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

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Abstract

Investors form policy expectations all the time, and the literature has mainly focused on monetary policy expectation. We document an increasingly important role of *fiscal policy* expectation through examining stock return responses to macro surprises in the past 10 years, using high-frequency and daily data, textual analysis, and cross-section evidence. In a persistent zero-lower-bound, low-interest-rate economy, when the main street suffers more than expected (e.g., initial jobless claims (IJC) are worse than expected), investors may expect a more generous federal government support through fiscal policy, *driving up* the expected future cash flow growth and the aggregate stock returns. In the cross-section, firms/industries that suffer more – both employment and finance – show *higher* individual stock returns than those that suffer less, when bad IJC surprises arrive. The Covid crisis (2020-2021) triggered an unprecedented adverse shock to the labor market, which helps unveil this "main street pain, wall street gain" phenomenon; during this period, a one standard deviation increase in the IJC surprise (8.7%) significantly predicts higher daily major stock index returns (except for Nasdaq) of 26-38 basis points. Our "High-Suffering minus Low-Suffering" portfolio has countercyclical returns, earning as high as 18 basis points on bad IJC days.

JEL Classification: G12, E30, E50, E60.
Keywords: return dynamics, macroeconomic news announcement, fiscal policy expectation, Covid-19, textual analysis, cross section

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"The number of Americans filing first-time applications for unemployment benefits unexpectedly rose last week... The weekly unemployment claims report from the Labor Department on Thursday, the most timely data on the economy's health, could add impetus to President Joe Biden's push for a \$1.9 trillion package to aid the recovery from the pandemic." — *Reuters, February 18, 2021 8:40AM EST*[1]

1. Introduction

The 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 increase in the initial jobless claims (IJC) surprise (8.7%) significantly predicts higher daily major stock index returns of 26-38 basis points. Put differently, during this period, while main street *pains*, wall street *gains*. While there is a growing literature on the dynamic aspect of return responses to macro announcement surprises, it seems hard for existing theories 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, Law, Song, and Yaron (2020) predict that rising unemployment news could be good news if lower interest rates are expected, but the interest rate is already at its zero lower bound during most of 2020-2021. This puzzling "main street pain, wall street gain" phenomenon during Covid-19 calls for other explanations of time-varying stock return responses to macro surprises.

We document an increasingly important role of *fiscal policy* expectation through examining stock return responses to macro surprises in the past 10 years, using high-frequency and daily data, textual analysis, and cross section evidence. First, we dissect the covid-period phenomenon to gain insights of the mechanisms. The phenomenon (a) appears only when bad news arrive, (b) is stronger for Dow Jones industrial or transportation index than for Nasdaq, (c) prices mainly through the cash flow component of stock returns, and (d) builds up throughout the morning and peaks around noon. Second, using actual IJC news articles manually collected from CNBC (2013-2021), we find that topic mentioning of fiscal policy significantly surpasses that of monetary policy since 2019, and peaks mostly during bad IJC surprise days. In light of both observations, we hypothesize and provide evidence for a new fiscal policy expectation channel. In a persistent zero-lower-bound, low-interest-rate economy, when the main street suffers (e.g., IJC is

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

higher/worse than expected), investors may expect a more generous federal government support through fiscal policy, *driving up* the expected future cash flow growth and the aggregate stock return responses. This aggregate result is robust using sample with or without 2020-2021, and using monthly macro announcements (particularly on employment, manufacturing, and consumption/consumer). In the cross section, during periods with high fiscal policy expectation, firms/industries that suffer more fundamentally show *higher* individual stock returns than those who suffer less when bad IJC surprises arrive, as investors may anticipate that more support should indeed get into these industries. Finally, in the low interest rate sample period we focus on, our evidence supports the important role of monetary policy expectation on good IJC surprise days, which is consistent with Law, Song, and Yaron (2020).

We provide more details next. First, we examine the asset price responses to IJC surprises (defined as relative changes of actual and expected IJC numbers) using stock, long-term government bond, 10-year yield rate, and several risk and risk aversion proxies that are available at the daily frequency. While most periods in the past 20 years exhibit "bad is bad", "good is good" pricing, we show that, since 2017, the relation has become mild; in the recent period from February 2020 to March 2021 (end of our sample), the "bad is bad" relation has even turned significantly opposite, and we coin it the "main street pain, wall street gain" phenomenon in this paper. Such effect is the strongest on bad IJC days, with Dow Jones stocks, prices through the cash flow channel according to a quasi Campbell and Vuolteenaho (2004) decomposition, and gradually builds up throughout the day as opposed to an acute response shortly after the announcement time.

