine responses of daily market returns (denoted by y_t) to IJC shocks on announcement days:

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

The first column of Table 1 uses the 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%.[7] Such conventional "bad is bad" / "good is good" return responses to macro shocks disappear during the COVID-19 period, which spans from the beginning of the NBER Covid-19 recession period, February 2020, to the end of our sample, March 2021. This period covers

[5]Boxplot outlier analysis using the ×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.

[6]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.

[7]It is typically found by researchers 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 find consistent evidence, as confirmed in our high-frequency evidence later.

54 weeks after excluding the three aforementioned IJC outliers and the overlapping FOMC announcement days. 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.

We call this observation the *"Main Street pain, Wall Street gain"* phenomenon. To understand where this phenomenon is more pronounced, which could help with mechanism examinations later, we next explore three groups of market return components that center around pricing channels, asymmetry, and intradaily patterns.

Pricing channels. Following Campbell and Vuolteenaho (2004) (henceforth, CV2004), 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 $0.95^{1/252}$.[8] 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.[9] Appendix B provides more details on the estimation procedure, our replication

[8]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)).

[9]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 SP 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 the 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

results to Campbell and Vuolteenaho (2004), and new results in the current sample period. In 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) now explains 31% (34%), with a positive covariance between NDR and NCF. Results are robust using open-to-close or daily stock 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.

The next three columns 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. We focus on comparing the *"Covid"* period (2020/02-2021/03) with the *"Normal"* period (2009/07-2016/12), given the similar expansionary monetary policy environment. 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. We also directly examine how Treasury portfolios (long-term bond returns, long-term yields, and Treasury implied volatility) respond to IJC shocks during the Covid period, and we find no significant responses (Appendix Table A3). Taken together, our evidence suggests that, during the year-long COVID-19 period, the economic mechanism of a macro shock may have changed so that the pricing channel is significantly more consistent with the cash flow channel.

Period 2 (2017/01-2020/01) experiences a contractionary monetary policy, with several continuing interest rate hikes. The return responses to IJC shocks invert, which is particularly due to the statistically significant decrease in the NDR coefficient (-51.178) from that of the normal period (82.743). When the IJC shock is lower (i.e., better labor news), the discount rate is expected to increase. This observation is consistent with Elenev, Law, Song, and Yaron (2022), as investors may expect a higher interest rate following a good IJC shock.

Asymmetry Further decomposing the total 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/worse than expected. We break the All-IJC sample into bad- and good-IJC subsamples. As shown in Table 2, all statistically significant return responses come from bad IJC days, with economically sizable magnitudes.

assumption that parameters may be different every day. Results are not statistically different.

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 or Transportation indices and the weakest effect in the Nasdaq 100. This is consistent with the stronger NCF response found in Table 1 as value stocks are more sensitive to market cash flow news other than discount rate news (e.g., Campbell and Vuolteenaho (2004)). In addition, from Panel B, negative coefficients on good IJC days are consistent with "good is good" pricing.

To directly visualize asymmetry, Figure 1 depicts 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 then trace out futures market reactions to IJC shocks using high-frequency data for, one, closer identification, and two, the behaviors of potential economic mechanisms. 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. (noon), and 3:30 p.m. (shortly before market close). Consistent with the literature, we find no pre-announcement drift for labor news. Then, we evaluate the intradaily return responses to IJC shocks.

The left panel of Table 3 shows that, during the normal period, Dow futures would 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. The economic magnitudes are similar: -114.518*** and -111.963*, respectively.

In the COVID-19 period (see the right panel), futures prices still decrease with IJC shocks until 8:35 a.m., but with a much smaller magnitude, and eventually they increase with IJC shocks, with a significant and positive coefficient (as we also see from the daily frequency evidence). The coefficients during the COVID-19 period are all significantly higher for most time stamps we report than during the normal period. This evidence suggests the new mechanism plays a counteracting force against traditional channels.

Moreover, this counteracting mechanism occurs particularly on bad-IJC days, or a "bad is good" response. 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, consistent with the daily evidence in Table 2, across asset classes, we find that Dow futures show stronger "Main Street pain, Wall Street gain" intradaily return responses than S&P 500 futures (Appendix Table A4) or Nasdaq futures (Appendix Table A5). Moreover, while decomposing NCF and NDR at such a high frequency is empirically challenging, we directly examine three futures markets that should be more sensitive to discount rate news in Appendix Table A6: 30-day Fed Fund futures, 10-year Treasury note futures, and VIX futures. We find no significant responses or differences between the normal- and the COVID-19-period price responses to IJC shocks. Taken together, investors do not seem to speculate that future monetary policy will be more expansionary (i.e., a lower interest rate and hence a higher 30-day Fed Fund futures price) when a worse IJC shock arrives. It is comforting to see the normal interest-rate effect, in Panel B; during normal period, the long-term Treasury note futures price increases significantly with a bad IJC shock 5 minutes after the announcement time, which is consistent with the standard interest rate channel, as a worse IJC shock may signal a weakening economy (see similar results in Kurov, Sancetta, Strasser, and Wolfe (2019)). All high-frequency data is obtained from TickData.

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 and is difficult to reconcile with existing theories. An array of robustness tests, using alternative IJC shocks and dropping April 9 2020 (an unscheduled Federal Reserve announcement day) show consistent results (see Appendix Tables A7 and A8).

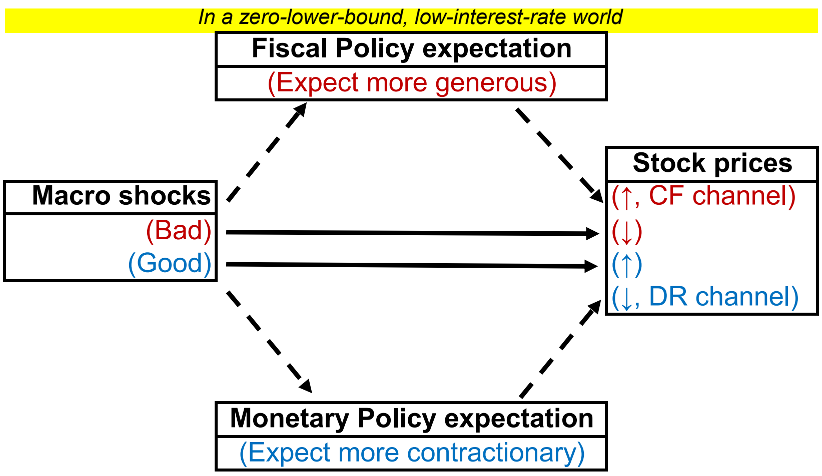
1. This phenomenon appears only when bad labor news arrives.
2. It is stronger for Dow Jones indices than for the Nasdaq index.
3. It revises the expected future cash flow growth according to a VAR framework, and triggers no significant responses in the Treasury portfolio.
4. It builds throughout the morning and peaks around noon, as opposed to the typical immediate response after the announcement time.

3. Mechanism

This special contractionary period, February 2020 - March 2021, seems to have triggered a new pricing channel of bad labor news, which is strong enough to overturn the conventional wisdom of "bad is bad." We hypothesize that, in a low-interest-rate and crisis environment, when Main Street suffers more than expected, investors may now expect more generous Federal Government support through *fiscal policy*, driving up the expected future cash flow growth and the aggregate stock return responses. This hypothesis is able to jointly explain the four stylized facts above, as typically fiscal spending are expected to behave like a "put" and value stocks are more sensitive to cash flow news.

In the existing literature, one group of papers explain the time variation in return responses to macro news with business cycle (e.g., McQueen and Roley (1993), Boyd, Hu, and Jagannathan (2005), Andersen, Bollerslev, Diebold, and Vega (2007)). However, recent empirical evidence has challenged the business-cycle explanation. In particular, the monetary policy (MP) expectation mechanism states that, when a good (bad) IJC shock arrives, a higher (lower) interest rate expectation may counteract the positive (negative) stock return response. In a low-interest-rate environment, which is our focus, this MP mechanism may be more relevant in explaining the less positive return responses when good IJC news arrives, as there is clear potential for the interest rate to increase. An example is the period from 2017 to 2019. However, it may not explain the "Main Street pain, Wall Street gain" phenomenon on bad IJC days from February 2020 to March 2021: one, the interest rate dropped to 0-0.25% on March 15, 2020 and remained at zero until the end of our sample period; two, in fact, the Survey of Professional Forecasters (SPF) shows that investors expected little changes in the annual rate during the remainder of 2020; moreover, most unconventional monetary policies were announced before April 1, 2020, while our results mainly come from May 2020-March 2021 (Appendix Table A1). It is hence less likely that investors expect the Federal Reserve emergency lending facilities (such as those introduced in March 2020) to become even more aggressive in late 2020 or early 2021. Meanwhile, the prolonged and high-profile nature of the stimulus bill law-making process could allow fiscal policy expectations to spurt and vary over time.

Taken together, the diagram below illustrates that, in this low-interest-rate economic environment, one policy expectation channel may become more relevant in explaining the pricing of bad or good IJC shocks:



Our hypothesis has two specific predictions. At the aggregate level, fiscal (monetary) policy expectations should be a more important driver for return responses to bad (good) IJC shocks. In the cross section, firms/industries that are expected to receive more fiscal support should exhibit higher individual stock returns when bad IJC shocks appear, hence a stronger "Main Street pain, Wall Street gain" phenomenon. We test these two predictions using both textual analysis and longitudinal survey data in this section and cross-sectional analysis in Section 4.

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

There is little to no literature on measuring fiscal policy (FP) expectations. As we are among the first to attempt a time series proxy at the aggregate level, we choose to conduct textual analysis to help us understand what people discuss when IJC news come out each Thursday, and so we construct topic mentions as our testable mechanisms. The idea that news mentions could capture expectations and beliefs is not new; for instance, Da, Engelberg, and Gao (2015) measure beliefs about recessions using internet search volumes, while Baker, Bloom, and Davis (2016) measure economic uncertainty using news articles. We relegate the technical details of our textual analysis to Appendix C and describe main steps and main interpretations of our measures below. In general, we provide both narrative and quantitative evidence that, during our sample period, increased FP (MP) mentions can be interpreted as higher expectations of fiscal spending (interest rate).

Text of interest. We focus on CNBC's IJC news articles, which are written and published each Thursday to describe and interpret that morning's IJC announcement. An article has an average of 327 words. 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. 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.

News on CNBC's website is not directly downloadable from well-known news aggregators (e.g., RavenPack, LexisNexis, Factiva). We use Python and then manually verify CNBC IJC news articles on announcement days for as far back as is available online. There are sometimes two articles on one IJC announcement day: one that describes the announcement statistics and has an economic discussion, and one that describes financial market reactions at the end of the day. We download 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 before 2013 from their website, while the number becomes quite stable afterwards. This motivates the start year of our aggregate analysis: 2013. The bottom plot depicts a stable bad and good IJC-day split per 60-week rolling window.

Topic mentioning scores. To retrieve the relative importance of words by topic in IJC news articles on announcement days, we use the 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.

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 needs in our research, we put together words that reflect discussions of government spending, grants to the states, transfers (augmented unemployment benefits), and law making, 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, the scenario 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:[10]

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."*

[10]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/

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 need to trace out, given our hypothesis, is monetary policy. The words we choose are fairly standard and general, such as "central 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 that mentions of this topic remain stable and high over time.

Time variation and asymmetry. How do the mentions of each topic compare with each other, and how do these mentions evolve over time? Given that each IJC article is relatively short (average=327 words), we construct topic mentions metrics using a 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.[11]

Next, the two policy mentions – fiscal (black solid) and monetary (red dashed) – show distinctive patterns. Both started at a similar level and with a downward trend and remained 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 is

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

49.0% lower than that at the beginning of the sample (t = -3.09). FP mentions remain low until April 2020, and then significantly increase until the end of the sample; from the beginning to the end of the sample, FP mentions increase by 57% (t = 2.87). Detailed statistical information on this can be found in Table A9 in the appendix.

The mentions of economic uncertainty reach a local peak around 2016, likely due to the Brexit referendum and the U.S. election. They increase again in late 2018 and 2019, likely due to the China-U.S. trade war, and peak during the first few months of 2020 because of the COVID-19 outbreaks worldwide; a mild local peak can also be seen around November 2020. The pattern is generally consistent with existing economic uncertainty measures, documented using various methodologies in the literature (such as Jurado, Ludvigson, and Ng (2015), Baker, Bloom, and Davis (2016), Bekaert, Engstrom, and Xu (2022)).

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, and respective statistical test results are reported in Table A9. In the upper left plot, the significantly increasing mentions of FP on bad IJC days (t = 3.38) explain the main increasing pattern from Figure 3, while FP mentions on good IJC days remain relatively stable and statistically similar to earlier periods. On the other hand, MP mentions on good IJC days exhibit 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.

Both observations, together with the narratives above, suggest that FP (MP) mentions during our sample period can be potentially interpreted as expansionary (contractionary) policy expectations. In fact, MP mentions on good IJC days have a significant and positive correlation with interest rate revision (the difference between one-quarter-ahead forecasts and nowcasts of the 3-month Treasury bill rate; source: SPF) at 0.46***, which we discuss later in Section 3.3 and Appendix Table A11.

Finally, the bottom left plot of Figure 4 shows that "bad" uncertainty and "good" uncertainty move in opposite directions prior to 2018 but move mostly in tandem after 2018, with the bad uncertainty dominating during COVID-19 period. This evidence also supports some recent assumptions used in asset pricing modeling, where good and bad uncertainty dynamics are assumed to behave differently, such as Segal, Shaliastovich, and Yaron (2015), Xu (2019), Bekaert, Engstrom, and Xu (2022). 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.

Links to our hypothesis. Our hypothesis becomes testable at the aggregate level, and the advantage here is that potential mechanisms are constructed under a consistent framework: policy expectations (FP, MP) and conventional pricing channels (risk perception). In Sections 3.2 and 3.3, we conduct two different testing frameworks (rolling and non-overlapping). We also use survey-based measures as alternatives for robustness.

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-day rolling window to construct return responses to IJC shocks and topic mentioning scores; 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 could *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.

The "Asymmetry" stylized fact established in Section 2 says that the "Main Street pain, Wall Street gain" phenomenon is significant using an all-IJC-day sample, and should be more pronounced on bad IJC days. We next examine the bad and good IJC day samples separately. In Panel A of Table 5, the consistently significant and positive coefficients for FP – not MP – demonstrate 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 could lead to a 26-34 basis point increase in stock returns, with a stronger response in the Dow Jones. In Panel B, monetary policy (MP) mentions explain more variation in return responses to good IJC shocks than fiscal policy. This evidence supports Elenev, Law, Song, and Yaron (2022) and our hypothesis; when monetary policy is expected to tighten (Appendix Table A11), stock prices can decrease even though the IJC numbers are better than expected.

Finally, we conduct an array of robustness tests and report some graphical evidence. In Tables 4 and 5, Columns (2) and (6) measure return responses in standard deviation terms (SD changes in returns given a one SD IJC shock), or "Economic Magnitude"; Columns (3) and (7) include uncertainty; Columns (4) and (8) use Dow Jones 65's open-to-close return responses. Table A10 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)[12] given a one SD "bad" IJC shock in the top plot (i.e., actual jobless claims are higher than expected)), and a -1 SD "good" IJC shock in the bottom plot. During 2020, a one SD bad IJC shock generates a 0.35 SD increase in returns, which can be explained through a 0.45 SD increase in cash flow news (dashed red line) minus a 0.15 SD increase in discount rate news (dotted blue line).[13] This is consistent with the COVID-19 period result in Table 1. On the other hand, from the bottom plot of Figure A2, a -1 SD IJC shock during 2017-2019 *increases* discount rate expectations by a magnitude of 0.2 SD (see the dotted blue line), which causes the overall return response to be negative. Similarly, Figure A3 shows that the three major market indices respond similarly, with the Dow Jones 65 exhibiting a stronger "Main Street pain, Wall Street gain" phenomenon than the Nasdaq 100. This is consistent with evidence in Table 2 and our hypothesis of the federal government helping Main Street cash-flow-sensitive businesses.

3.3. Mechanism evidence using non-overlapping data

While the rolling analysis is straightforward, there may be concerns given the built-in persistence in an econometric analysis. Next, we test our hypothesis using non-overlapping quarterly state variables to directly identify the time variation in the return coefficient of IJC shocks. The specification is as follows:

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

where t and τ denote weekly 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 first three state variables we consider are topic mentions using the 12 articles within 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 ("$\Delta Tbill3m$"), where both forecast and nowcast are provided given the last quarter ($\tau - 1$) 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 (end of paper sample).

The quarterly time-series patterns of these textual-based state variables appear less contin-

[12]See discussions on return decomposition in Section 2 and Appendix B.

[13]Notice that 0.45-0.15 does not equal 0.35. This is because standardization is done separately within return, NCF, and NDR regressions, and NCF and NDR are correlated.

uous 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 directional interpretation of MP mentions: high MP mentions can be interpreted as more contractionary MP expectations. Investors then started to expect a lower interest rate in the second half of 2019; given that COVID-19 was unanticipated, the difference between forecast and nowcast interest rates does not show significant revision during 2019Q4 or 2020Q1.[14]

Table 6 reports the regression results of Equation (3) and examines the relative importance of multiple state variables; the interaction coefficients are of interest.[15] 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 in the future interest rate $\Delta Tbill3m$ state variables 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 Elenev, Law, Song, and Yaron (2022) as well as the second half of our hypothesis, counteracting the "good is good" conventional pattern. When we include $\Delta Tbill3m$, replacing $goodMP$, in the last column of Table 6, and 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 and 496.752* using the S&P 500 in Table A13 in the appendix). Both results are robust to including uncertainty.

Together with previous evidence, we find that when bad IJC news arrives, fiscal policy mentions, which can be interpreted as expansionary expectations, tend to increase compared to monetary policy mentions. This rising FP expectation significantly and quantitatively explains the "Main Street pain, Wall Street gain" phenomenon observed in major index returns.

[14]Evidence mentioned above is shown in Figure A4 and Table A11 in the appendix.
[15]We relegate univariate results to Table A12 in the appendix.

4. Cross-Sectional Evidence

Our hypothesis also predicts that 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 price responses. There are two empirical challenges when testing this.

One, the passing of fiscal policy and budget allocations typically result from a long period of congressional debates and vetting, which adds complications to dynamic sorting strategies. However, the COVID-19 period provides a unique sample to test our hypothesis, one where the fiscal stimulus bills have received unprecedented public attention and were relevant for almost all industries and firms. We can potentially observe *heterogeneous* individual stock return responses to IJC shocks from April 2020 to March 2021 across firms/industries.

Two, we face a challenge similar to one in the aggregate study: it is close to empirically impossible to measure firm-level or industry-level fiscal policy expectations, given the lack of futures markets or longitudinal survey platforms. Therefore, we collect three micro 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 between individual returns and IJC shocks) during COVID-19 should occur to:

1. Firms that are expected to suffer more during the early period of COVID-19;
2. Industries that are mentioned more in actual bills;
3. Firms that are promised more fiscal funding by the U.S. government.

Sections 4.1, 4.2 and 4.3 present evidence using these three cross-sectional measures, and lastly, Section 4.4 compares across the three cross-sectional measures. All cross-sectional tests robustly support our hypothesis.

4.1. Cross-sectional evidence 1: Firm COVID-19 impact measures

4.1.1. Measures

We use four measures to capture to what extent a firm has been and will likely continue to be negatively affected by COVID-19. Both realized and expected impacts likely enter active policy deliberations, and hence are meaningful to our research. We primarily consider the firm universe of the S&P 500, consistent with our aggregate analysis.

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.[16] Data are obtained from Compustat Annual and Compustat Quarter, and we use the number of employees from 10-K as employment data are not available in 10-Q. 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 491 tickers. For robustness, we also consider revenue changes and EPS changes from FY 2019 to FY 2020 at the firm level.

We relegate the summary statistics of the six COVID-19-impact measures to Appendix Table A14. In general, the lower (more negative) a measure is, the more a firm is negatively impacted by COVID-19. Our forward-looking job posting measure tells that almost all firms reduced their job listings by -39% on average when the initial impact of COVID-19 arrived. 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 cross-sectional analysis next (i.e., lower rank = more negative effects).