To reconcile our empirical findings, we hypothesize that, in a persistent zero-lower-bound (ZLB) and low-interest-rate world, when main street suffers, investors may now expect a more generous federal government support through *fiscal policy*, driving up the expected future cash flow growth and the aggregate stock return responses. The Law, Song, and Yaron (2020) channel through monetary policy expectation may be more relevant on good IJC days, as the ZLB macro environment gives obvious potency for interest rate to climb instead of dropping. Our analysis faces an obvious measurement challenge: how to measure expectations of fiscal policy versus monetary policy in preferably a unified framework? One empirical contribution of our paper is that we are among the first to use textual analysis to formally analyze and categorize what people discuss when IJC news come out, and construct topic mentionings to test mechanisms. To retrieve the relative importance of topics, we use the state-of-the-art "Term Frequency-Inverse Document Frequency" scores in the textual analysis literature. In particular, when words such as "congress" "lawmaker" "Federal government" "aid" "extend" "benefit" appear in one article, the scenario typically reflects an ongoing federal-level discussion of fiscal policy. The words that may describe monetary policy discussions include for instance "central bank" "inflation" "Federal Reserve" and so on. An uncertainty measure, similar to Baker, Bloom, and Davis (2016), is also constructed using IJC articles. Due to text data availability (see more discussions in Section 3.1), we focus on 2013-2021.

The two policy mentionings – fiscal (FP) and monetary (MP) policy – exhibit distinctive time series patterns: the MP mentioning increases around 2017 and 2018 but has been in decline since until the end of the sample in March 2021, whereas the FP mentioning increases around 2013-2014, remains low until April 2020, but has since then increased. In particular, the increasing mentioning of FP mainly comes from bad IJC days while the hump-shape mentioning of MP mainly comes from good IJC days, meaning that FP (MP) was much more discussed and speculated when initial claims numbers were worse/higher (better/lower) than expected. This observation suggests that, during this period, FP (MP) mentioning likely refers to expansionary (contractionary) policy implications.

We use two empirical frameworks to test our hypothesis at the aggregate. Our hypothesis predicts that "FP expectation" ("MP expectation") is a significant driver of how asset returns react to bad (good) IJC news. We first directly regress rolling return responses to rolling topic mentioning of FP, MP and Uncertainty; in the second test, we construct non-overlapping quarterly textual state variables and include quarterly survey data on expectation revisions of future interest rate (as an alternative proxy for the MP channel, as used in Law, Song, and Yaron (2020)) to span the time variation in return coefficients of IJC shocks. Both tests show not only same directional implications but also similar economic magnitude, and are robust to controlling for business cycle state variables such as uncertainty:

First, on bad IJC announcement days when fiscal policy mentioning is one SD higher than its average, stock returns could significantly *increase* by 24-26 basis points with a 10% IJC shock (higher the shock, worse the news). The MP mentioning state variable shows insignificant explanatory power, supporting our hypothesis that the "main street pain, wall street gain" phenomenon on bad IJC days is mostly due to higher-than-average fiscal policy expectation.

Second, fiscal policy mentioning does not explain the time variation in return responses to good IJC shocks; instead, on good IJC announcement days when monetary policy mentioning is one SD higher than its average, stock returns could significantly decrease by 16-30 basis points with a -10% IJC shock (lower the shock, better the news). This evidence lends supports to Law, Song, and Yaron (2020) as well as the second half of our hypothesis; that is, increases in monetary policy intervention expectation matters more on good IJC days, counteracting the "good is good" conventional wisdom. To interpret the MP expectation in our sample period, we find that our textual-based MP mentioning on good IJC days is significantly and positively correlated with expectation revisions of future interest rate: higher MP mentioning typically occurs when survey data shows that professionals expect interest rates to increase. Our mechanism tests at the aggregate level support our core hypothesis, and are also robust using a sample period until December 2019 to address a potential concern that the results are purely driven by 2020-2021.

While the paper so far focuses on identifying counteracting forces to the "bad is bad" / "good is good" pricing of macro shocks, we also document significant mechanisms within the same framework that reinforce this conventional pricing effects. We show that stock returns respond to bad (good) IJC news more negatively (positively) when investors are more pessimistic (optimistic) or expect more (less) uncertainty about future economy. This result is potentially consistent with the Bayesian updating theory in David and Veronesi (2013) (when times are bad, people take time to learn, hence reinforcing the pricing of macro shocks) and several recent empirical papers (e.g., Andersen, Bollerslev, Diebold, and Vega (2007), Baele, Bekaert, and Inghelbrecht (2010) and Xu (2019)).

In the last part of the paper, we exploit the Covid period and conduct two more analyses to better understand the "main street pain, wall street gain" phenomenon, given that it may be hard to find another period (pre-2020) that is long enough with knowingly higher fiscal policy expectation. First, in a *cross-section analysis* using firms of S&P500, we find that firms/industries that suffer more – more declines in revenue, EPS, employment, and our new all-internet job postings from 2019 to April/May of 2020 – exhibit higher individual stock returns on bad IJC surprise days. This is consistent with our hypothesis, as investors may expect that these firms/industries should receive more government support. We find that Mining, Transportation and Warehousing, and Accommodation and Food Services are three most damaged industries, controlling for the total number of firms in the universe of S&P500. To understand which firm- or industry-level suffering measure captures the "main street pain, wall street gain" phenomenon more saliently, we form a portfolio using the difference between value-weighted returns of the "Most-Suffering" bin and the "Least-Suffering" bin using returns from February 2020 to March 2021. We find that the average daily portfolio returns on bad IJC days are positive, ranging from 5 to 16 basis points, and significantly higher than those on good IJC or non IJC days. Our forward-looking labor suffering measure using changes in all-internet job postings generate the largest portfolio return compared to financial suffering measures.