4.1.2. Result: Firm-level analysis

To make stock return responses to IJC shocks comparable across firms, our main dependent variable here is SD changes in 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 $Corr^i$ below. In "bad is bad" / "good is good" pricing, the firm-level correlation between firm returns and IJC shocks should be negative; on the other hand, our "Main Street pain, Wall Street gain" phenomenon should exhibit a *positive* correlation. The sample period to calculate firm-level return correlations with IJC shocks spans from February 2020 to March 2021 (the end of our sample).[17] Three correlations can be calculated for each firm, using all, bad, or good IJC day samples, where the first can be dubbed as an unconditional

[16] "2020Q2" ("2019Q2") refers to 10-Q numbers reported in 2020 (2019) July, August, or September from Compustat.

[17] In this section, we consistently drop the 03/19/2020, 03/26/2020, 04/02/2020, and 04/09/2020 IJC announcement dates. The first three are identified as IJC outliers as mentioned in Section 2 and Table A1; 04/09 is an unscheduled Federal Reserve announcement day. Results are cautiously stronger if we include these four days.

correlation and the other two as conditional correlations. Here is the firm-level specification:[18]

$$
\begin{aligned}
Corr^i_{All} &= a_{All} + b_{All} CovidImpact^i + \varepsilon^i_{All}; \\
Corr^i_{Bad} &= a_{Bad} + b_{Bad} CovidImpact^i + \varepsilon^i_{Bad}; \\
Corr^i_{Good} &= a_{Good} + b_{Good} CovidImpact^i + \varepsilon^i_{Good}.
\end{aligned} \tag{4}
$$

Table 7 reports the regression results (N=491). From the first two rows, the average $Corr^i_{All}$ is significant and positive at 0.141 (or 14.1%); the average $Corr^i_{Bad}$ is around 0.176, whereas the average $Corr^i_{Good}$ remains negative at -0.075.[19] 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 $Corr^i_{All}$s. To make sense of the coefficients, a one SD below average job posting change (-39%-21%=-60%; see Table A14) corresponds to a significant increase in return-IJC correlation of 1.85% (21%×-0.088), hence a stronger "Main Street pain, Wall Street gain" phenomenon. Considering the average correlation is 14.1%, 1.85% 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 5, where we split firms uniformly into 20 bins (represented as dots) and 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.

4.1.3. Result: Portfolio formation and returns

We also examine our hypothesis using portfolio sorting techniques. We sort our 491 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 6 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

[18] We also use individual return sensitivities to IJC shocks as the left-hand-side variables, and results are robust. Detailed results are available upon request.

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

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 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 A5 in the appendix shows robust 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 (end of 2019), which may help us further rule out alternative mechanisms when interpreting Figure 6. 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 7 shows that small and value firms and firms with cash shortage outperform when IJC numbers are worse than expected, according to the solid bars. This finding is consistent with the cash flow pricing channel in Section 2, 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 growths, as investors anticipate more generous government support. On the other hand, on good IJC days (shaded bars) or non-announcement days (hollow bars), such cash-sensitive firms perform worse. This is consistent with the textual analysis evidence that there are fewer FP mentions in the pricing of good IJC shocks.

We also sort on firms' pre-COVID leverage or riskiness conditions, where leverage is defined as (long-term debt+short-term debt)/shareholder equity.[20] 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 should 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 to test 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.

4.2. Cross-sectional evidence 2: Industry mentions in actual bills

Investors may also infer the likelihood of a particular industry/firm receiving more fiscal support than others from direct industry mentions in actual bills. This motivates our second cross-sectional exercise, where we identify industry mentions in the bills using textual analysis.

We search industry mentions in the following four stimulus legal bills; of these, the three COVID-related stimulus bills were signed into law: (1) The Coronavirus Aid, Relief, and Eco-

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

nomic 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 now-known-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, and 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 reached no deal in the next 6 months, until Congress passed the CAA instead in December 2020. We use final versions of these bills (source: Congress.gov) to conduct textual analysis, and consider one bill at a time. Actual bills rarely name specific firms; therefore, we construct mentions at the industry level, and use an exogenous source to put together keywords for each industry. To be specific, for each 2-digit NAICS industry (20), keywords are unique words from the 6-digit NAICS website (except for stop words).[21] We then search and calculate simple industry mentions in the actual bill.

To construct industry-level correlations, we calculate individual return-IJC correlations and then calculate the simple industry average. Three 2-digit NAICS industries cannot be found in the 491 firm pool, and three other industries have fewer than 5 firms.[22] We therefore focus on the remaining 14 industries, which have ≥5 firms in the 491 firm pool.

Figure 8 plots industry mentions in the CARES Act in the x-axis (higher=more mentions) against industry return correlations with IJC shocks in the y-axis (i.e., higher=stronger "Main Street pain, Wall Street gain" effect). We document a significant and positive relationship between industry 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 A6.

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

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

[22]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.

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).

4.3. Cross-sectional evidence 3: Promised COVID-19 spending and the Paycheck Protection Program

For our last cross-sectional evidence, we use a detailed dataset of fiscal distribution to each firm. Intuitively, investors would expect certain firms to receive more fiscal support if they are *promised* to receive more. We obtain both promised and total actual award amounts (i.e., an award according to the database means "forgiven") to each company during the COVID-19 period, if any, using information from https://www.usaspending.gov/. This database contains full detailed breakdowns 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), and other firm-level non-financial information. This database enables us to identify, at least partially, the forgiven beneficiaries from COVID-19-related fiscal stimulus packages. Appendix D provides more details of this database. Given our research objective, we are interested in all COVID-19 spending (according to the Disaster Emergency Fund Codes), and particularly the Paycheck Protection Program (PPP) outlays, as they are labor-related fiscal support. To the best of our knowledge, this is one of the first efforts linking this firm-level PPP data to stock market data in the literature.

In the S&P 500 universe, we are able to identify 138 companies mentioned in the government spending data.[23] COVID-19-related funding is highly skewed: out of the 138 companies, 108 companies received less than one million dollars; 24 companies received one million to one billion dollars; 6 companies received more than one billion dollars. The healthcare and transportation industries were promised and actually did receive large amounts.[24] As COVID-19 funding was delivered in staggered phases as dictated the multiple government acts, we also observe negative numbers in the data. This means that the government revoked the funding or reduced the award amount. As a result, when calculating the obligated or total amounts, we consider

[23] We create a linking file to match the recipient name 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 belongs to the Compustat company.

[24] 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.

both "All" (positive+negative amounts on records) and "Positive" (positive amounts only). In summary, we 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 Payback Protection Program only, and the log of the actual total gross outlays.

In Table 8, we show that individual stock return-IJC shock correlations increase significantly at the 1% level with firms' obligated amounts from the U.S. government. This result is robust using positive amount items only or PPP items only. In Figure 9, we group these 491 companies into four brackets by obligated PPP funding and plot average return-IJC correlations. The stock return-IJC shock correlation is on average 11.8% for the 353 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 17.4% in return-IJC correlation. To complement Table 8 and Figure 9, the cross-sectional results are also robust if we construct return-IJC news correlations with bad days only; Appendix Table A15 shows slightly higher coefficients and they remain statistically significant, and Appendix Figure A7 exhibits a consistent pattern, particularly the upticking trend from 14.0% (received no PPP) to 21.5% (received substantial PPP).

4.4. Discussion: Who gets what?

In the three cross-sectional analyses thus far – expected COVID-19-damage (firm-level), bill mentioning (industry-level), and obligated and actual fiscal support (firm-level), we find supportive evidence that firms/industries that are expected to receive more fiscal support exhibit a stronger "Main Street pain, Wall Street gain" phenomenon. These three cross-sections, collected from various data sources, allow us not only to draw a conclusion with the potential *fiscal*-related interpretation but to provide collective answers to this ongoing debate: During COVID-19, who gets what? The following findings are not exactly the focus of the present research, but may be useful to other researchers.

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 our CS1 (firm COVID-19 impact measures) and CS2 (industry mentions in actual bills), subfigure (b) shows that the majority of the industries align with the speculation that industries get 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, we also find a few inconsistencies, as illustrated in different colors in subfigure (b). 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 could pick up their keywords when the 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 491) 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 the other three bills. Robustness results are shown in Figure A8 in the appendix.

The two bottom plots of Figure 10 compare bill mentions and fiscal support proxied by two measures – the fraction of firms in an industry that receives > $0 fiscal support, shown in subfigure (c), and promised PPP outlays, shown in subfigure (d). Both plots show significant and 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. External Validation: Monthly Macro Announcement Surprises

For our analysis, the advantage of focusing on weekly initial jobless claims announcements is twofold. One, 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 test the "Main Street pain, Wall Street gain" phenomenon using monthly macro announcement surprises. This external validation then also offers a unique cross-macro variable perspective that can help us further test our hypothesis, 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.

Table 9 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,[25] during a "normal" benchmark period (2009/07-2016/12, as motivated in Section 2)

[25]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. EST 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. EST variables such as the manufacturing index (Institute of Supply Management),

and during the COVID-19 period (2020/02-2021/03). Appendix E provides the corresponding scatter plots.

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-19 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 overlapping days with other 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% test. 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. In Panel B, we see 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-19 period, bad macro news are 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.

6. A conceptual asset pricing framework: Long-run risk, uncertainty, and 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.

the consumer confidence index (Conference Board), etc. are released.

6.1. 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) is,

$$m_{t+1} = \theta \log \beta - \frac{\theta}{\psi} g_{t+1} + (\theta - 1) r_{m,t+1}, \tag{5}$$

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 monetary policy rule for simplicity. The modeling of dividend growth follows the general dynamic process with time-varying expected growth and real growth comovement.

6.2. 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 finally, log dividend growth from period t to $t+1$ (Δd_{t+1}) are given as follows, respectively:

$$g_{t+1} = \mu_g + x_t + \sqrt{v_t}\varepsilon_{g,t+1}, \tag{6}$$

$$v_{t+1} = \mu_v + \rho_v v_t + \sigma_v \varepsilon_{v,t+1}, \tag{7}$$

$$\text{[Long-run risk]} \quad x_{t+1} = \rho_x x_t + \sigma_{xg}\sqrt{v_t}\varepsilon_{g,t+1} + \underbrace{\sigma_{xFP}}_{>0} FP_{t+1} + \sigma_x \varepsilon_{x,t+1}, \tag{8}$$

$$\text{[Expected fiscal spending growth]} \quad FP_{t+1} = \underbrace{\sigma_{FPg}}_{<0}\sqrt{v_t}\varepsilon_{g,t+1} + \sigma_{FP}\varepsilon_{FP,t+1}, \tag{9}$$

$$\Delta d_{t+1} = \mu_d + \rho_{dx} x_t + \sigma_{dg}\sqrt{v_t}\varepsilon_{g,t+1} + \sigma_d \varepsilon_{d,t+1}, \tag{10}$$

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

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 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.

6.3. Price-dividend ratio

We derive asset prices using the SDF mentioned in Equation (5) 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:

$$E_t\left[\exp\left(\theta\log\beta - \frac{\theta}{\psi}g_{t+1} + (\theta-1)r_{m,t+1} + r_{i,t+1}\right)\right] = 1 \Leftrightarrow \tag{11}$$

$$E_t\left(\theta\log\beta - \frac{\theta}{\psi}g_{t+1} + (\theta-1)r_{m,t+1} + r_{i,t+1}\right) + \frac{1}{2}V_t\left(\theta\log\beta - \frac{\theta}{\psi}g_{t+1} + (\theta-1)r_{m,t+1} + r_{i,t+1}\right) = 0. \tag{12}$$

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 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 (12). 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:

$$-\frac{\theta}{\psi}+\theta\left[\rho_{dx}+k_1A_1\rho_x-A_1\right]=0, \tag{13}$$

$$\theta(k_1A_2\rho_v-A_2)+\frac{1}{2}\left[-\frac{\theta}{\psi}+\theta\sigma_{dg}+\theta\, k_1A_1\left(\sigma_{xg}+\sigma_{xFP}\sigma_{FPg}\right)\right]^2=0. \tag{14}$$

The highlighted part is where 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 $\theta=-19.5$), $k_1=0.95$, $\rho_x=0.979$, $\rho_v=0.987$, $\sigma_{dg}=4.5$, $\sigma_{xg}=0.044$):

$$A_1=\frac{\rho_{dx}-\frac{1}{\psi}}{1-k_1\rho_x}=33.3576>0. \tag{15}$$

A positive A_1 means that the intertemporal substitution effect dominates the wealth effect, and therefore when expected growth increases, agents would 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:

$$A_2=\theta\frac{\frac{1}{2}\left[-\frac{1}{\psi}+\sigma_{dg}+\ k_1A_1\left(\sigma_{xg}+\sigma_{xFP}\sigma_{FPg}\right)\right]^2}{1-k_1\rho_v}<0. \tag{16}$$

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, price-dividend ratio decreases as risk premium demanded increases. In this framework, the *sources* of the demanded volatility compensation are through 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, 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.

6.4. Equity risk premium and contemporaneous log market returns

Next, we derive the equity risk premium and contemporaneous log market returns, and discuss the role of fiscal policy enters the equilibrium price (which is in highlighted parts 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:

$$
\begin{aligned}
E_t\left(r_{m,t+1}-rf_t\right)+\frac{1}{2}V_t(r_{m,t+1}) &= -Cov_t(m_{t+1},r_{m,t+1})\\
&= \underbrace{\left[\frac{\theta}{\psi}\left(\sigma_{dg}+k_1A_1(\sigma_{xg}+\sigma_{xFP}\sigma_{FPg})\right)+(1-\theta)\left(\sigma_{dg}+k_1A_1(\sigma_{xg}+\sigma_{xFP}\sigma_{FPg})\right)^2\right]}_{\equiv B_{erp}(\sigma_{FPg})} v_t\\
&+(1-\theta)\left[\sigma_d^2+(k_1A_1\sigma_x)^2+(k_1A_1\sigma_{xFP}\sigma_{FP})^2+(k_1A_2\sigma_v)^2\right]. \qquad (17)
\end{aligned}
$$

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:

$$
\begin{aligned}
r_{m,t} &= \Delta d_t + k_1 z_t - z_{t-1} + k_0,\\
&= constant + \left[\rho_{dx}+k_1A_1\rho_x - A_1\right]x_{t-1} + \left[k_1A_2\rho_v - A_2\right]v_{t-1}\\
&+ \underbrace{\left[\sigma_{dg}+k_1A_1\left(\sigma_{xg}+\sigma_{xFP}\sigma_{FPg}\right)\right]}_{\equiv B_r(\sigma_{FPg})\ ①}\sqrt{v_{t-1}}\varepsilon_{g,t}\\
&+ \sigma_d\varepsilon_{d,t} + k_1A_1\sigma_x\varepsilon_{x,t} + \underbrace{k_1A_1\sigma_{xFP}\sigma_{FP}}_{③}\varepsilon_{FP,t} + \underbrace{k_1A_2\sigma_v}_{②}\varepsilon_{v,t}. \qquad (18)
\end{aligned}
$$

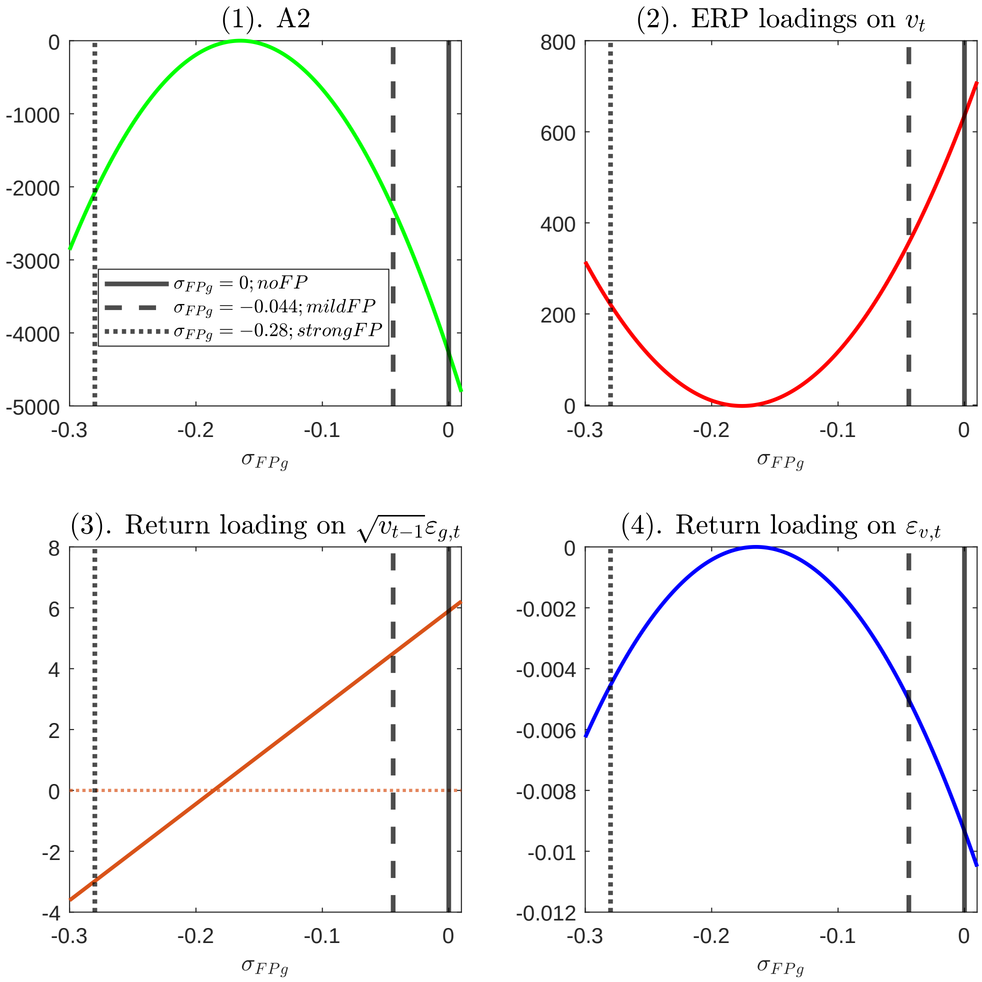
Next, let's focus on how the *fiscal policy expectation* plays a role in the equilibrium log market return. In a world without the fiscal rule, when a bad output news $\varepsilon_{g,t}$ arrives (which is probably also accompanied with positive $\varepsilon_{v,t}$), increasing risk premium and lower expected future growth lead to decreases in asset prices. The fiscal rule enters the pricing in three ways at the equilibrium:

- ***First, expected cash flow channel.*** "①" in Equation (18) demonstrates that, fiscal policy could counteract the conventional positive relationship between expected growth (x_t) and 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 "bad is good" scenario as we observe in the empirical evidence. The effect should increase monotonically with the magnitude of σ_{FPg}.
- ***Second, risk premium channel.*** "②" in Equation (18) demonstrates changes in market prices coming from risk premium, and the closed-form solution above shows that A_2 is a non-linear function of σ_{FPg}. From Equation (17), 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 6.5 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} moving 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 compensations for the increasing volatility.

- ***Third, discretionary fiscal shock.*** "③" in Equation (18) 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.

6.5. 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 $\sigma_{FPg} = 0$, this is no fiscal policy rule; when $\sigma_{FPg} = -0.044$, this completely cancels out the standard expected growth loading on macro shock ($\sigma_{xg} = 0.044$), hence dubbed as "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}), hence dubbed as "strong FP."[26]

Plot (1) above 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 in handling the Covid-19 crisis – a bad macro news may trigger fiscal policy to respond so that the expected growth increases. The magnitudes of A_2, equity risk premium loading on volatility and return loading on volatility shock rebounce, through the higher risk compensation demanded given the high fluctuation fiscal policy may introduce to the economy. This rationalizes the **risk premium** channel, or referred to as the second channel Section 6.4. The covid implication is that the market compensation for stochastic volatility risk increases when a bad macro shock arrives, hence driving down the asset prices.

Next, Plot (3) depicts the effect of fiscal effect through the **expected growth** channel, or referred to as the first channel Section 6.4. The initial mild counteracting is intuitive. The covid scenario is likely represented towards the left/lower end of the spectrum; the implication is that return could load negatively on the macro shock, as the fiscal rule could precisely offset dividend growth and changes in price-dividend ratio that is driven by changing expected growth.

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

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

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

6.6. Cross-sectional implications

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

$$x^i_{t+1} = \rho^i_x x_t + \sigma^i_{xg}\sqrt{v_t}\varepsilon_{g,t+1} + \sigma^i_{xFP} FP_{t+1} + \sigma^i_x \varepsilon^i_{x,t+1}, \tag{19}$$

$$\Delta d^i_{t+1} = \mu^i_d + \rho^i_{dx} x^i_t + \sigma^i_{dg}\sqrt{v_t}\varepsilon_{g,t+1} + \sigma^i_d \varepsilon^i_{d,t+1}, \tag{20}$$

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 (18), 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, hence resulting in a less positive or more negative coefficient in response to macro news.

7. 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 great 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 persistent zero-lower-bound, low-interest-rate 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 the 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.

As Mr. Powell said in his October 6^{th}, 2020 address (Powell (2020)), "*the recovery will be stronger and move faster if monetary policy and fiscal policy continue to work side by side to provide support to the economy until it is clearly out of the woods.*" Moving forward, in this post-COVID-19 era, stimulus checks from the previous bills are still being distributed as of 2022. Our paper is among the first to document that investors appear to incorporate fiscal policy expectations into pricing. If so, the fact that people have formed expectations of 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 investment decisions. Future research should further examine the role of fiscal policy *expectations* in the macro economy and financial market — a novel form of the Federal Government *intervention* in the market.

Finally, this "Main Street pain, Wall Street gain" phenomenon we document is a precise example of the "big disconnect" between the real economy and financial markets. Indeed, a fiscal stimulus can be effective in helping firms and workers timely through subsidies or awards. However, fiscal spending could also simultaneously benefit shareholders disproportionately. 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 72.6 billion dollars on bad IJC days, 17.5 billion dollars on good IJC days, and 44.2 billion dollars on non-IJC days. These are economically sizable amount given that there are $525 billion PPP loans approved in 2020 (Autor, Cho, Crane, Goldar, Lutz, Montes, Peterman, Ratner, Villar, and Yildirmaz (2022)). In comparison, the average daily market capital gain from 2000 to 2019 is 2.1, 7.9, and 1.5 billion dollars on bad, good, and non-IJC days, respectively (Appendix Table A16). While equilibrium frameworks race to evaluate who benefits from fiscal stimulus spending – labor or capital – in the long-run, our work implies that the distributional effect of fiscal policy could also transmit through this "government put" expectation, which gets capitalized at the high frequency. Optimal fiscal stimulus should consider *fiscal policy expectations* for the fairness 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 three non-overlapping sample period post the Global Financial Crisis, based on the general macro environment and monetary policy "MP" regimes at zero-lower-bound "ZLB" or not). **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 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:** "S&P500" denotes the daily open-to-close log returns (unit: basis points; source: DataStream). Then, we include unexpected returns, NCF, and NDR (unit: 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 yield the total unexpected return. **Reporting:** Row "IJC shock coeff." reports the regression coefficients, with robust standard error, t-statistics 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%.

	S&P500	**Unexpected return**	**NCF**	**NDR**
Period 1, *"Normal"*: 2009/07-2016/12; ZLB				
IJC shock coeff.	-97.163	-86.736	-3.993	**82.743***
(SE)	(107.303)	(106.271)	(79.224)	**(48.330)**
[t]	[-0.905]	[-0.816]	[-0.050]	**[1.712]**
SD chngs per 1SD shock	-0.042	-0.037	-0.002	**0.037**
R2%	0.18%	0.15%	0.00%	**0.55%**
Period 2, *"Contractionary MP"*: 2017/01-2020/01; non-zero interest rate				
IJC shock coeff.	109.978	111.454	60.276	-51.178
(SE)	(85.849)	(86.420)	(62.499)	(52.804)
[t]	[1.281]	[1.290]	[0.964]	[-0.969]
SD chngs per 1SD shock	0.085	0.086	0.037	-0.040
R2%	0.72%	0.74%	0.40%	0.57%
Period 3, *"Covid"*: 2020/02-2021/03; ZLB				
IJC shock coeff.	**307.916***	299.961	**298.903****	-1.058
(SE)	**(186.945)**	(186.761)	**(133.464)**	(103.733)
[t]	**[1.647]**	[1.606]	**[2.240]**	[-0.010]
SD chngs per 1SD shock	**0.197**	0.192	**0.197**	-0.001
R2%	**3.90%**	3.68%	**7.56%**	0.00%

Table 2: Asymmetry and Assets.

This table focuses on the Period, *"Covid"* (2020/02-2021/03, end of our sample) and provides further evidence on the source and asymmetry of this "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 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 shock on bad IJC days (Panel A) or on 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)
[t]	**[2.240]**	**[2.233]**	**[2.134]**	[-0.681]	[1.535]	**[2.181]**	**[2.022]**	**[1.758]**	[1.065]
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)
[t]	[-0.430]	[-0.429]	[-0.224]	[0.574]	[0.024]	[-0.996]	[-0.951]	[-0.767]	[-1.376]
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.

This table provides intradaily return responses of E-mini Dow futures on IJC shocks. Intradaily returns (in basis points) are calculated using the same start time of 8:00AM Eastern Time and an end time of interest (from left to right): pre-announcement, 8:25AM ET; shortly after the announcement, 8:35AM ET; noon, 12:30PM ET; shortly before the close, 3:30PM ET. The left four columns display results using Period "Normal", which is a generally normal period with the majority of the time at the zero lower bound (2009/07-2016/12); the right four columns use Period "Covid" (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 TickData. 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)
[t]	[-1.564]	[-6.162]	[-1.663]	[-1.360]	[-0.304]	[-0.836]	[1.839]	[1.681]
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)
[t]	[-0.172]	[-1.670]	[0.020]	[-0.189]	[-0.458]	[-1.738]	[-0.067]	[-0.657]
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 (SDs changes in return given 1 SD IJC shock), and rolling Dow Jones 65 return coefficient. Each variable of topic mentions (fiscal policy "FP", monetary policy "MP", uncertainty "UNC"; see Section 3.1 for topic mention calculation) is standardized in these regressions, for interpretation purpose; Newey-West standard error (Newey and West (1987)) and the number of SD changes in return responses given 1 SD topic mentions are reported as well. Appendix Table A10 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 (SDs changes in return given 1 SD IJC shock), and rolling Dow Jones 65 return coefficient. Each variable of topic mentions (fiscal policy "FP", monetary policy "MP", uncertainty "UNC"; see Section 3.1 for topic mention calculation) is standardized in these regressions, for interpretation purpose; Newey-West standard error (Newey and West (1987)) and the number of SD changes in return responses given 1 SD topic mentions are reported as well. Appendix Table A10 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:

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

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 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 one-quarter-ahead forecast and nowcast of the 3-month Treasury bill rate ("$\Delta Tbill3m$"), where both forecast and nowcast are provided given last quarter information set (source: Survey of Professional Forecasters, or SPF). Time series of all quarterly state variables are shown in Figure A4; due to news file availability, sample runs from 2013Q1 to 2021Q1; correlation table is shown in Appendix Table A11. Univariate regression results are shown in Appendix Table A12, and more results using S&P500 are shown in Appendix Table A13. 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: Relationship between firm stock return responses to IJC shocks and firm Covid impact measures.

This table uses economic magnitude (SD changes in returns given 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; 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 491 out of 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 change from fiscal year (FY) 2019 to FY 2020 percentile rank; (3) revenue change from 2019Q2 to 2020Q2 percentile rank; (4) Earnings per share (EPS) change from 2019Q2 to 2020Q2 percentile rank; (5) revenue change from FY 2019 to FY 2020 percentile rank; (6) EPS change from FY 2019 to FY 2020 percentile rank. For (1), the online job posting data is from a proprietary source (source: LinkUp); the rest are 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 A14. 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	**-0.088*****	**-0.114*****	0.0275
		(0.023)	**(0.031)**	(0.037)
2	Employment Change; FY 2019-2020	**-0.060*****	**-0.054****	**0.100*****
		(0.017)	**(0.025)**	**(0.023)**
3	Revenue Change; 2019Q2-2020Q2	**-0.082*****	**-0.065*****	**0.102*****
		(0.018)	**(0.024)**	**(0.023)**
4	EPS Change; 2019Q2-2020Q2	**-0.081*****	**-0.073*****	0.021
		(0.017)	**(0.024)**	**(0.023)**
5	Revenue Change FY2019-2020	**-0.106*****	**-0.073*****	**0.086*****
		(0.017)	**(0.024)**	**(0.024)**
6	EPS Change FY 2019-2020	**-0.057****	-0.038	**0.044***
		(0.018)	**(0.025)**	**(0.023)**

Table 8: Cross-section evidence: Covid-Stimulus and the Paycheck Protection Program.

This table regresses the individual return-IJC shock correlation on the Covid-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":

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

Columns (1) and (2) use the *obligated* amount (i.e. promised awards) of all Covid spending, respectively; Columns (3) and (4) use the *obligated* amount of 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 amount of negative amounts, which are related to revoke decisions or 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
Coefficient	0.249***	0.249***	0.287***	0.287***	0.310***	0.289***
(SE)	(0.090)	(0.090)	(0.094)	(0.094)	(0.099)	(0.095)
Obs	491	491	491	491	491	491

Table 9: External validation: Correlations between monthly macro announcement surprises and daily open-to-close S&P500 returns.

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

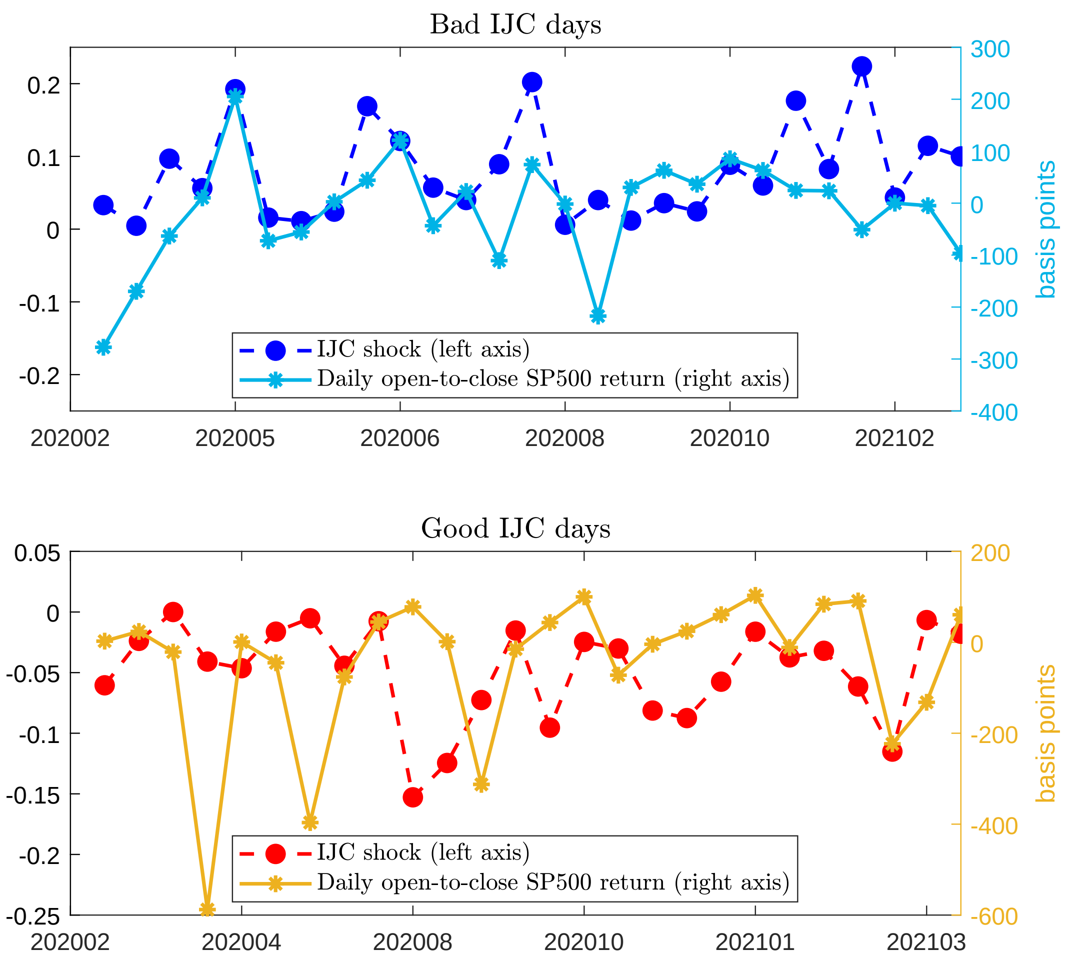


Figure 1: Relation between daily open-to-close S&P500 returns and IJC shocks during the Covid period of interest (2020/02-2021/03), excluding IJC shock outliers (2020/3/19, 3/26, 4/2), FOMC days, and other major Federal Reserve announcement (2020/4/9).

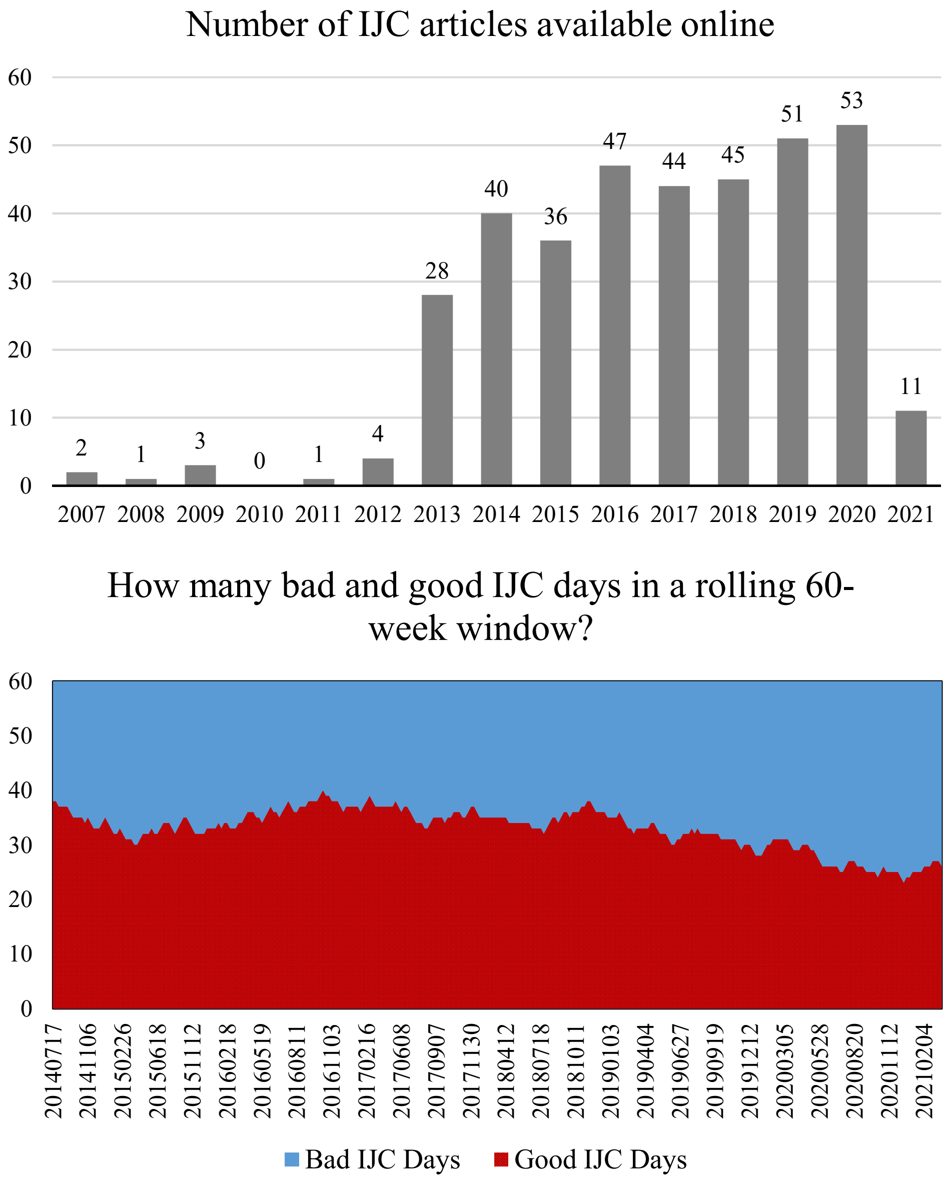


Figure 2: Summary of CNBC jobless claim articles, until the IJC announcement date on 2021/3/18 (end of our sample).

The data collection process is described in Section 3.1 and more 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/.

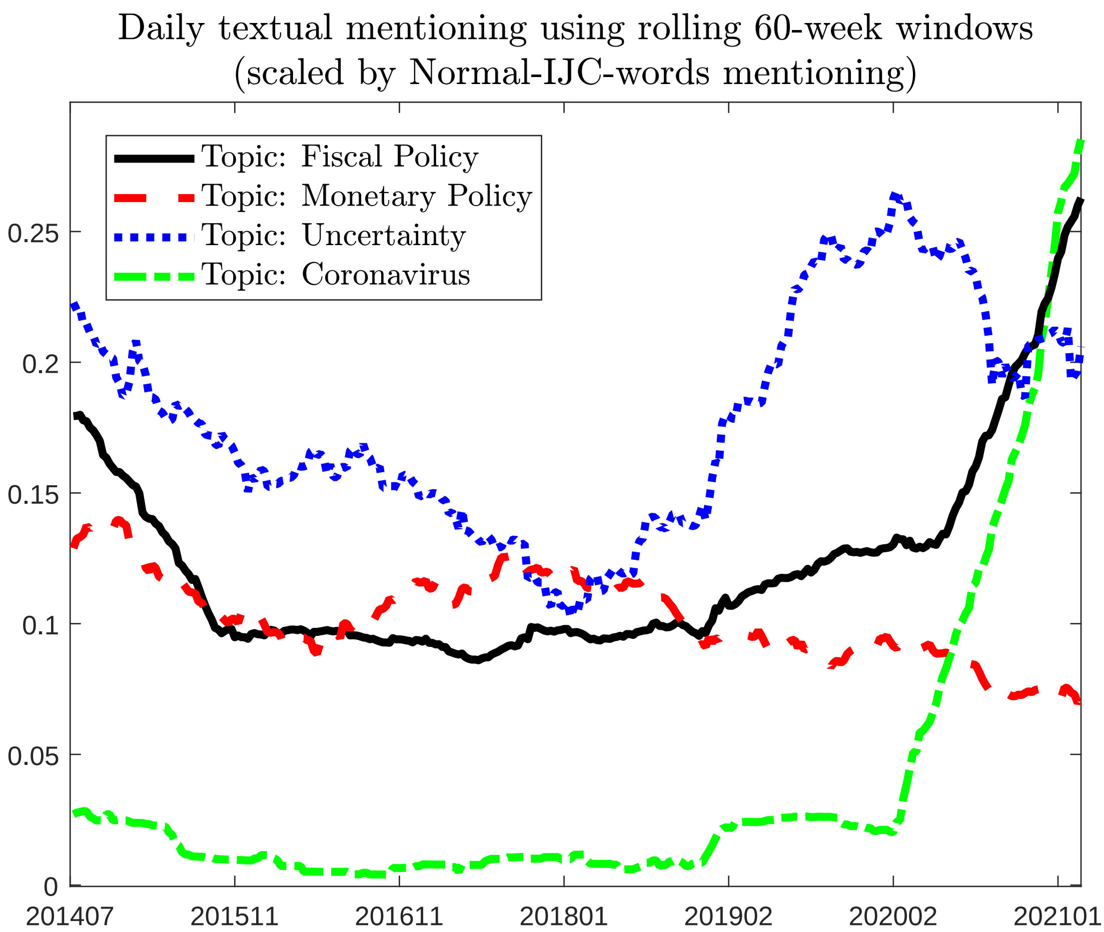


Figure 3: What do people talk about on IJC announcement days?

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 can be interpreted as this topic keywords are mentioned 20 times per 100 normal IJC words. The datestamp always refers to the last day of the rolling window.