Second, in an *external validation analysis*, we evaluate the comovement between daily open-to-close S&P500 returns and seven mainstream *monthly* macro announcement surprises. Our evidence verifies the "main street pain, wall street gain" phenomenon when using monthly macro announcement data, particularly those that plausibly paint a health report on main street households (such as non-farm payrolls, unemployment rate, manufacturing, and retail sales).

Our research has several contributions to the literature:

First, our work joins existing papers that study the time series pattern of stock market reactions to macro announcement surprises, which is an important topic with massive modeling and investment implications for macrofinance and asset pricing. 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 bad macro shocks may be priced as good (bad) news in the stock market during expansions (recessions) because discount rate (cash flow) news dominate. Then, recent theories (Law, Song, and Yaron (2020) and Yang and Zhu (2021)) argue that time-varying return responses to macro news likely depend on policy intervention expectations. In particular, Law, Song, and Yaron (2020) argue that it depends on whether there are revisions in future interest rates (which do not necessarily move with the business cycle in empirical evidence and in theory); for instance, after the Global Financial Crisis, there is a long period of time with no-to-low expectations that future interest rates would increase, and this is also a period when stock market exhibits strong "good is good" pricing. As a theoretical contribution, our paper points out that, in a persistent zero-lower-bound, low-interest-rate modern world, neither existing explanation dovetails with the novel "main street pain, wall street gain" phenomenon during the covid period (February 2020 to March 2021) that we document; with no room for interest rates to go even further, the interest rate channel should be less potent. One may point out that investors may still expect more unconventional monetary policy, which is less likely the reason; most programs were forcefully announced and set expectations of before the end of March 2020, whereas the "main street pain, wall street gain" phenomenon stays in the data as we move into 2021 and is in fact stronger from May to October 2020. This puzzling new phenomenon calls for other explanations of time-varying stock return responses to macro surprises in a more modern age of capital markets, which makes our research question more relevant.

Second, we fill the gap by proposing a new theoretical channel: fiscal policy expectation. When the main street suffers more than expected, investors may expect a more generous federal government support through fiscal policy, *driving up* the expected future cash flow growth and the aggregate stock return responses. On the other hand, monetary policy expectation matters more in explaining time-varying return responses when good news arrive; this directional result is also consistent with theory in Law, Song, and Yaron (2020). Then, we show consistent evidence using samples *with or without 2020* that different policy expectation channels may matter differently to the time-varying return responses, depending on bad or good macro surprises. The covid crisis triggered an unprecedented adverse shock to the labor market, the "main street", which helps unveil this new fiscal policy mechanism in the prolong recent zero-lower-bound economy.

Third, while there is a long literature on the macroeconomic effects of fiscal policy (see e.g. Easterly and Rebelo (1993), Perotti (1999), Mankiw (2000), Auerbach and Gorodnichenko (2012), Correia, Farhi, Nicolini, and Teles (2013), D'Acunto, Hoang, and Weber (2018) and so on), there is scant literature on the relationship between fiscal policy and stock market. Among the few, papers often focus on examining within an equilibrium framework long-term or short-term effects of tax policies and public deficit on capital markets or use parametric methods in estimating these fiscal policy shocks (see recent influential work in Agnello, Castro, and Sousa (2012), Agnello and Sousa (2013), Gomes, Michaelides, and Polkovnichenko (2013)). As Goldstein, Koijen, and Mueller (2021) also comment in the *Review of Financial Studies* Covid-19 special issue (pp.5146), "Understanding the short- and long-run effectiveness of such fiscal policy interventions ... is an important question for future research." To answer our research question, instead of using model-implied fiscal policy expectations, we circumvent this measurement challenge using textual analysis and identify time series of fiscal policy expectation as revealed real-time by news broadcasters. The idea that "news mentioning" reflecting "expectation" and "beliefs" has been widely used in existing literature; for instance, Da, Engelberg, and Gao (2015) measure beliefs on recessions using internet search volumes, while Baker, Bloom, and Davis (2016) measure economic uncertainty[2] using news articles.

Fourth, our paper joins the current discussion on how the covid crisis affects financial markets and the real economy (see a summary article in Goldstein, Koijen, and Mueller (2021)).[3] Most papers focus on the *immediate* effects on capital markets (Gormsen and Koijen (2020), Landier and Thesmar (2020), Baker, Bloom, Davis, and Terry (2020a)), households (Baker, Farrokhnia, Meyer, Pagel, and Yannelis (2020b), Pástor and Vorsatz (2020), Levine, Lin, Tai, and Xie (2021)), economy (Eichenbaum, Rebelo, and Trabandt (2021), Fahlenbrach, Rageth, and Stulz (2021)), labor market (Papanikolaou and Schmidt (forthcoming), Bartik, Bertrand, Lin, Rothstein, and Unrath (2020)), banks (Li, Li, Macchiavelli, and Zhou (2021)), and policy responses (Darmouni and Siani (2021),

[2]In extant asset pricing theories, economic uncertainty is a concept that closely relates to the expected future growth volatility and ultimately the expected amount of risk, as shown and derived in these paradigm model variants in Bansal and Yaron (2004), Jurado, Ludvigson, and Ng (2015), Bekaert and Engstrom (2017), Xu (2021) and so on.