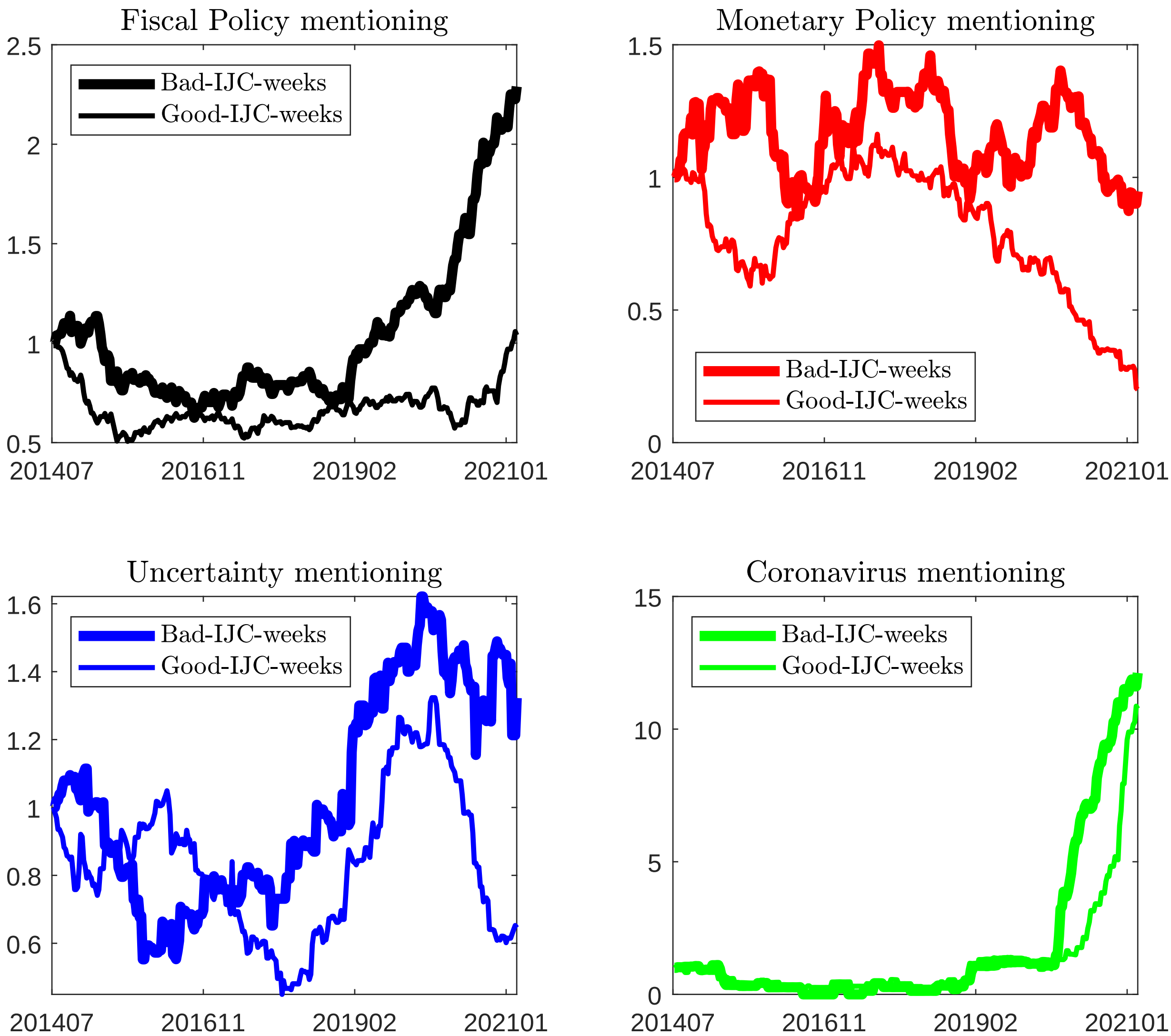
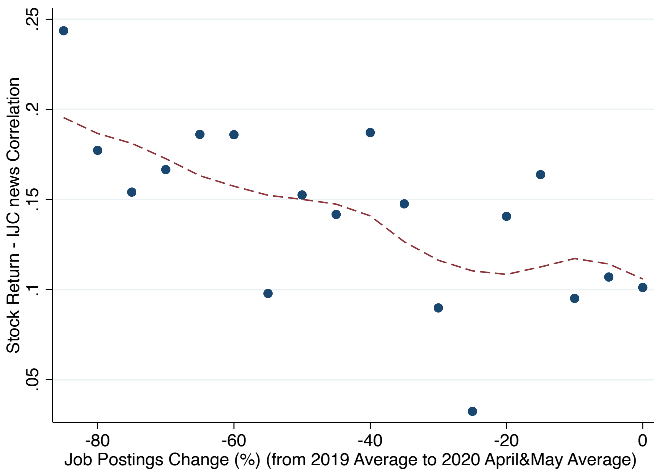
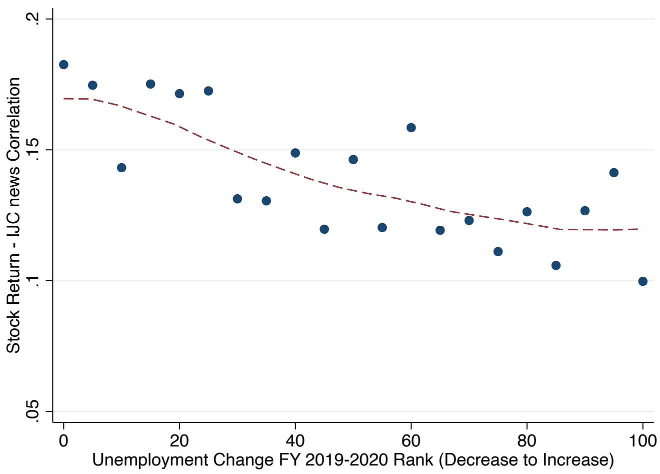


Figure 4: What do people talk about on "bad" and "good" IJC announcement days?

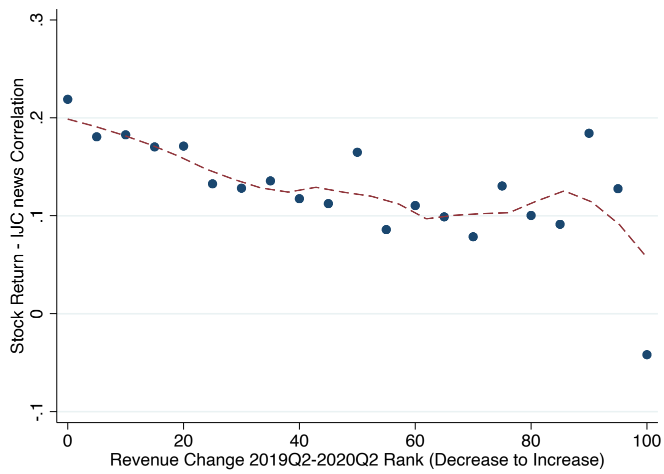
This table complements Figure 3 and shows the relative topic mentions on bad (thick lines) and good (thin lines) IJC days within the same 60-week rolling window. For interpretation purpose, each line is scaled with the first value in its series, as in Table A9. The "1.5" means that the mentions of this 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.



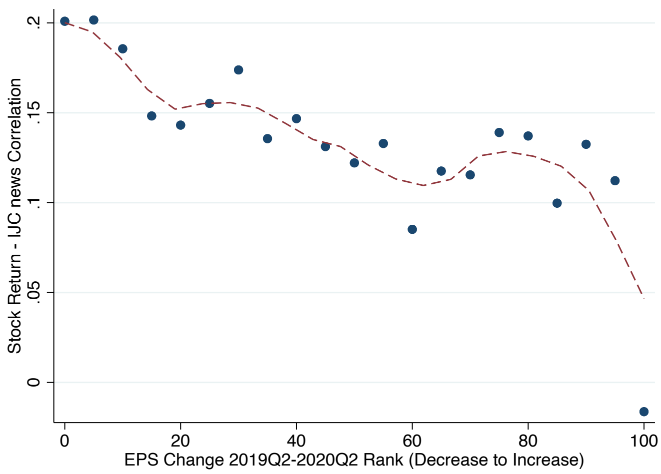
(a)



(b)



(c)



(d)

Figure 5: 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 (491 out of 500 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 stronger "Main Street pain, Wall Street gain" phenomenon (captured by the higher SD changes in individual stock returns given 1 SD IJC shock). The x variable in subfigure (a) is the raw changes in the number of all-internet job postings, where "-80" indicates that for 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 compare fiscal year 2019 and 2020 (due to data availability), whereas revenue and EPS changes compare 2019Q2 and 2020Q2 (to capture the initial Covid effect); we use "rank" in the x-axis due to the skewness of firm-level data as shown in Appendix Table A14.

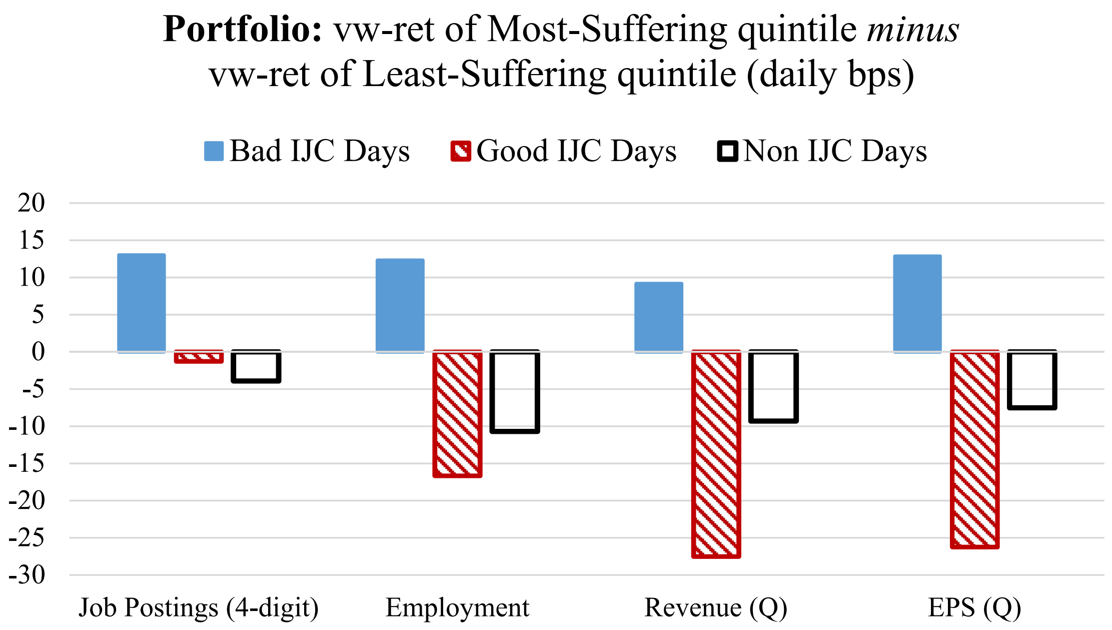


Figure 6: Investment strategy.

Step 1: We sort S&P500 firms into 5 bins based on our four main "firm Covid impact" measures as in Figure 5 and Table 7: (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; sample period runs from February 2020 to March 2021 (end of the sample) excluding 03/19, 03/26, 04/02, 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 A5 in the appendix.

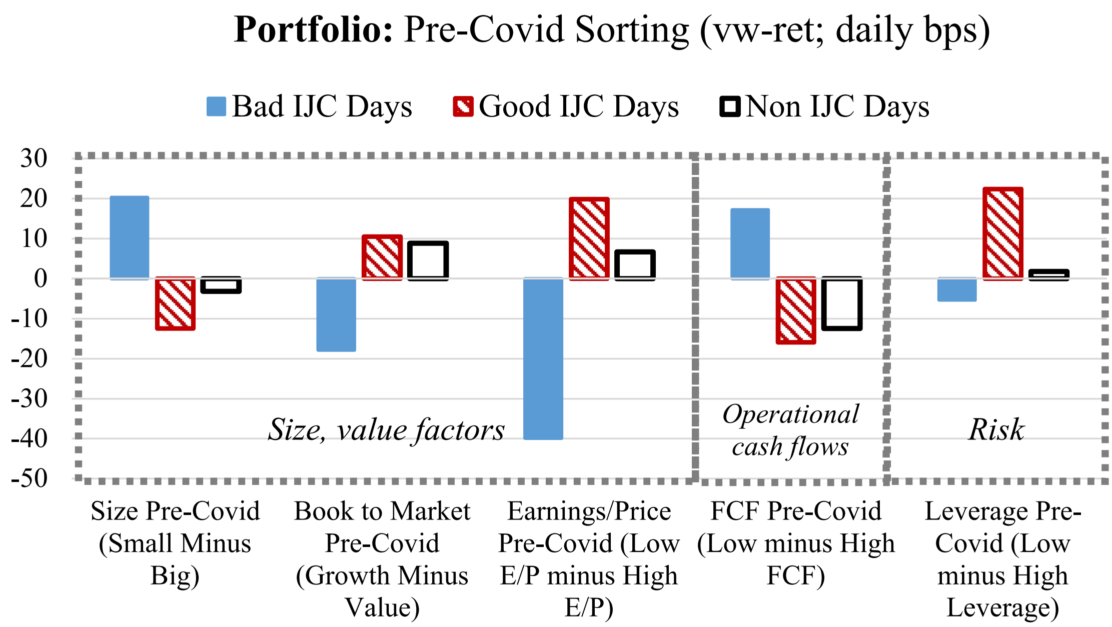


Figure 7: Standard firm characteristics.

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 6.

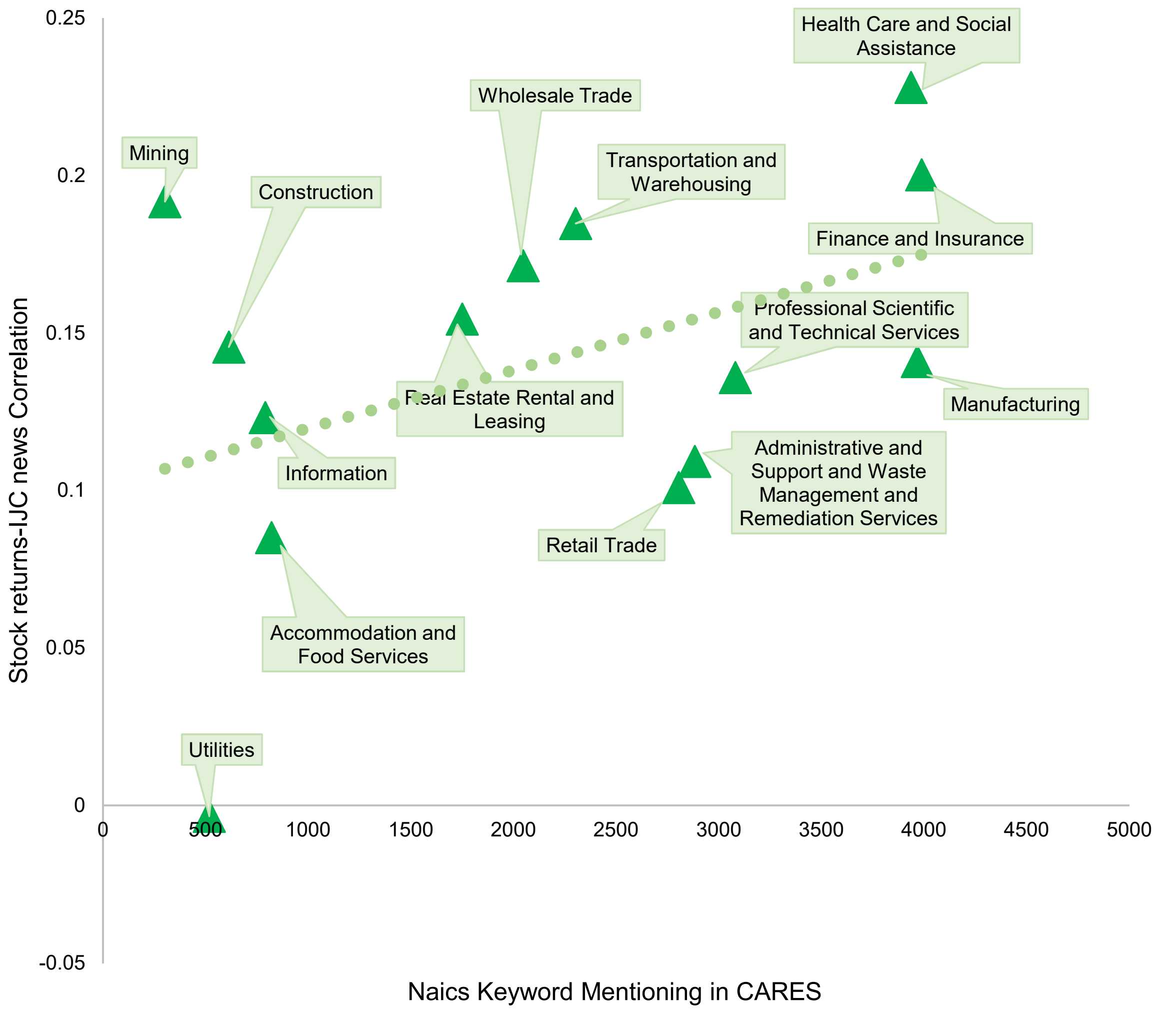


Figure 8: Cross-section evidence: Industry bill mentions and return-IJC correlations.

This figure depicts the relationship between industry return-IJC shock correlations and their mentions in this 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 491 stocks (that we are able to identify all three cross-sections in this paper), and then calculate the industry average. We use the 2-digit NAICS to classify firms. Six industries have less than 5 with firm representations among the 491 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 doing proper data cleaning such as 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 in the law by President Donald Trump on March 27, 2020. In the Appendix Figure A6, we re-produce exact the same plot using HEROES, CAA, and ARP acts as robustness tests. The fitted line above yields a significant and high correlation of 0.44 (SE=0.24).

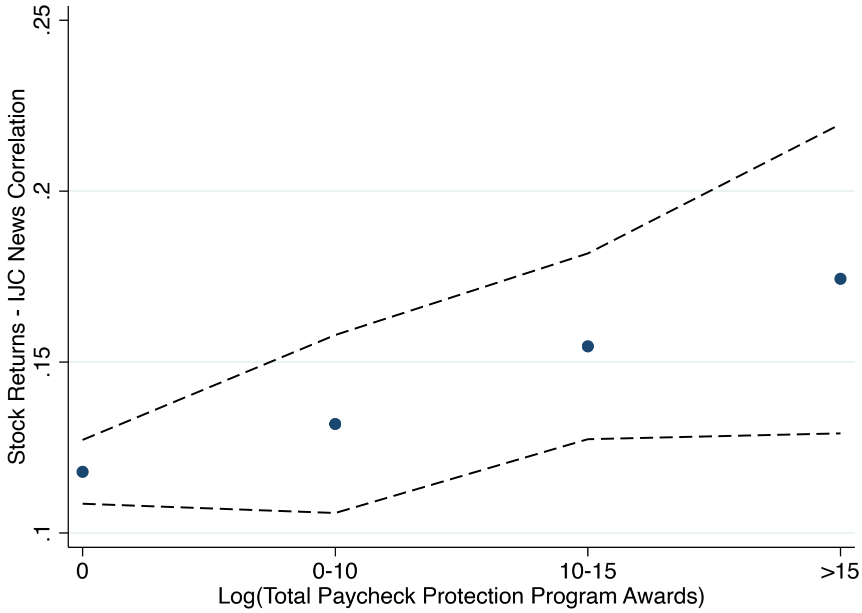
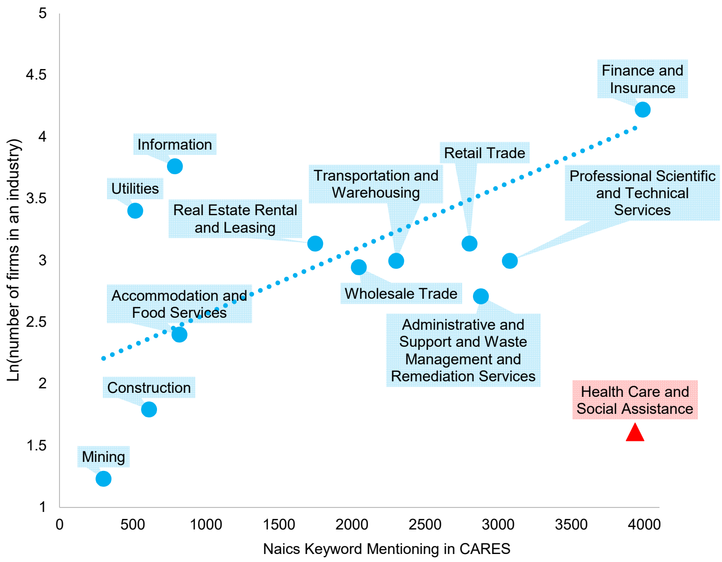
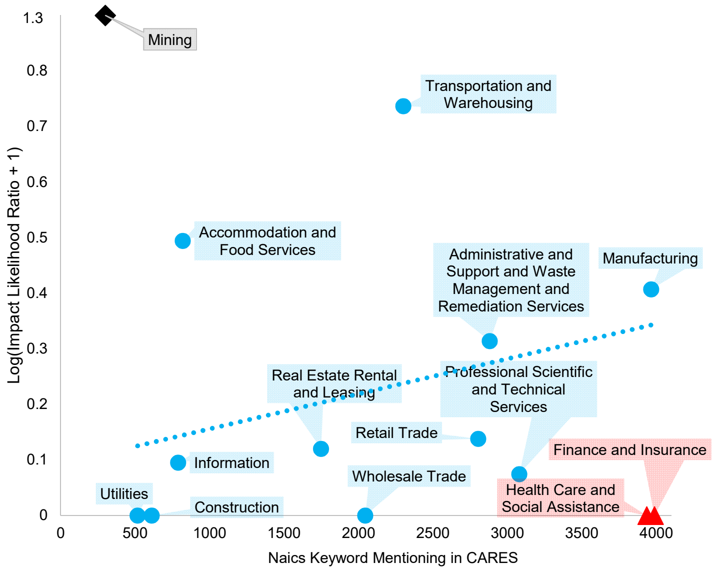


Figure 9: Cross-section evidence: Obligated Paycheck Protection Program awards and return-IJC correlations.

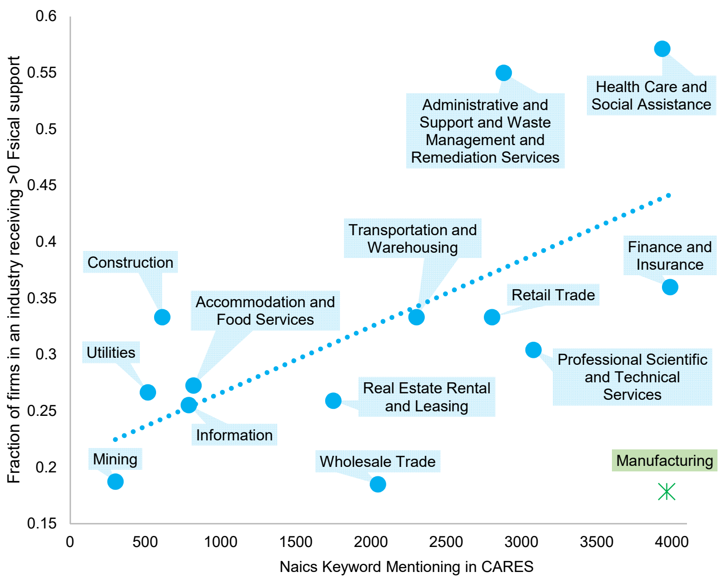
This figure depicts the average return-IJC shock correlations of four groups of firms sorted by their obligated paycheck protection program award amounts: Not Covid-funding recipient (log(award+1)=0); log(award+1) from 0 to 10; log(award+1) from 10 to 15; and log(award+1) above 15. The dashed lines indicate the actual 90% confidence interval. The company sample contains the 491 companies in S&P 500.



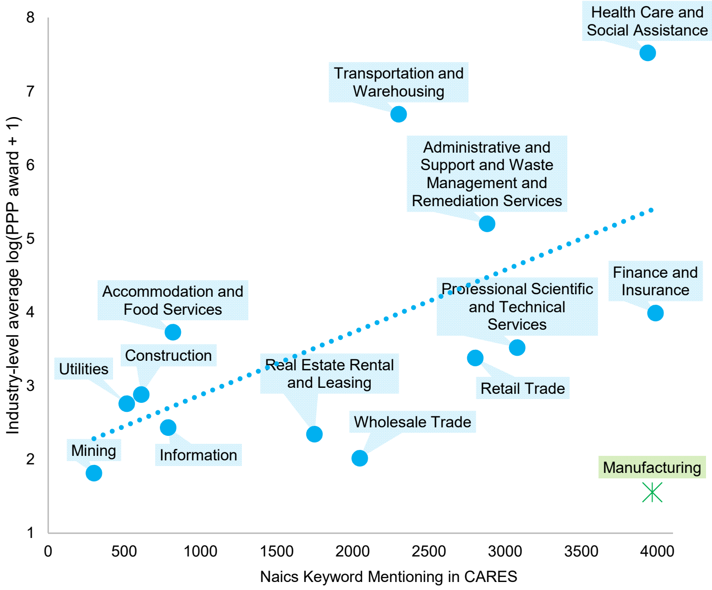
(a) y-axis: Industry presence in S&P500 (our 491 firm pool)



(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 impact, and (c,d) its fiscal supports. **Y-axes:** (a) uses the log of 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% tail compared to its likelihood in the least damaged 50% where the damage measure uses the changes in job postings: $Ratio = \frac{Prob(\#\text{Firm in the most damaged } 15\%)}{Prob(\#\text{Firm in the least damaged } 50\%)}$; (c) calculates the fraction of firms in an industry that receive any covid-related spending out of its total presence in the 491 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.

For Online Publication

“Main Street’s Pain, Wall Street’s Gain”
by Nancy R. Xu and Yang You

A. Additional Tables and Figures

Table A1: Timeline of all Federal Reserve actions from March 15, 2020 to 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
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4/1/2020		Fed loosens bank capital requirements https://www.federalreserve.gov/newsevents/pressreleases/bcreg20200401a.htm
4/6/2020	Fiscal	Fed implements CARES Act community bank capital ratio https://www.federalreserve.gov/newsevents/pressreleases/bcreg20200406a.htm
4/9/2020	Fiscal	Fed announces three new emergency lending facilities designed to implement the relief provided by the CARES Act, support the work of Treasury and the Small Business Administration (SBA): 1. Paycheck Protection Program liquidity facility (PPPFL) 2. Main Street Business Lending Program 3. Municipal Liquidity Facility https://www.federalreserve.gov/newsevents/pressreleases/monetary20200409a.htm
4/23/2020	Fiscal	Fed Commits to Transparent Disclosure of Companies Receiving Financial Aid through the liquidity and lending facilities using Coronavirus Aid, Relief, and Economic Security, or CARES, Act funding https://www.federalreserve.gov/newsevents/pressreleases/monetary20200423a.htm
4/23/2020	Fiscal	Fed to expand access to PPPLF Program https://www.federalreserve.gov/newsevents/pressreleases/monetary20200423b.htm
4/27/2020	Fiscal	Fed expands access to municipal lending facility https://www.federalreserve.gov/newsevents/pressreleases/monetary20200427a.htm
4/30/2020	Fiscal	Fed expands Main Street Lending Program https://www.federalreserve.gov/newsevents/pressreleases/monetary20200430a.htm
5/11/2020	Fiscal	Fed releases term sheet for municipal liquidity facility clarifying pricing https://www.federalreserve.gov/newsevents/pressreleases/monetary20200511a.htm
5/15/2020	Fiscal	Fed provides first report to congress on PPPLF facility https://www.federalreserve.gov/monetarypolicy/ppplf.htm
5/15/2020		Fed loosens bank capital requirement (again) https://www.federalreserve.gov/newsevents/pressreleases/bcreg20200515a.htm
5/19/2020	Fiscal	Main Street Business Lending Program and Municipal Liquidity Facility Programs to commence end of may https://www.federalreserve.gov/newsevents/testimony/powell20200519a.htm
6/3/2020	Fiscal	Municipal Liquidity Facility opens and access once again expanded https://www.federalreserve.gov/newsevents/pressreleases/monetary20200603a.htm
6/8/2020	Fiscal	Fed significantly expands access to proposed Main Street Lending Facility https://www.federalreserve.gov/newsevents/pressreleases/monetary20200608a.htm
6/15/2020	Fiscal	Main Street Lending Facility opens for lender registration https://www.bostonfed.org/news-and-events/press-releases/2020/.. ../federal-reserves-main-street-lending-program-opens-for-lender-registration.aspx?source=email
6/15/2020		Fed expands SMCCF, begins buying debt directly from large corporations https://www.newyorkfed.org/newsevents/news/markets/2020/20200615?source=email
6/15/2020	Fiscal	Fed requests feedback on extending Main Street Lending Program to Nonprofits https://www.federalreserve.gov/newsevents/pressreleases/monetary20200615b.htm
7/17/2020	Fiscal	Fed begins purchasing loans through Main Street Lending Program; opens program to non-profits https://www.federalreserve.gov/newsevents/pressreleases/monetary20200717a.htm
10/30/2020	Fiscal	Fed lowers main street lending program minimum loan amount to $100,000 https://www.federalreserve.gov/newsevents/pressreleases/monetary20201030a.htm
11/3/2021		Fed announces that it will reduce pace of asset purchases https://www.federalreserve.gov/newsevents/pressreleases/monetary20201030a.htm

Table A2: Summary statistics of Initial Jobless Claims (IJC) shock

This table shows summary statistics of IJC shocks in three subsamples as mentioned in the paper:

Period 1	*2009/07-2016/12*		*Expansionary-ZLB*
Period 2	*2017/01-2020/01*		*Contractionary-Low interest rate*
Period 3	*2020/02-2021/03*	*Covid*	*Expansionary-ZLB*

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 Employment and Training Administration (ETA) on Thursday of current week t, and $E_{t-\Delta}(IJC_t)$ indicates the median survey forecast submitted until 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)*		
	Period 1	**Period 2**	**Period 3**	**Period 1**	**Period 2**	**Period 3**
Min	-0.117	-0.141	-0.153	-38	-43	-255
1st	-0.091	-0.115	-0.152	-33	-29	-254
5th	-0.067	-0.074	-0.112	-25	-18	-131
10th	-0.053	-0.062	-0.083	-18	-14	-78
25th	-0.026	-0.036	-0.038	-10	-8	-30
50th	-0.003	-0.008	0.005	-1	-2	1
75th	0.025	0.020	0.058	8	5	68
90th	0.054	0.050	0.131	19	12	171
95th	0.079	0.065	0.190	25	15	213
99th	0.144	0.178	0.223	49	38	477
Max	0.203	0.216	0.224	64	53	481
Mean	0.000	-0.004	0.019	0.209	-1.158	43.954
Mean-Bad	0.036	0.036	0.083	12.949	8.147	135.482
Mean-Good	-0.030	-0.039	-0.049	-10.720	-9.133	-54.615
SD	0.044	0.051	0.087	15.766	11.845	188.383
SD-Bad	0.033	0.041	0.068	12.187	9.264	218.860
SD-Good	0.024	0.027	0.040	8.696	7.008	63.375
Skewness	0.672	0.990	0.550	0.701	0.735	3.577
Skewness-Bad	1.930	2.576	0.738	1.876	2.697	3.401
Skewness-Good	-1.023	-1.108	-0.946	-0.990	-1.778	-1.872
N-Total	379	156	54	379	156	54
N-Bad	175	72	28	175	72	28
N-Good	204	84	26	204	84	26

Table A3: Treasury portfolios on IJC days during the Covid period.

This paper complements Table 2 by examining the Treasury portfolio. **Additional LHS (from left to right):** "Gov Bond Return" denotes the daily log bond returns using the long-term Government bond index (unit: basis points; source: DataStream); "Chgs in 10-yr Yield" denotes the first differences in the 10-year Treasury Yield (unit: annual percents; source: DataStream); "Chgs in Treasury IV" denotes the first differences in the Treasury implied volatility "VXTLT" (same unit as VIX, i.e. annual percents; source: CBOE). See other notation details in Table 2. ***, p-value <1%; **, <5%; *, <10%.

	Gov Bond Return	**Chgs in 10-yr Yield**	**Chgs in Treasury IV**
Period 3, "Covid": 2020/02-2021/03; ZLB			
IJC shock coeff.	60.588	-0.087	-2.182
(SE)	(61.521)	(0.066)	(2.342)
[t]	[0.985]	[-1.310]	[-0.932]
SD chngs per 1SD shock	0.132	-0.177	-0.121
R2%	1.75%	3.13%	1.46%
Sample: Bad IJC days			
IJC shock coeff.	50.631	-0.085	-1.299
(SE)	(100.391)	(0.108)	(2.136)
[t]	[0.504]	[-0.785]	[-0.608]
SD chngs per 1SD shock	0.034	-0.155	-0.100
R2%	0.98%	2.41%	0.99%
Sample: Good IJC days			
IJC shock coeff.	297.762	-0.333	-12.639
(SE)	(251.122)	(0.271)	(8.498)
[t]	[1.186]	[-1.228]	[-1.487]
SD chngs per 1SD shock	0.073	-0.279	-0.244
R2%	7.10%	7.78%	5.96%

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

This table complements Table 3 and provides intradaily return responses of E-mini S&P 500 futures on IJC shocks. Intradaily returns (in basis points) are calculated using the same start time of 8:00AM Eastern Time and an end time of interest (from left to right): pre-announcement, 8:25AM ET; shortly after the announcement, 8:35AM ET; noon, 12:30PM ET; shortly before the close, 3:30PM ET. The left four columns display results using Period "Normal", which is a generally normal period with the majority of the time at the zero lower bound (2009/07-2016/12); the right four columns use Period "Covid" (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 TickData. 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)
[t]	[-1.829]	[-6.153]	[-1.545]	[-1.321]	[-0.219]	[-0.633]	[1.651]	[1.616]
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)
[t]	[-0.597]	[-2.961]	[-0.581]	[-0.545]	[0.223]	[0.700]	[1.373]	[2.097]
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)
[t]	[0.174]	[-1.150]	[0.102]	[-0.240]	[-0.137]	[-1.264]	[0.348]	[-0.199]
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: High-frequency evidence using E-mini Nasdaq futures.

This table complements Table 3 and further drops the 2020/4/9 (Thursday) which has a series of new Federal Reserve announcements regarding CARES implementation (see Appendix Table A1). It is consistent with our story that results using Nasdaq futures are a bit weaker, as growth stocks are in general less exposed to cash flow risk. 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. All IJC days								
IJC shock coeff.	-9.516	-109.988***	-72.495	-88.873	-2.099	-41.493	125.514	192.267
(SE)	(9.795)	(21.494)	(82.126)	(97.372)	(16.241)	(43.168)	(159.308)	(219.451)
[t]	[-0.971]	[-5.117]	[-0.883]	[-0.913]	[-0.129]	[-0.961]	[0.788]	[0.876]
SD chngs per 1SD shock	-0.041	-0.262	-0.042	-0.043	-0.015	-0.155	0.104	0.123
Closeness (Covid-normal)?					0.39	1.42	1.10	1.17
Panel B. Bad IJC days								
IJC shock coeff.	-2.636	-91.369**	-10.217	-3.001	23.750	84.814	124.092	458.302**
(SE)	(18.032)	(36.307)	(164.444)	(188.163)	(37.956)	(81.649)	(179.127)	(213.454)
[t]	[-0.146]	[-2.517]	[-0.062]	[-0.016]	[0.626]	[1.039]	[0.693]	[2.147]
SD chngs per 1SD shock	-0.009	-0.166	-0.005	-0.001	0.127	0.234	0.113	0.298
Closeness (Covid-normal)?					0.63	**1.97**	0.55	1.62
Panel C. Good IJC days								
IJC shock coeff.	9.567	-47.555	142.765	32.200	3.084	-107.887	410.173	196.725
(SE)	(26.945)	(51.633)	(195.851)	(263.233)	(57.856)	(93.270)	(664.213)	(935.504)
[t]	[0.355]	[-0.921]	[0.729]	[0.122]	[0.053]	[-1.157]	[0.618]	[0.210]
SD chngs per 1SD shock	0.021	-0.066	0.044	0.008	0.011	-0.219	0.126	0.049
Closeness (Covid-normal)?					-0.10	-0.57	0.39	0.17

Table A6: High-frequency evidence using interest rate futures and VIX futures (risk proxies).

This table complements Table 3 and tests whether the main "Bad IJC day" results appear in discount-rate-related asset prices (interest rate and VIX futures). Panel A uses log changes in the 10-year Treasury note futures prices (ticker symbol ZN); Panel B uses first differences in the 30-day Fed Fund futures (ticker symbol ZQ), as the index is directly related to (the inverse) Effective Fed Funds Rate; Panel C uses first differences in the VIX futures (ticker symbol VX); all are traded on the Chicago Mercantile Exchange (CME) and the merge with IJC data need adjusting time zones. 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 (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)
[t]	[0.219]	[-1.278]	[0.621]	[0.431]	[0.024]	[0.024]	[-0.595]	[-0.844]
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 (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)
[t]	[0.786]	[2.034]	[0.933]	[1.506]	[0.627]	[0.757]	[1.479]	[0.543]
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
Panel C. VIX Futures (LHS: first-differences); Bad IJC days								
IJC shock coeff.	-0.130	0.071	1.174	1.022	0.414	1.152	-2.420	-5.820*
(SE)	(0.204)	(0.459)	(1.680)	(1.675)	(0.574)	(1.069)	(1.938)	(3.403)
[t]	[-0.636]	[0.155]	[0.699]	[0.610]	[0.721]	[1.078]	[-1.248]	[-1.710]
SD chngs per 1SD shock	-0.043	0.015	0.074	0.052	0.188	0.273	-0.207	-0.345
Closeness (Covid-normal)?					0.89	0.93	-1.40	-1.80

Table A7: 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 given a series of new Federal Reserve announcements 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*	
Period 1	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)**
	[t]	[-0.977]	[-0.048]	**[1.979]**	[-0.816]	[-0.050]	**[1.712]**
	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%**
Period 2	IJC shock	0.489	0.273	-0.216	111.454	60.276	-51.178
	(SE)	(0.362)	(0.261)	(0.221)	(86.420)	(62.499)	(52.804)
	[t]	[1.351]	[1.047]	[-0.977]	[1.290]	[0.964]	[-0.969]
	SD chngs per 1SD shock	0.088	0.039	-0.039	0.086	0.037	-0.040
	R2%	0.77%	0.44%	0.55%	0.74%	0.40%	0.57%
Period 3	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)
	[t]	**[1.679]**	**[3.446]**	**[1.811]**	[1.468]	**[1.871]**	[-0.373]
	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 A8: Asymmetry and Assets.

This table complements Table 2 and further drops the 2020/4/9 (Thursday). 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)
[t]	**[2.050]**	**[1.707]**	[-1.429]	**[2.035]**	**[1.757]**	**[1.928]**	**[1.945]**	**[2.257]**	[0.395]
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)
[t]	[-0.429]	[-0.224]	[0.574]	[-0.430]	[0.024]	[-0.996]	[-0.951]	[-0.767]	[-1.376]
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 A9: What do people talk about on IJC announcement days?

This table complements Figure 4 and provides exact relative topic mentioning values in six non-overlapping subsamples from 2013-2021. Each subsample has (around) 60 weeks each; block "All days" uses all 60 weeks to compute topic mentioning, and block "Bad days" ("Good days") uses bad (good) IJC days within the same 60-week subsample. **Panel A** reports text mentioning 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 continuous version of bad and good relative mentioning. **Panel B** provides the t statistics of whether the relative mentioning of the same topic during bad days is the same as that during good days (i.e., the higher the t, the higher relative mentioning in bad bays; 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 A10: Relationship between return responses and topic mentions from rolling windows – More robustness results.

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

- Robustness (1), (2), (3) are already reported in Tables 4 and 5: using economic magnitude (in standard deviation rather than in basis points); including uncertainty mentions; using Dow Jones 65 open-to-close returns.
- Robustness (4) here: Dropping the 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, 60-day rolling window, rather than 80-day. Table format follows Table 4.
- Robustness (6) here: Using 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 A11: Correlation among quarterly state variables used in Tables 6 and A12 (next). The "badX" means topic mentions of state variable X during bad IJC days only within the quarter. "$\Delta Tbill3m$" follows Elenev et al. (2022) and denotes the differences between one-quarter-ahead forecast and nowcast of the 3-month Treasury bill rate, where both forecast and nowcast are provided given last quarter information set (source: Survey of Professional Forecasters, or SPF).

(N=33)	badFP	badMP	badUNC	goodFP	goodMP	goodUNC	$\Delta Tbill3m$
badFP	1	0.21	**0.69***	0.25	**-0.44***	0.02	**-0.43**
badMP		1.00	**0.36**	**-0.29***	0.04	-0.10	-0.05
badUNC			1.00	0.26	-0.09	**0.33***	**-0.50***
goodFP				1.00	-0.05	0.22	-0.25
goodMP					1.00	-0.07	**0.46***
goodUNC						1.00	-0.24
$\Delta Tbill3m$							1.00

Table A12: 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 weekly 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 one-quarter-ahead forecast and 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 information set (source: Survey of Professional Forecasters, or SPF). Time series of all quarterly state variables are shown in Figure A4; due to news file availability, sample runs from 2013Q1 to 2021Q1; correlation table is shown in Appendix Table A11. ***, p-value <1%; **, <5%; *, <10%.

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

Table A13: Robustness to mechanism results.

This table complements Columns (1) and (5) of Table 6 using S&P500 returns. See other table details in Table 6. ***, p-value <1%; **, <5%; *, <10%.