[3]There is a voluminous literature in general.

Gourinchas, Kalemli-Özcan, Penciakova, and Sander (2021)). In particular, among the few studying fiscal policy, Gourinchas, Kalemli-Özcan, Penciakova, and Sander (2021) conclude that "fiscal support in 2020 achieved important macroeconomic results". Consistently, as Mr. Powell said in his October 6 2020 address at the National Association for Business Economics Virtual Annual Meeting (Powell (2020)), "The fiscal response was...by far the largest and most innovative fiscal response to an economic crisis since the Great Depression." However, apart from these period-specific discussions, one crucial question still remains: How to examine and put the covid period in a bigger context and longer sample of macroeconomic and asset pricing studies? What state variables are changing and how do these changes affect capital markets and investor beliefs? Our paper implores a mixed methodology featuring textual analysis and survey data to identify the changing states of the underlying economy in a unified framework.

On policy implications, our paper is among the first to document that investors may have already been putting fiscal policy expectation into pricing with a unprecedented weight, and the covid period helps unveil this phenomenon. Future research should further examine the role of fiscal policy expectation in financial market, which may be a novel form of *federal government* intervening the market.

The remainder of the paper is organized as follows. Section 2 establishes the main empirical phenomenon – "main street pain, wall street gain" – using aggregate daily and high-frequency evidence and sample period from 2002 to 2021. We examine empirical sources of this aggregate phenomenon in terms of pricing channels, asymmetry, and heterogeneous effects in stock indices. Section 3 investigates plausible mechanisms using professional survey data and textual analysis where we directly sort through what "topics" news articles talk about following the IJC announcements. Section 4 tests the fiscal policy expectation mechanism established in Section 3 in the cross section. Sections 5 and 6 provide external validation and concluding remarks, respectively.

2. Asset Price Responses to Main Street News

In this section, we examine how asset prices respond to initial jobless claims (henceforth, IJC) surprises[4] using daily, open-to-close, and high-frequency data from February 2002 to March 2021. Different from existing literature, we start by examining across a wide range of aggregate asset prices and risk variables, which provides information about the pricing channel and ultimately the mechanism that we test in Section 3. We also focus on initial jobless claims as our primary macro announcement shocks for several rea-

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

sons. First, economically, jobless numbers closely reflect how the "main street" is doing and should matter to policy makers; second, the existing empirical literature has found that particularly labor news could induce stronger financial market reactions than other macro news (see e.g. Aruoba, Diebold, and Scotti (2009), Kurov, Sancetta, Strasser, and Wolfe (2019), Law, Song, and Yaron (2020), Diebold (2020)); third, among various macro announcements in the US, only IJC is released at the weekly frequency (08:30AM 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.

Section 2.1 establishes main empirical results at the aggregate level. Section 2.2 discusses pricing channels, asymmetry, and implications from high-frequency evidence. Section 2.3 provides robustness.

2.1. Aggregate evidence from 2002 to 2021

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) released by Employment and Training Administration (ETA) on Thursday of the current week t, and $E_{t-\Delta}(IJC_t)$ indicates the median survey forecasts submitted before the announcement time. Both actual and median expected claims are obtained from Bloomberg. We consider IJC announcement days between February 2002 and March 2021, except for overlaps with Federal Open Market Committee meetings (henceforth FOMC) and other major macro announcements. Note that a simple level difference, $IJC_t - E_{t-\Delta}(IJC_t)$, is another intuitive way to construct macro shocks as used in several papers using pre-2020 sample (e.g., Balduzzi, Elton, and Green (2001), Kurov, Sancetta, Strasser, and Wolfe (2019) and so on). However, we find it less suitable in studying our research question due to the structural break in the level (and its first differences) of initial claims during March and April of 2020. Figure A1 in the appendix shows the time series of our main IJC shock and the alternative IJC shock, with or without identified statistical outliers[5] and overlapping days with FOMC. The alternative shock exhibits quite different economic magnitude before and after 2020 (see statistics in Table A1 in the appendix), which may cause difficulties to interpret the results.

[5]Boxplot outlier analysis using the ×2 interquantile 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.