	Panel A. Bad IJC days			Panel B. Good IJC days		
LHS:	**S&P500**					
Constant	4.065	3.807	2.968	-1.612	-7.149	-12.419
(SE)	(8.539)	(8.574)	(8.348)	(10.916)	(11.396)	(12.060)
IJC shock	-52.565	-43.868	-38.678	67.661	23.892	-57.120
(SE)	(146.232)	(147.813)	(136.334)	(196.004)	(192.633)	(200.286)
Quarterly FP (standardized)	**-16.552****	**-23.418****	**-22.028****	20.197	16.444	23.425
(SE)	**(7.647)**	**(9.453)**	**(9.114)**	(13.305)	(12.810)	(14.576)
IJC shock*Quarterly FP (standardized)	**258.381*****	**318.925****	**277.973****	371.513	321.106	444.435
(SE)	**(99.014)**	**(156.811)**	**(132.818)**	(241.694)	(234.386)	(271.070)
Quarterly MP (standardized)	-6.252	-9.063		2.103	2.460	
(SE)	(6.912)	(7.227)		(9.674)	(9.395)	
IJC shock*Quarterly MP (standardized)	58.787	86.546		190.288	186.148	
(SE)	(118.594)	(136.256)		(156.953)	(147.157)	
Quarterly $\Delta Tbill3m$ (standardized)			-2.377			**24.328***
(SE)			(8.862)			**(14.490)**
IJC shock*Quarterly $\Delta Tbill3m$ (standardized)			-58.290			**496.752***
(SE)			(155.283)			**(283.129)**
Quarterly UNC (standardized)		10.777	5.053		**24.300***	**26.855***
(SE)		(10.559)	(11.495)		**(14.516)**	**(14.503)**
IJC shock*Quarterly UNC (standardized)		-105.486	-66.787		**407.240***	**443.793***
(SE)		(210.394)	(197.364)		**(244.847)**	**(240.262)**

Table A14: Summary statistics of raw Covid-impact measure across 491 firms.

		p5	p25	p50	p75	p95	Mean	SD
1	Job Postings Change; 2019 Average-2020 April&May Average , 4-digit NAICS	-0.76	-0.51	-0.39	-0.29	-0.04	-0.39	0.21
2	Employment Change; FY 2019-2020	-0.22	-0.05	0.00	0.06	0.22	0.02	0.20
3	Revenue Change; 2019Q2-2020Q2	-0.41	-0.08	0.01	0.10	0.37	0.02	0.46
4	EPS Change; 2019Q2-2020Q2	-9.74	-1.91	-0.16	1.01	4.43	-0.91	7.66
5	Revenue Change; FY2019-2020	-0.37	-0.09	-0.01	0.07	0.31	0.02	0.60
6	EPS Change; FY 2019-2020	-10.62	-1.93	-0.37	0.73	4.02	-1.42	8.28

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	0.65	1.00				
EPS Rank	0.35	0.58	1.00			
Revenue Rank (Q)	0.61	0.87	0.54	1.00		
EPS Rank (Q)	0.38	0.59	0.72	0.57	1.00	
Job Post Change (4-digit)	0.24	0.28	0.23	0.29	0.21	1.00

Table A15: Cross-section evidence: Covid-Stimulus and return-IJC correlation on **bad IJC** days

This table complements Table 8 and regresses the return-IJC shock correlation, from bad IJC days, on the Covid-relief funding 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"):

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

Columns (1) and (2) use the *obligated* amount (i.e. promised awards) of all Covid spending, respectively; Columns (3) and (4) use the *obligated* amount of 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 amount of negative amounts, which are related to revoke decisions or 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%.

LHS:	Return-IJC Shock Correlation on bad IJC days					
Obligated or actual:	Obligated Amount		Obligated Amount		Actual Amount	
Award type:	All		Paycheck Protection		All	
	(1)	(2)	(3)	(4)	(5)	(6)
	All	Positive	All	Positive	All	Positive
Coefficient	0.303**	0.301**	0.347***	0.346***	0.342***	0.331***
(SE)	(0.119)	(0.119)	(0.125)	(0.124)	(0.131)	(0.125)
Obs	491	491	491	491	491	491

Table A16: Cumulative and average daily capital gain in the US stock market.

This table calculates simple cumulative and average daily capital gains of S&P500 stocks, on bad-, good- and non-IJC days, during Covid period and a general non-Covid period. Average daily capital gain is cumulative/number of days. This table uses surprises that are economically sizable when calculating the average for better 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)

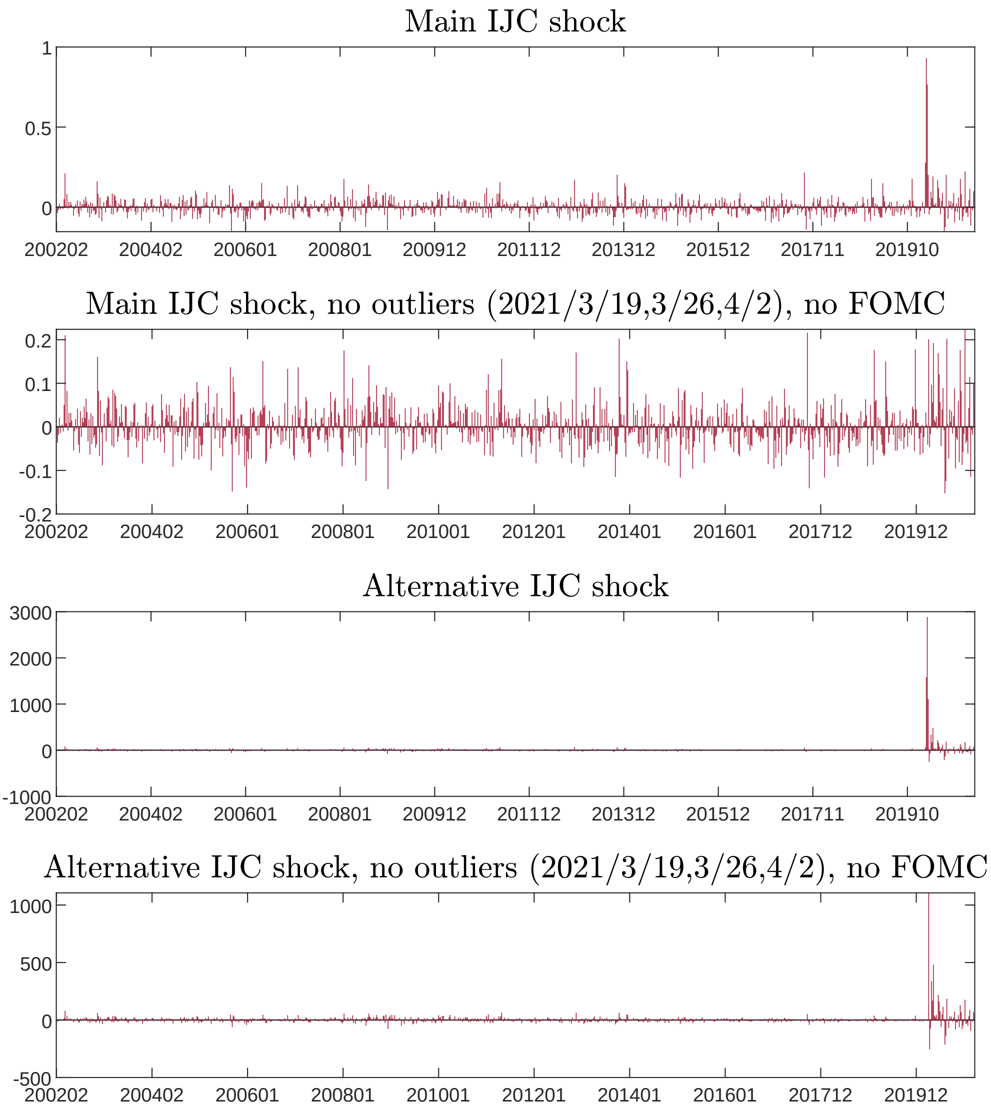
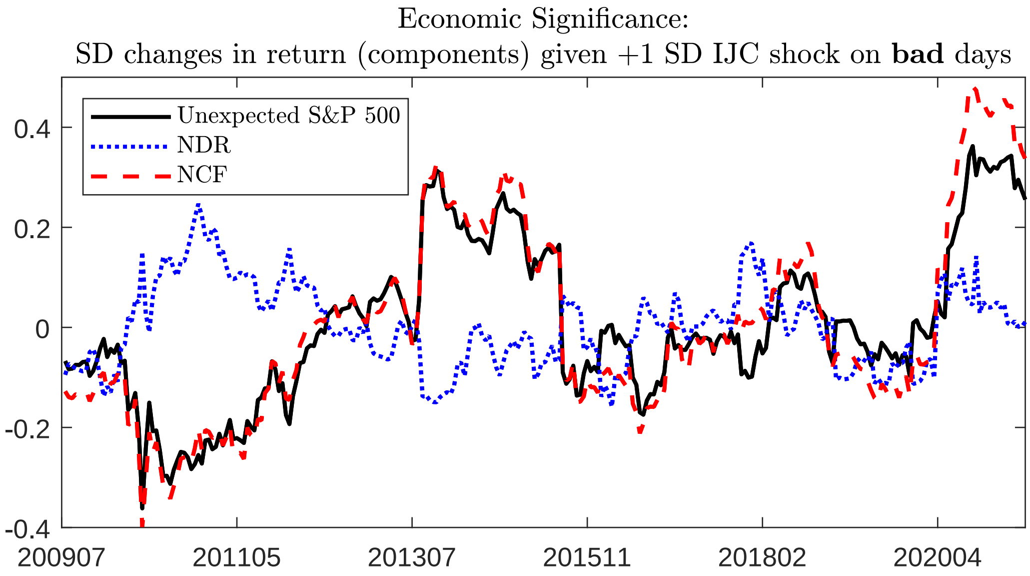


Figure A1: Time series of main IJC shocks ($\frac{IJC_t - E_{t-\Delta}(IJC_t)}{E_{t-\Delta}(IJC_t)}$) and alternative IJC shocks ($IJC_t - E_{t-\Delta}(IJC_t)$), with or without the identified outliers and FOMC days.



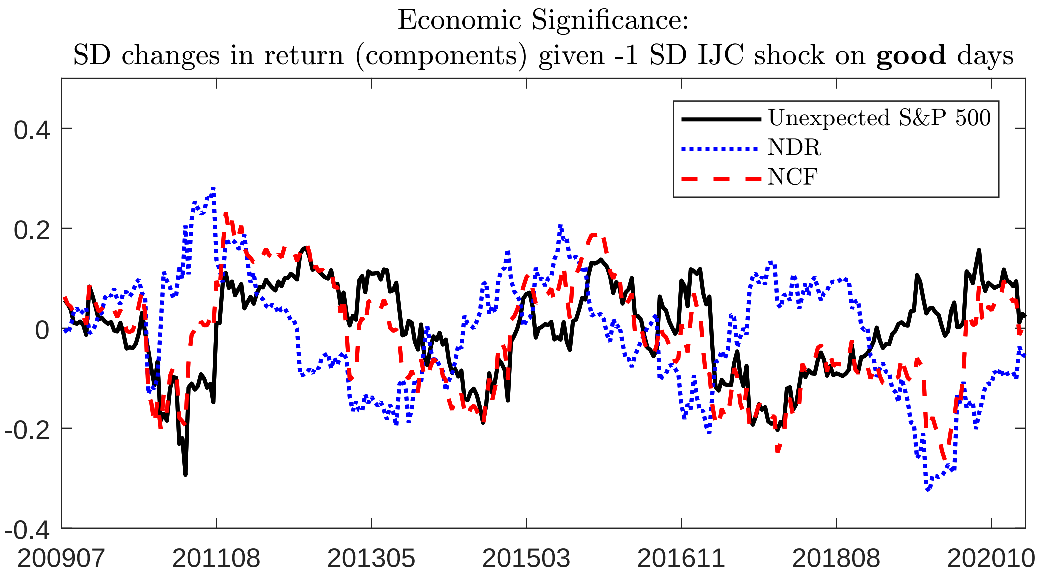
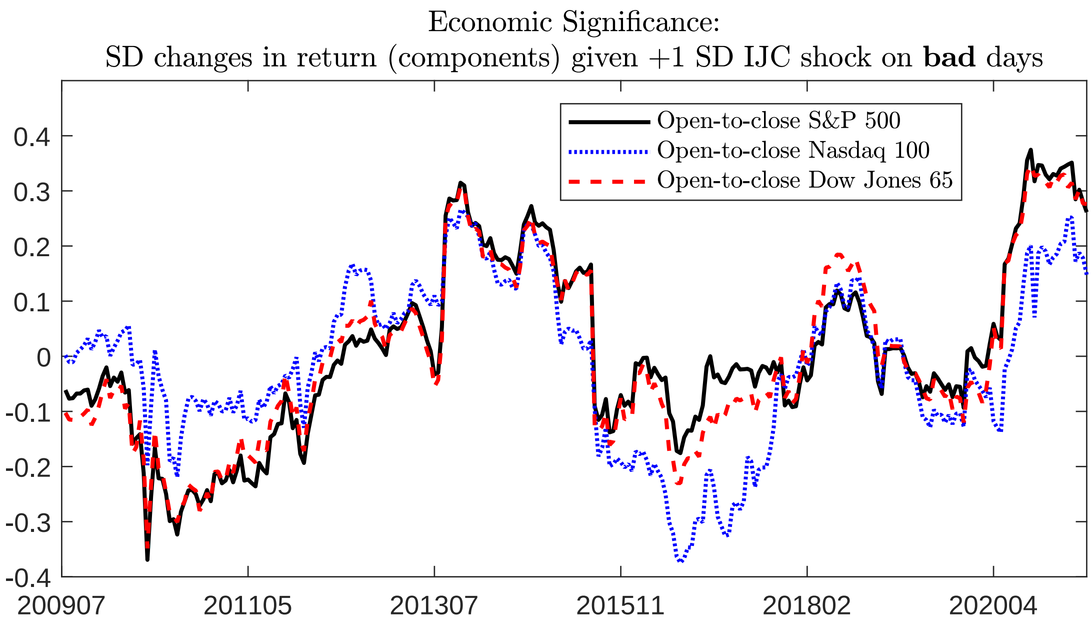


Figure A2: Time variation in return responses to IJC shocks, on bad and good IJC days: NCF and NDR.

This figure focuses on economic magnitude of return responses (SDs changes in returns given 1 SD shock), obtained from 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 +1SD IJC shock (jobless claims are higher/worse than expected); bottom plot: if "good is good", risky asset returns should *increase* given -1SD IJC shock (jobless claims are lower/better than expected).



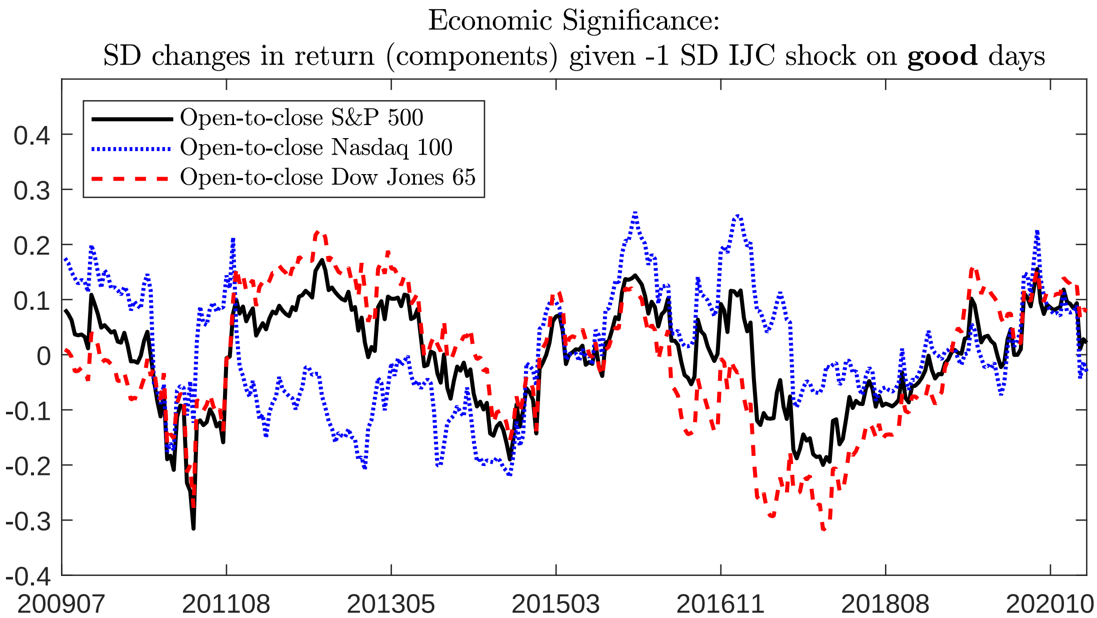


Figure A3: Time variation in return responses to IJC shocks, on bad and good IJC days: S&P, Nasdaq and Dow Jones.

This figure focuses on economic magnitude of return responses (SDs changes in returns given 1 SD shock), obtained from 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 +1SD IJC shock (jobless claims are higher/worse than expected); bottom plot: if "good is good", risky asset returns should *increase* given -1SD IJC shock (jobless claims are lower/better than expected).

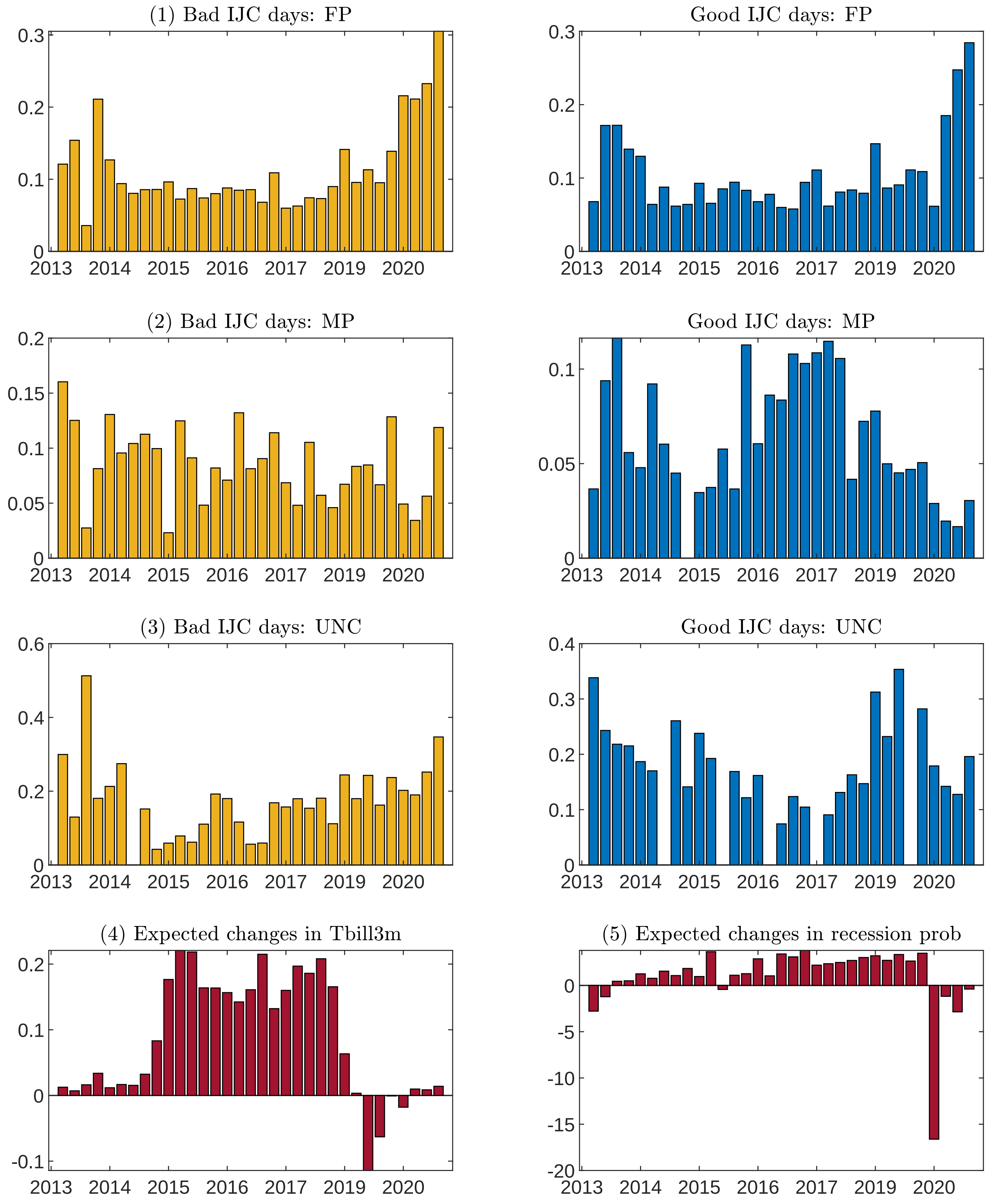
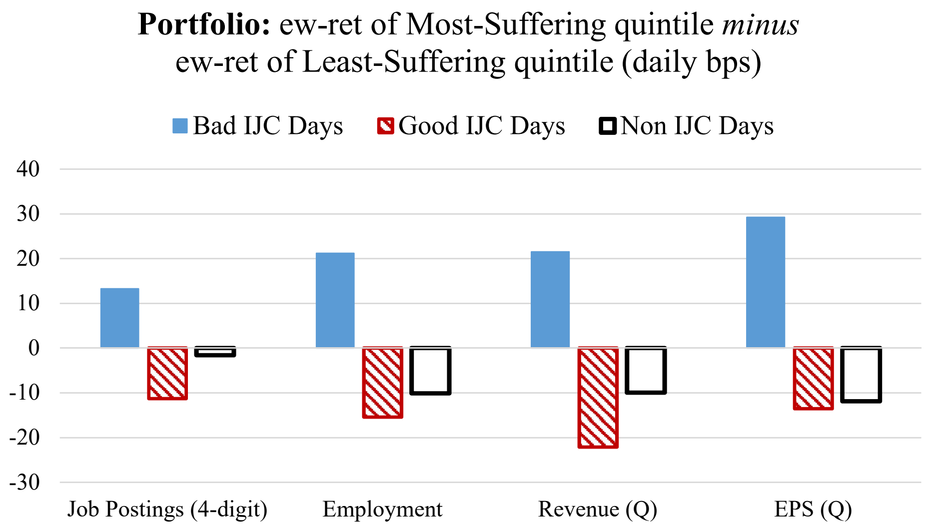
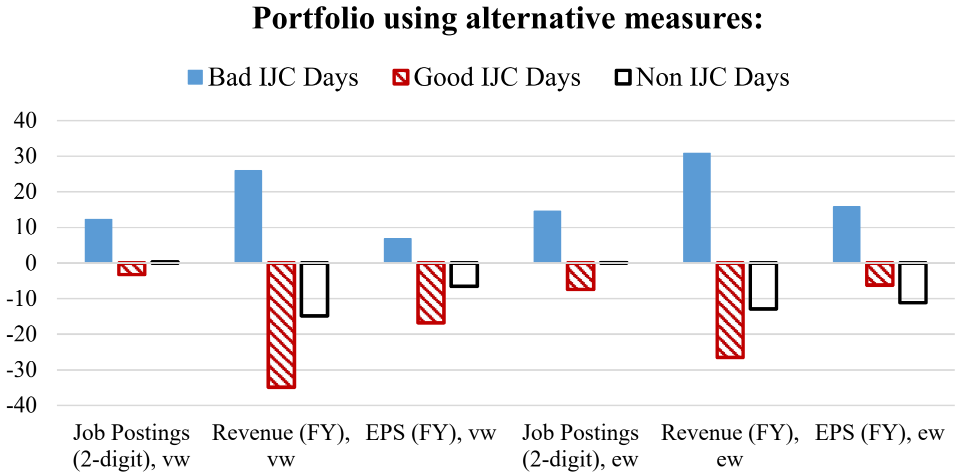


Figure A4: Quarterly state variables.

This figure depicts our non-overlapping quarterly topic mention 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 (first three rows), and the Survey of Professional Forecaster for the bottom two plots (last row).





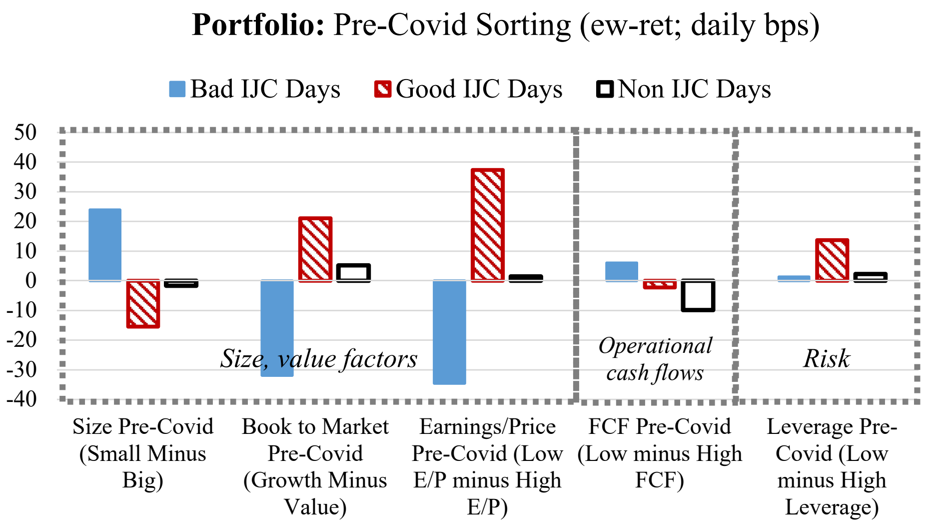
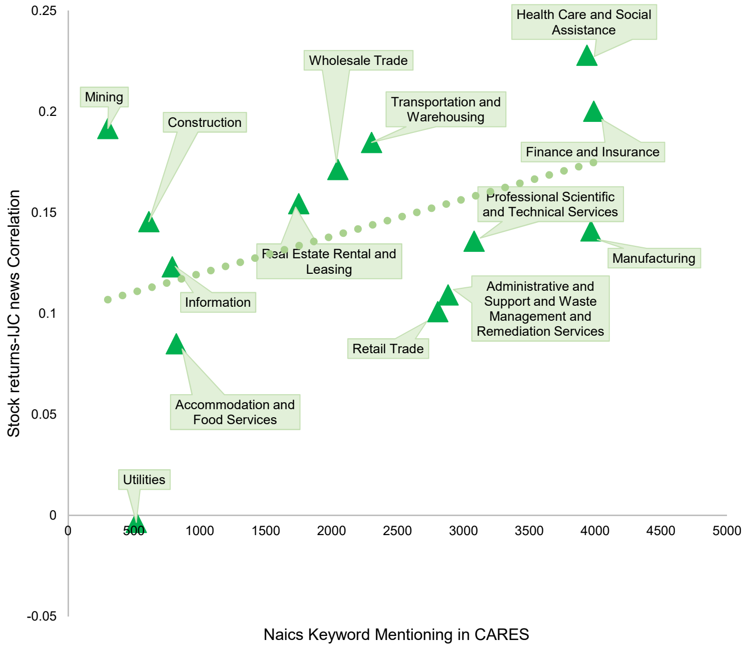
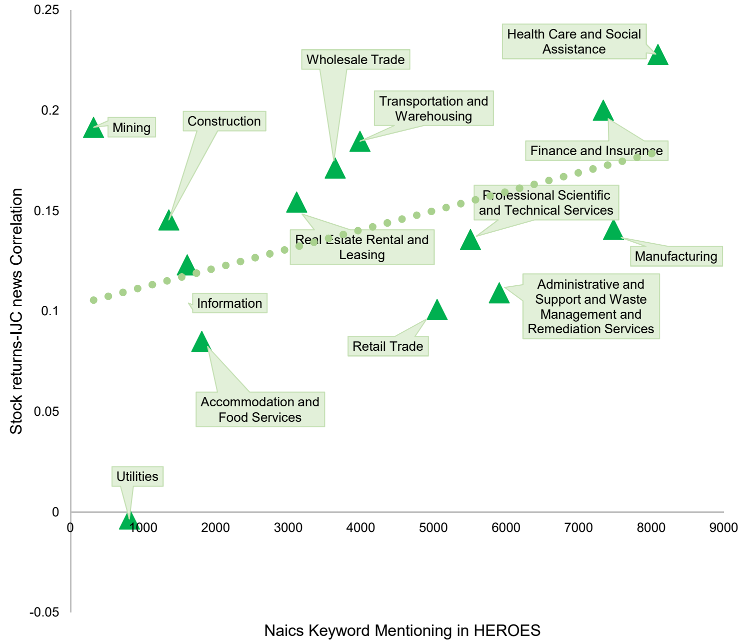


Figure A5: Robustness: Portfolio returns

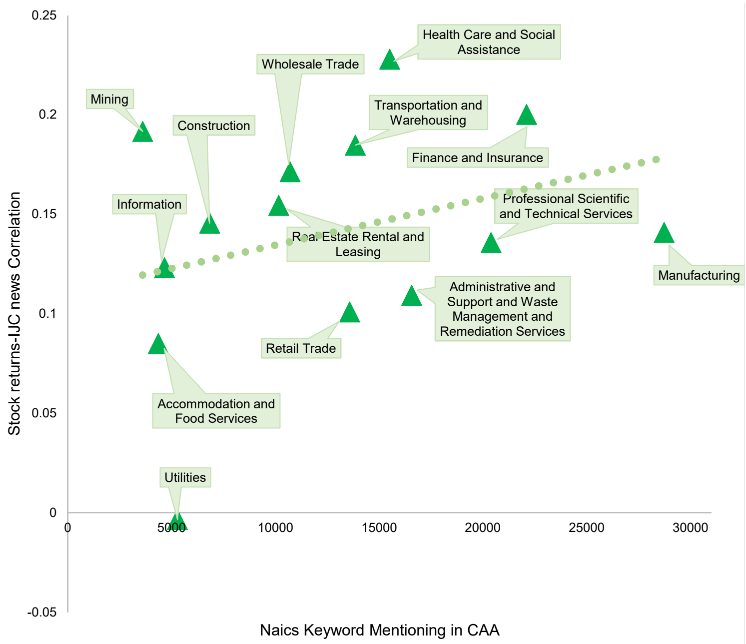
The first two plots provide robustness results to Figure 6, using equal weights (plot 1) and using alternative (cautiously, less accurate) Covid-impact measure at the firm level (plot 2). The third plot complements Figure 7 using equal weights. See other details in Figures 6 and 7.



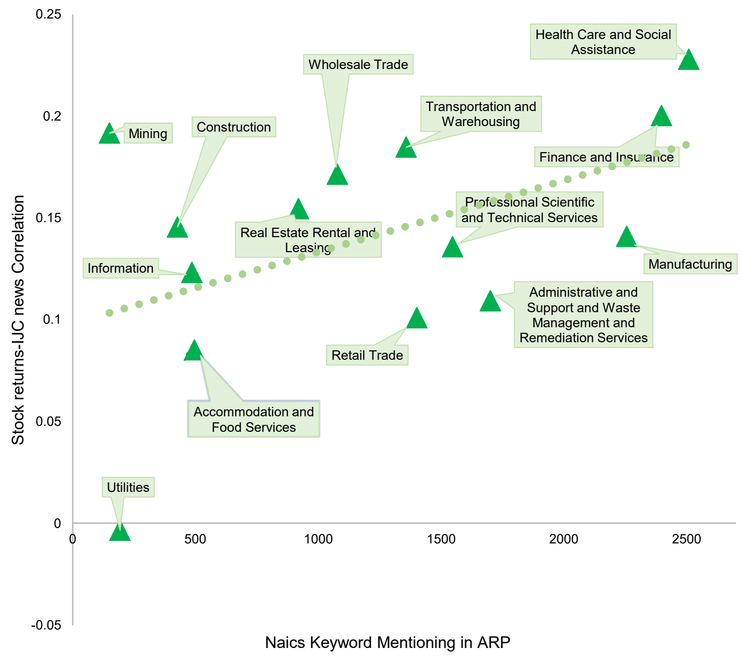
(a) x-axis: Industry mentions in the CARES Act



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



(c) x-axis: Industry mentions in the Consolidated Appropriations Act



(d) x-axis: Industry mentions in the ARP act

Figure A6: Robustness evidence to Figure 8: Industry mentions in actual bills.

This figure extends Figure 8 by using three other bills besides the CARES Act; y-axis: Correlation between returns and IJC shocks; x-axis, 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 in the 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 act as 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 the 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.

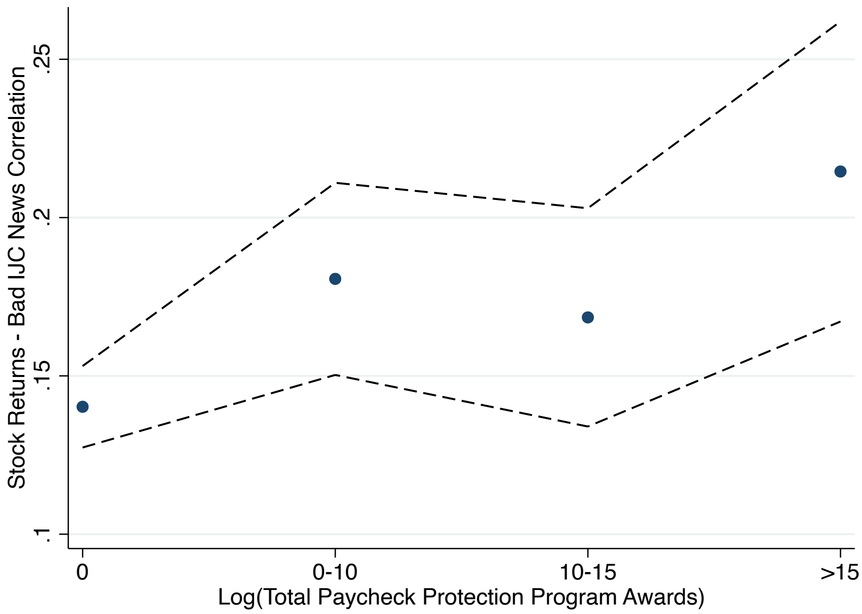
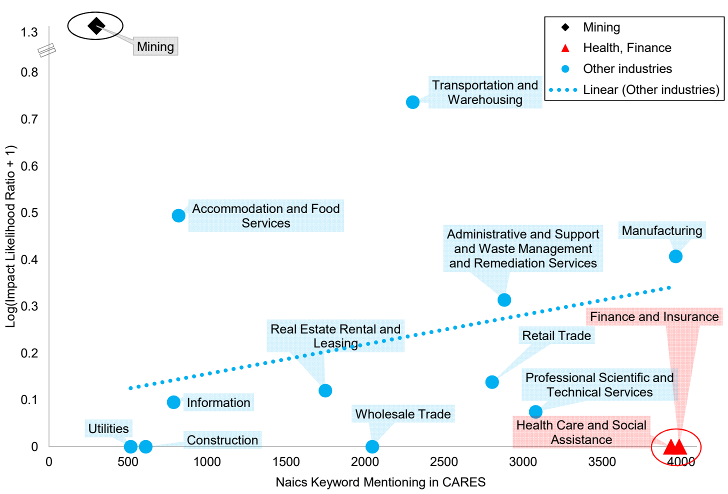
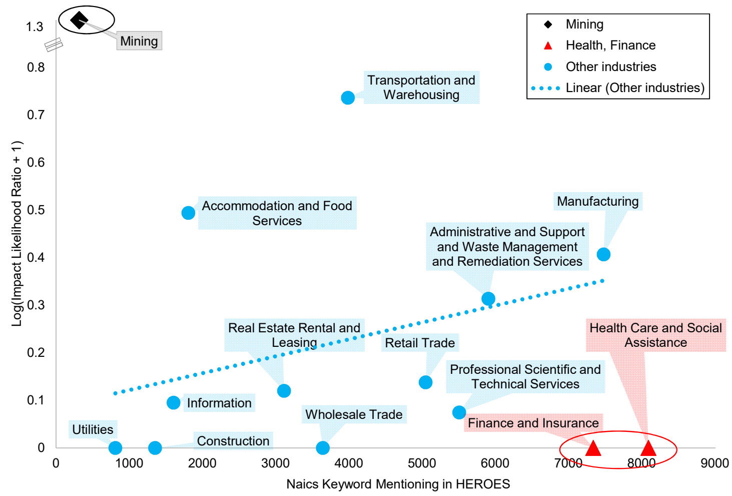


Figure A7: Robustness evidence to Figure 9: Stock Return - Bad IJC shock Correlations by Paycheck Protection Program Awards.

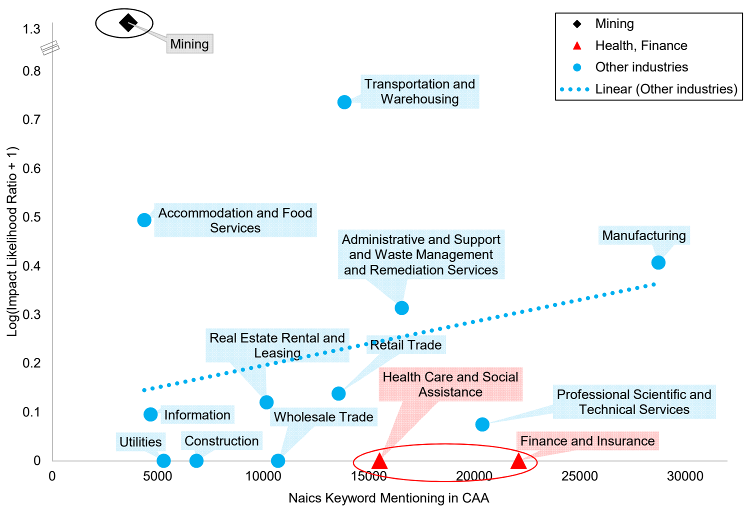
This figure depicts the average return-bad IJC shock correlations of four groups of firms sorted by their obligated paycheck protection program award amounts: Not Covid-funding recipient (log(award+1)=0); log(award+1) from 0 to 10; log(award+1) from 10 to 15; and log(award+1) above 15. The dashed lines indicate the actual 90% confidence interval. The company sample contains the 491 companies in S&P 500.



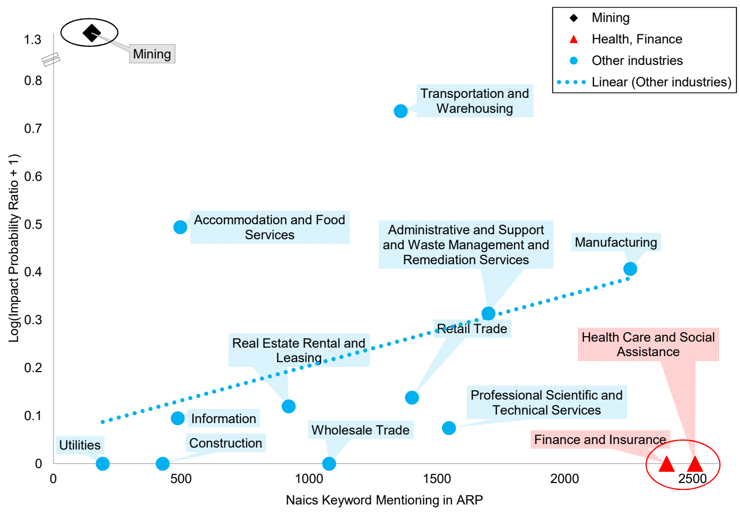
(a) x-axis: Industry mentions in the CARES Act



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



(c) x-axis: Industry mentions in the Consolidated Appropriations Act



(d) x-axis: Industry mentions in the ARP act

Figure A8: Robustness evidence to 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 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 Day 1, 23, 45 ...; subsample 2 uses daily data from Day 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. Here are data sources for daily data: excess market returns, CRSP for 1982-2020 and Datastream for 2021; yield spread between 10-year and 2-year government bond yields, FRED; the log ratio of the S&P500 price index to a ten-year moving average of SP500 earnings, or a smoothed PE, `http://www.econ.yale.edu/~shiller/data.htm`; 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. In 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 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 now. 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, adn the remaining columns show R^2 and F statistics. Bootstrapped standard errors are in parentheses (2,500 simulated realizations).