Table 1 shows the summary statistics of our main IJC shock. To summarize it better, we group 2002-2021 into five general economic periods with different phases of (a) business cycle and (b) monetary policy – motivated from the two existing competing theories in explaining time-varying return responses to macro shocks:[6]

Period 1	*2002/02-2007/11*		*Contractionary-High interest rate*
Period 2	*2007/12-2009/06*	*Global Financial Crisis*	*Expansionary-ZLB*
Period 3	*2009/07-2016/12*		*Expansionary-ZLB*
Period 4	*2017/01-2020/01*		*Contractionary-Low interest rate*
Period 5	*2020/02-2021/03*	*Covid, during & post*	*Expansionary-ZLB*

Here are two main observations. One, although initial claims during Period 5 are not at the same range of magnitude as previous periods (e.g., reaching 6.65 million during the week ending March 27, 2021, which is 10 times higher than that during the peak of the Global Financial Crisis in 2009), our shock proxy (after dropping the three outliers) appears with similar distribution. Two, in Period 5, shock skewness is slightly lower but shock volatility is slightly higher than in other periods. A one standard deviation (SD) IJC shock above average in Period 3, which can be dubbed as a "normal" expansionary-ZLB period, corresponds to a 4.4% shock, whereas 1 SD IJC shock above average in Period 5, a "covid" expansionary-ZLB period, corresponds to a 10.6% shock (1.9%+8.7%). Summary statistics using bad and good IJC days only are also well-behaved.

Next, we examine responses of a wide range of asset prices and risk variables, denoted by y, to IJC shocks on announcement days:

$$y_t = \beta_0 + \beta_1 IJCShock_t + \varepsilon_t. \quad (1)$$

Comparing results across dependent variables in this section serves as suggestive evidence on pricing channels (which we elaborate in Section 2.2). Table 2 lists nine dependent variables (from left to right): (1) open-to-close log S&P500 returns, (2) daily log changes in the US 10-year Government bond total return index, (3) daily changes in 10-year Treasury yield, (4) daily changes in 3-month Treasury bill secondary market rate, (5) daily changes in a financial proxy to real economic growth uncertainty, (6) daily changes in 1-month realized variance in S&P500, (7) daily changes in the Economic Policy Uncertainty, (8) open-to-close changes in the volatility index, and (9) daily changes in a financial proxy to aggregate relative risk aversion. Asset prices and indices (including open and close prices when available) are obtained from DataStream; yield data are from FRED; daily

[6]It is worth pointing out that the period classification here does not enter our main mechanism analysis, and it should be viewed as a way to help us sort through our aggregate results. We are also aware that there is an extensive ongoing literature on identifying expansionary and contractionary monetary policy periods; for our purpose, we adopt the simple rule of the level of interest rates ex-post.

financial proxies of uncertainty and risk aversion are provided by Bekaert, Engstrom, and Xu (2021), and daily text-based economic policy uncertainty is provided by Baker, Bloom, and Davis (2016).

For a long time since the turn of the century, as IJC shock increases by 0.1 unit (0.1 unit corresponding to about the size of a +1 SD shock, according to Table 1), daily open-to-close stock returns decreases by around 10 basis points.[7] Daily US long-term government bond returns increase by around 17 (34) basis points during non-GFC (GFC) period, while the 10-year government yield rate decreases. In terms of risk premium variables, a 1 SD bad IJC shock corresponds to a 0.04∼0.1 SD increase in the expected future economic uncertainty on the announcement day; risk aversion also increases with a similar magnitude. VIX seems to have mixed reactions, which is expected because VIX contains a risk premium component (increasing with IJC shock) as well as a component reflecting stock market volatility (decreasing with IJC shock, according to column "RV1m"). Overall, we observe quite strong responses from the discount rate channel – interest rate and risk premium – when IJC shocks arrive in early periods of the sample.

Such conventional "bad is bad" / "good is good" pricing disappears during Period 5, which spans from the beginning of the NBER Covid19 recession period, February 2020, to the end of our sample, March 2021. That covers 54 weeks after dropping out the three aforementioned IJC outliers and overlapping FOMC announcement days. Stock returns increase by about 31 basis points with a 10% IJC shock, or 27 basis points with a 1SD IJC shock (8.7% from Table 1); in terms of economic magnitude in standard deviations, that is, a 1SD IJC shock corresponds to a 0.2SD increase in daily open-to-close stock returns. We coin this observation the "main street pain, wall street gain" phenomenon in this paper.

The last few rows of Table 2 also show that asset or risk variables that typically move with discount rate do not respond significantly to macro surprises in Period 5, which stands in stark contrast to evidence from previous periods. Yet, stock returns respond. Taken together, our evidence suggests that, when a bad IJC shock arrives, the expected cash flow growth may increase, driving up the stock returns. In the next section, we dissect this aggregate evidence further using market return decomposition, effect asymmetry, other stock market indices, and high-frequency evidence.

[7] It is widely known that high-frequency stock returns shortly after the announcement reflect the strongest reaction to the announcement news, and results using daily returns become milder; we find consistent evidence and elaborate more in Section 2.2.

2.2. Pricing channels, Asymmetry, and High-frequency evidence

Pricing channels Following Campbell and Vuolteenaho (2004) (henceforth, CV2004), we decompose 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):

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

where r_{t+1} is log S&P500 return, Δd_{t+1} is the log changes in dividend, E_t (E_{t+1}) denotes a rational expectation at time t ($t+1$) about future, and ρ is a discount coefficient in the loglinear approximation of stock returns. One challenge is that our research question focuses on the 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 the daily frequency is not trivial: one, the choice of ρ at the daily frequency is not as straightforward as $0.95^{1/252}$;[8] and two, some variables in the state vector simply cannot be constructed at the daily frequency, for instance, 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.[9] 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.[10] Appendix B provides more estimation details, replication to Campbell and Vuolteenaho (2004), and 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), and NDR and NCF are weakly negatively correlated, which makes sense in a model where a

[8]John Campbell has argued in multiple papers, including Campbell (1996) and Campbell and Vuolteenaho (2004), of letting the average consumption-wealth ratio determine the discount coefficient ρ, and 0.95 ($0.95^{1/12}$) is typically hence applied in an annual (monthly) frequency. However, consumption wealth ratio is knowingly not available at the daily frequency.

[9]Here are the data sources (monthly data for the VAR system, and daily data for the imputation): 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.

[10]In unreported results, we also considered re-estimating the monthly system within each sample (which is unclear being a better strategy given the underlying assumption that parameters may be different every day); results are not statistically different.

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. Results are robust using open-to-close or daily stock market returns. Hence, one useful takeaway is that, from the long-term time series perspective, pure cash flow innovations exhibit increasing power in explaining total return dynamics, from 19% in a long pre-2000 sample to 34% in a modern sample from 1982 to 2021.

Table 3 presents the same regression framework with dependent variables being the unexpected stock market return, NCF, and NDR, during the five periods as mentioned before. The unexpected return by construction equals NCF minus NDR; that is, higher cash flow news and/or lower discount rate news are good market news. We focus on comparing Period 5 (2020/02-2021/03, "covid") with Period 3 (2009/07-2016/12, "normal"); both are in expansionary ZLB monetary policy regimes and hence are comparable from the perspective of interest rate environment. During Period 3, as the IJC shock increases by 0.1 unit, 8.3 bps out of the total 8.7 bps decrease in the daily stock returns can be explained by the increases in the expected future discount rate, according to column "NDR". In contrast, during Period 5, a 0.1 unit increase in the IJC shock is associated with an increase in daily stock returns by 30 bps (as also seen in Table 2), and it is mostly explained through increases in the expected future cash flow, according to column "NCF". This result is also consistent with evidence in Table 2 which investigates reactions of several more discount-rate-driven asset prices and risk variables to IJC shocks, and reactions are much weaker during Period 5. In summary, the new mechanism seems to affect stock price via more of a cash flow channel.

Moreover, Period 4 (2017/01-2020/01) undergoes a contractionary regime with several interest rate hikes. The weaker return responses are consistent with Law, Song, and Yaron (2020); when more interest rate increases may be expected, returns no longer increase as much when good macro shocks arrive.

Asymmetry Further decomposing the total return response into bad- and good-IJC-day responses, we find that the "main street pain, wall street gain" stock return response to IJC shocks during Period 5 mostly comes from the bad days (when actual IJC number is higher than expected). As shown in Table 4, all statistically significant return responses come from bad IJC days, with economically meaningful magnitudes. When bad IJC news arrive, 1 SD bad IJC shock corresponds to a 0.4 SD increase in stock prices, with the strongest effect in Dow Jones indices, Industrial or Transportation, and the weakest effect in Nasdaq 100. This is consistent with the stronger NCF response found in Table 3 as value stocks are more sensitive to market cash flow news other than discount rate news

(Campbell and Vuolteenaho (2004)).

In addition, return responses on good IJC days exhibit signs that are consistent with "good is good" pricing; when IJC shock is more negative or the initial claims are lower/better than expected, stock returns go up (higher future cash flow expectation and lower future risk expectation). Figures 1 and 2 demonstrate the asymmetry, using time series plot and scatter plots, respectively. Returns and IJC shocks tend to move in the same direction on bad IJC days, yielding a positive slope (as consistently shown in Table 4), while moving 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 particular date; from the top plot of Figure 1, in fact, the time between April 2020 and November 2020 and then again after February 2021 exhibits quite strong positive comovement between bad IJC shocks and good stock returns.

High-frequency evidence For identification advantage, the literature has been tracing out market reactions to macro shocks using high-frequency data (e.g., Gürkaynak, Sack, and Swanson (2005), Bernanke and Kuttner (2005), and many others). With labor announcement surprises in particular, we typically observe no pre-announcement drift, and the full effect should be able to be captured, during the same day, after the announcement (e.g., Kurov, Sancetta, Strasser, and Wolfe (2019) and Law, Song, and Yaron (2020)). In our high-frequency exercise, we follow both papers and construct cumulative returns from 8:00AM ET (30 minutes before the IJC announcement time) to several representative time stamps during the day: 8:25AM (pre-announcement), 8:35AM (shortly after the announcement), 12:30PM (noon), and 3:30PM (shortly before the close). Then, we evaluate the intradaily return responses to IJC shocks.