	Constant						
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)		

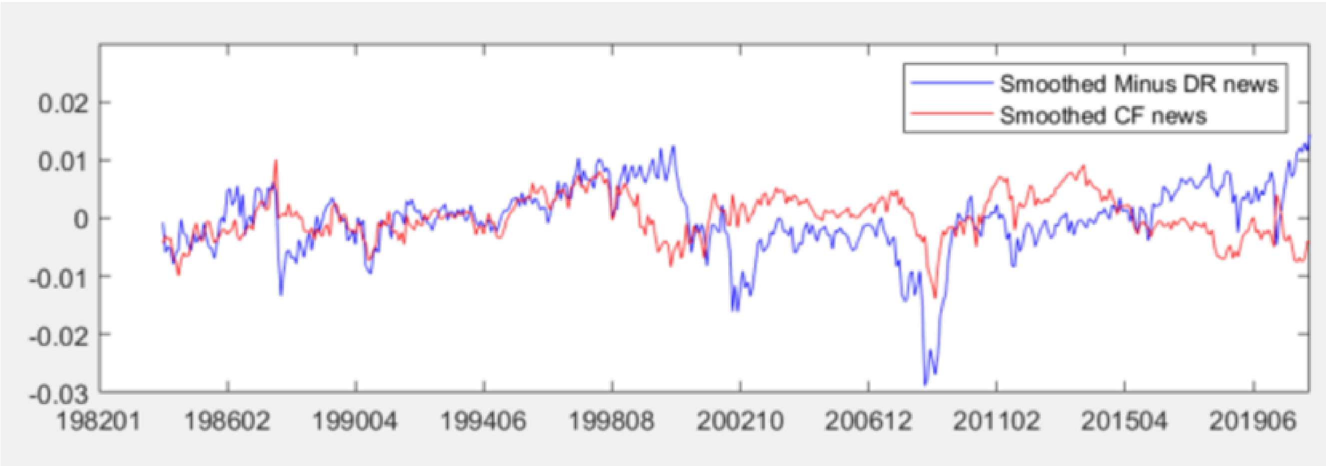


Figure B1: Replicate Figure 1 of Campbell and Vuolteenaho (2004) using our Sample 4: Cash flow and the minus discount rate news, smoothed with a trailing exponentially weighted moving average and estimated from Sample 4. The decay parameter is set at 0.08 per month. Estimation details are in Table B2.

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 adds up 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%.

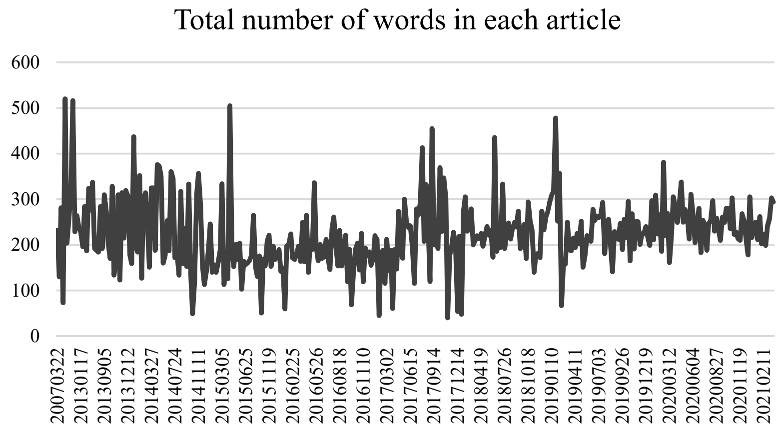
	Sample 1			Sample 2		
	NCF	NDR	NCF,NDR	NCF	NDR	NCF,NDR
Std/Corr	0.02412	0.05298	0.13237	0.02571	0.04340	-0.12449
	(0.00095)	(0.00244)	(0.06036)	(0.00101)	(0.00174)	(0.05281)
Var/Cov	0.00058	0.00281	0.00017	0.00066	0.00188	-0.00014
	(0.00005)	(0.00025)	(0.00008)	(0.00005)	(0.00015)	(0.00006)
r^e shock 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 it from a tabulated version from Bloomberg which provides both actual and survey median. 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. For recent articles, they can be easily found on this website by scrolling down, https://www.cnbc.com/jobless-claims/. Here we often come across with multiple articles which have the same keywords i.e. jobless claims articles for the same dates — some entirely related to the stock market, futures market, etc; but we make sure that we select the links to only those articles which are categorized in *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 was finalized manually, after using the google search package on Python; that package typically found not only CNBC articles, but other news articles too (that may be referring to CNBC), and therefore we need manual effort to finalize it.

Next, once we had the final list of dates and corresponding url links on CNB, the package used for scraping the articles is "BeautifulSoup" – wherein the links to be scraped are read from the excel sheet which was 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 (either using 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 mentioning scores; as mentioned in the paper, for instance,"bad" uses all weeks within the same 60-week interval that corresponds to bad IJC announcements. As in Figure 4, we standardize the series with its first data value for interpretation purpose (that is, 1.5 means that the mentions are 50% higher than around its 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 with, we read all the txt files in the folder and store them in a list call and then we 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 tokenize 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 *sklearn* package with parameters: "`min_df=2`", "`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 less than 2 of the reports. And 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 sort 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				

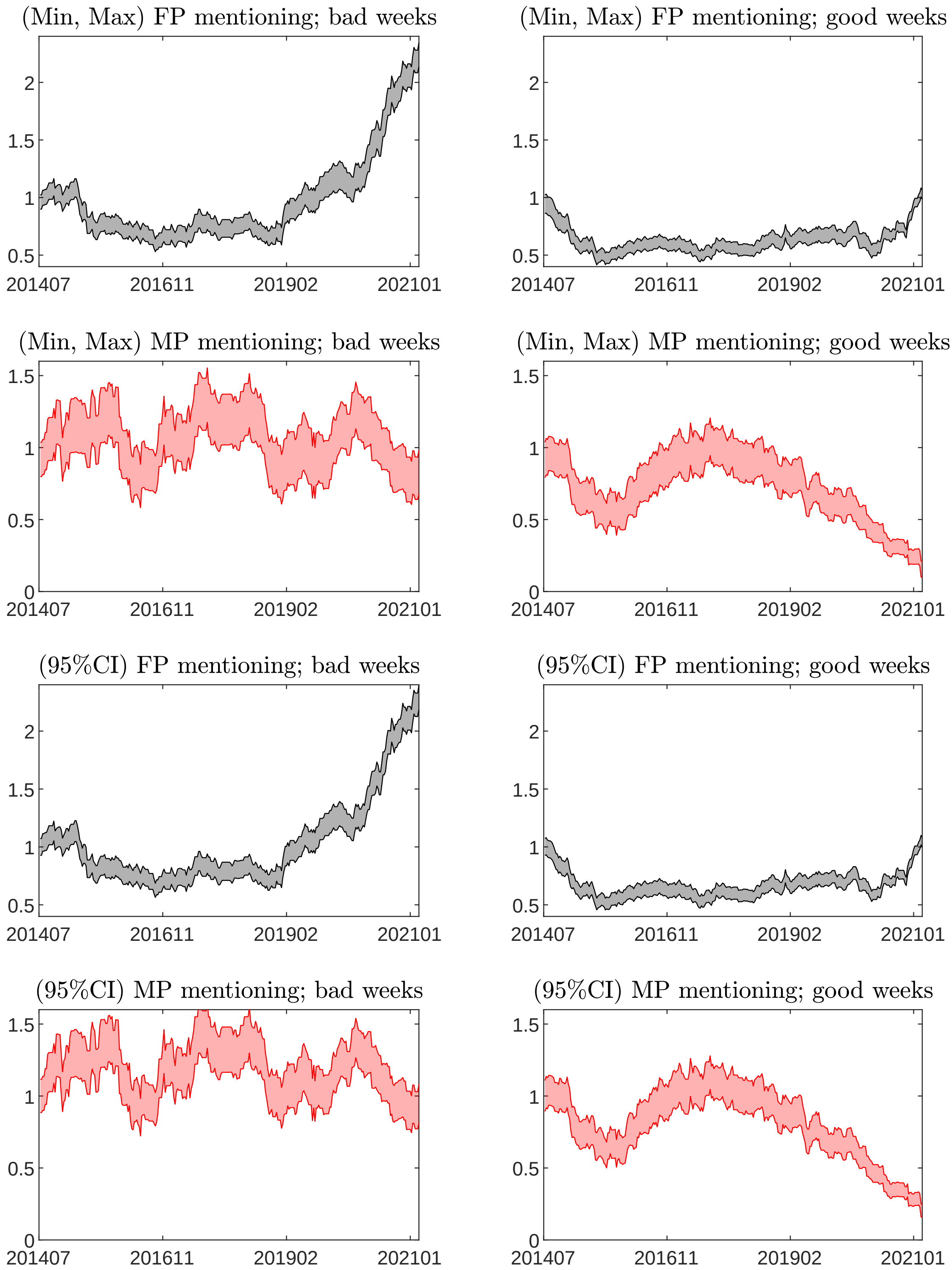


Figure C1: Jackknife exercise of the scaled rolling topic mention values. This table complements Figure 4 in the main text and provides measurement uncertainty. In this plot, we drop one keyword at a time and recalculate the bad and good rolling topic mentioning scores using all bad and good IJC announcement weeks within the same 60-week interval, respectively. Top four plots show the min-max bandwidth. 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 of 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, receipt 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 to the government but not paid yet; gross outlay amount refers to the award the company received. The obligated amount contains some negative values as the government might adjust promised funding allocation from time to time.

We obtain the Compustat companies traded in January 2020 and match them with recipients' names in COVID-19-related government awards. To locate relevant records, we create a company name mapping between the recipient (parent) names in USAspending.gov and Compustat companies. Compustat names are legal names for corporate filing 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 the company names from Yahoo! Finance to achieve better mapping results.

Then, we implement a fuzzy matching algorithm to identify two recipients (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, the company names with and without "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 Map to locate the establishment and check whether this establishment belongs to the Compustat company. After the manual verification, 11,018 records are identified for 1670 Compustat companies matched with recipient (parent) names in Covid-spending records at the time of writing in FY 2020. Table D1 presents the summary statistics:

Table D1: Summary of Covid-related Spending in 2020 (in Million dollar)

	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

This appendix section complements Table 9 and provides the exact scatter plots that produce the table. Note that we drop macro data corresponding to March 2020 (abnormal underestimates of the impact of Covid lockdowns) and May 2020 (abnormal underestimates of the rebounce) – both can be identified as outliers using box plot analysis. As in Table 9, we display return relationships with macro news about the labor market, manufacturing, consumption, and some other economic variables (which are likely priced through monetary policy and risk channels) in three subsequent figures below.

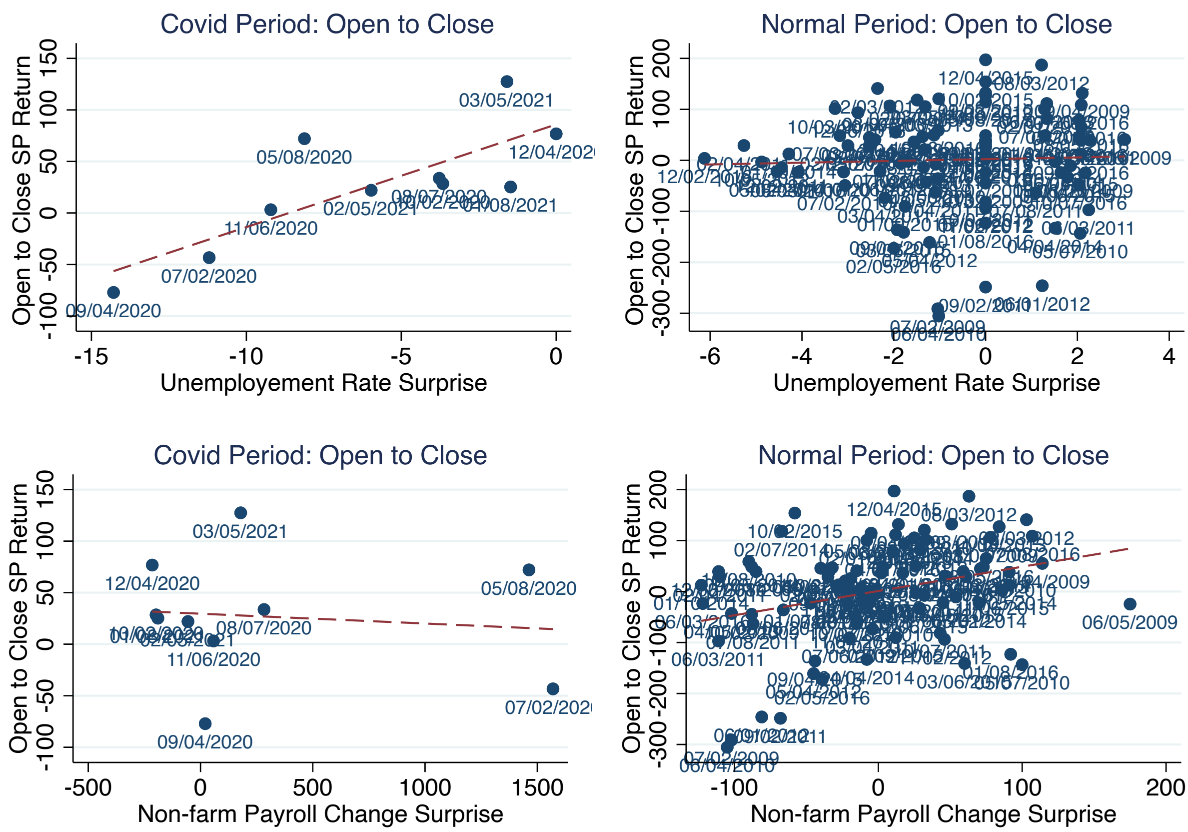


Figure E1: Employment news and daily open-to-close returns

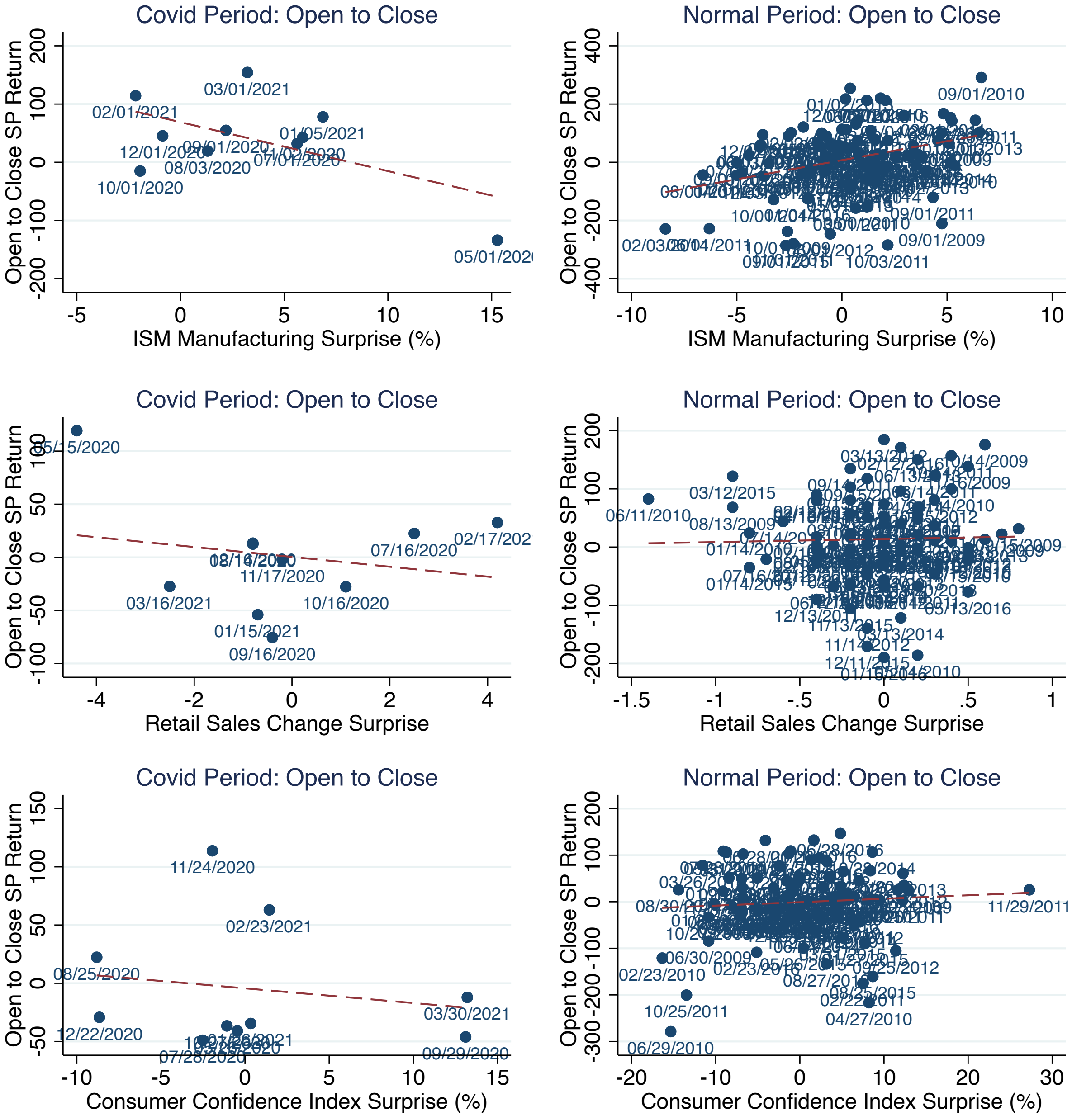


Figure E2: Manufacturing, consumption/consumer news and daily open-to-close returns

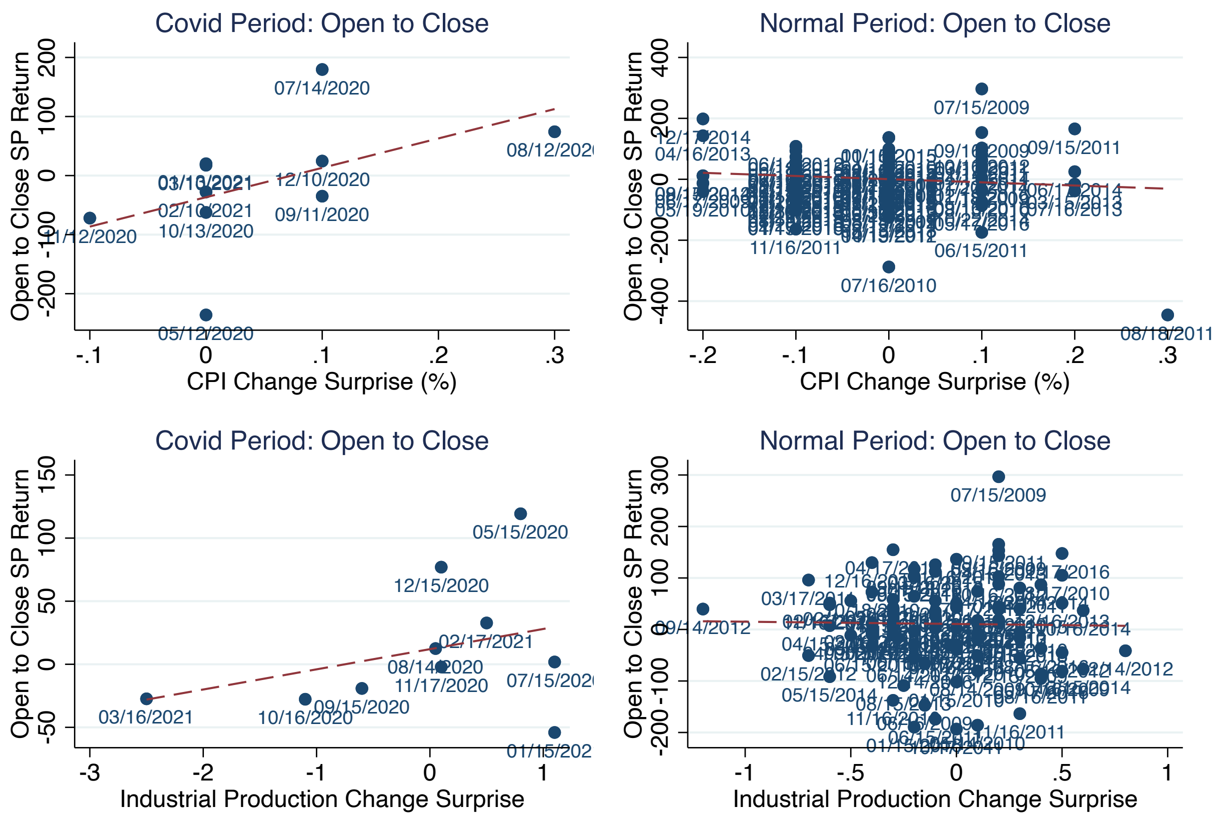


Figure E3: Other economy news and daily open-to-close returns