Table 5 and 6 consider E-mini S&P500 futures and Dow futures, respectively; as motivated above, we interpret Period 3 as "normal" to Period 5 given their similar ZLB monetary policy environment. All high-frequency data are obtained from TickData. Consistent with daily evidence in Table 4, Dow futures show stronger "main street pain, wall street gain" intradaily return responses than Nasdaq futures.[11] Such effect only shows up on bad IJC days, and is significantly different from the counterpart coefficients during a normal period, for each time stamp that we focus on. One difference is that, the normal period "bad is bad" response is more acute whereas the new "bad is good" effect builds up throughout the morning until noon and is persistent since then. This observation motivates our textual analysis in Section 3 as we obtain direct evidence on what people discuss after the IJC announcements while looking for new mechanisms.

Lastly, the intradaily evidence shows that there is no statistical difference between

[11] We relegate results using E-mini Nasdaq-100 Futures to Table A5 in the appendix.

normal and covid periods regarding how futures market responds to *good* IJC surprises. From Panel C, the coefficients from both periods reach significant and negative (meaning that asset returns are higher when $IJCShock_t$ is more negative) 5 minutes after the announcement time, typically reverse a bit during the day, but eventually land with a negative coefficient at the end of the day.

2.3. Robustness

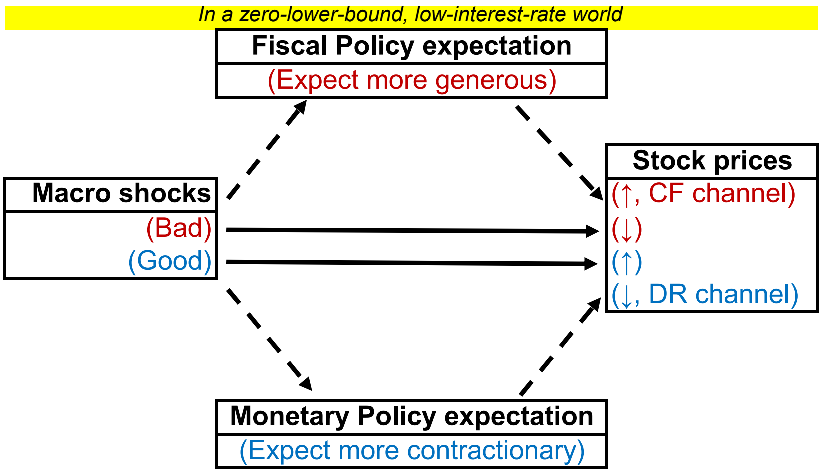
The main results control for obvious IJC outliers (as motivated in Section 2.1) and overlapping days with FOMC and other macro announcements. We conduct an array of robustnesses, and results are consistent. First, we consider an alternative IJC shock using actual minus median survey (see Tables A1, A2 and A3 in the appendix); note that we argue in Section 2.1 that such shocks may be less suitable for our research objective given the structurally different IJC levels in late March and early April of 2020. Second, besides FOMC days, the Federal Reserve took a series of unconventional actions to support the economy; March 17, March 18, March 23, and April 9, 2020 are major dates, and the last one is a Thursday. Evidence from Table A2, A4 and Figure A2 show that the new "main street pain, wall street gain" phenomenon we document here as well as NCF-NDR decomposition remain quite robust, with similar economic magnitude.

To summarize, we start with time-varying return sensitivities to IJC surprises; while most periods in the past 20 years exhibit "bad is bad" pricing, we show that, since 2017, the relation has become mild, and in the recent period since 2020 (until even going into 2021), the relation has even turned significant and opposite, and we coin it the "main street pain, wall street gain" phenomenon. The phenomenon (a) appears only when bad news arrive, (b) is stronger for Dow Jones industrial or transportation index, (c) prices likely through the cash flow news component of stock returns according to a quasi Campbell-Vuolteenaho decomposition, and (d) builds up throughout the morning and peaks around noon as opposed to an acute response shortly after the announcement time. These facts provide new guideline information when we search for mechanisms in the next section.

3. Mechanism

This particular period of time post 2020 seems to have triggered the pricing channel of bad news to change, which is strong enough to overturn the conventional wisdom of "bad is bad." Moreover, we believe that the underlying mechanism is likely different from the existing discussions on the time-varying stock market reaction to announcement surprises. Here are two existing explanations. One group of papers explains the time variation with business cycle (e.g., McQueen and Roley (1993), Boyd, Hu, and Jagannathan (2005), Andersen, Bollerslev, Diebold, and Vega (2007)), comparing stock market responses in the slow-moving recessions and expansions. Boyd, Hu, and Jagannathan (2005) predict that rising unemployment news should be bad news for stocks during economic contractions as it signals bad future dividend growth. Recent empirical work has challenged the cyclicality of the time variation, such as Law, Song, and Yaron (2020), Yang and Zhu (2021) and our own work; our evidence in Table 2 show that GFC- and Covid-related periods show opposite responses. Second, Law, Song, and Yaron (2020) provide an alternative explanation through monetary policy (MP) expectation; that is, when a good (bad) IJC shock arrives, a higher (lower) interest rate expectation may counteract the positive (negative) stock return response. This explanation may be more relevant in explaining less significant return responses when good IJC news arrive at a low-interest-rate environment, as there is a clear potency for interest rate to increase and for monetary policy to exert; a representative example may be 2017 to 2019, or our Period 4. However, we suspect that monetary policy expectation lacks power to explain the significant "main street pain, wall street gain" phenomenon during the period after 2020. The interest rate already dropped to 0-0.25% on March 15 2020 and remains at zero since then; the interest rate cannot be expected to go further down. In fact, the Survey of Professional Forecasters (SPF) shows an expectation of 0-0.01% annual rate increase in the rest of 2020.

To reconcile our empirical findings, we hypothesize that, in a persistent zero-lower-bound, low-interest-rate world, when main street suffers more than expected, investors may now expect a more generous federal government support through *fiscal policy*, driving up the expected future cash flow growth and the aggregate stock return responses. The covid-19 crisis triggers an unprecedented adverse shock to the labor market (see summaries in Bartik, Bertrand, Lin, Rothstein, and Unrath (2020) on the overall labor, Borjas and Cassidy (2020) on the immigration labor, Papanikolaou and Schmidt (forthcoming) on the supply-side impact among many others), which helps unveil this potential new mechanism. Moreover, this hypothesis would also predict that firms/industries that suffer more (both labor and financial aspects such as employment, revenue, sales, net profit) should exhibit stronger "main street pain, wall street gain" phenomenon in their respective stock prices, as investors may expect that these firms/industries would receive more government support. In the rest of the paper, we test our hypothesis predictions using both textual analysis (this section) and cross-sectional evidence (Section 4). The diagram below illustrates our hypothesis with the new *fiscal policy* expectation channel, building on the existing monetary policy-focused explanation (Law, Song, and Yaron (2020)). In this zero-lower-bound, low-interest-rate economic environment (which is likely to sustain for a foreseeable period of time post covid), different policy expectation channels may be triggered, depending on bad or good IJC surprises:



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

We use textual analysis to understand what people discuss when IJC news come out, and measure topic mentionings as testable mechanisms. We relegate technical details to Appendix C, and describe main reasoning and observations below.

Obtain the texts. In the first step, we obtain texts to be analyzed, and we focus on CNBC's IJC news articles written on announcement days for several reasons. CNBC is a major business news broadcaster with a reasonably wide network of investors, reporters and commentators. Unlike other news sources such as WSJ or Bloomberg, CNBC has a designated website for Initial Jobless Claims (`https://www.cnbc.com/jobless-claims/`). This is an advantage to our research question as it filters out noisy ex-post articles that may mention "initial jobless claims" but do not have it as the key discussion; hence, this website provides a consistent and reliable source of IJC news. This website also aggregates news from Reuters. Moreover, we focus on news articles released on the announcement days for identification purpose; on CNBC, articles typically get finalized around noon. However, news on this website are not directly downloadable from well-known news aggregators (e.g., RavenPack, LexisNexis, Factiva); to the best of our knowledge, we are among the first to examine this website in a systematic way.

We use Python and then manually verify CNBC IJC news articles on announcement days for as far back as we can find online. There may still be multiple articles on this website on an announcement day, and typically there are two types of news: one that describes the announcement statistics and discusses the economy, and one that describes financial market reactions at the end of the day. We always use the former type given our research objective, and it is typically categorized with *US Economy* or *Economy* headers. In summary, we are able to identify 366 IJC articles from the CNBC website until March 18 2021 (end of our sample). Figure 3 shows the distribution over time. From the top plot, it is noticeable that we are able to identify only a few articles before 2013 from their website, while the number becomes quite stable afterwards. The bottom plot depicts a stable bad- and good-IJC-day split per 60-week rolling window. On average, these articles have on average of 327 words (see Appendix C for more details).

Construct topic mentioning scores. To retrieve the relative importance of words (and hence bags of words, "topics") mentioned in the IJC news articles on announcement days, we use the simple, state-of-the-art "Term Frequency-Inverse Document Frequency" or "TF-IDF" scores in 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)), and is offset by the number of documents in which it occurs, to adjust for the fact that some words appear more frequently in general (Jones (1972)). TF-IDF has become the state-of-the-art and popular term-weighting method, as Beel, Gipp, Langer, and Breitinger (2016)'s recent survey documents that, in the information retrieving literature, 83% of text-based recommender systems in digital libraries use TF-IDF. In our research, the average of TF-IDF scores of all words in the same topic then becomes the topic's score.

Results. For our research, we are interested in measuring topic mentioning, over time:

First, 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 key words. We mainly focus on words that reflect discussions of government spending, grants to the states, transfers (augmented unemployment benefits), and legislation, as a way to capture fiscal policy mentioning. For instance, when words such as "aid" "extend" "benefit" "congress" "lawmaker" "Federal government" all appear in one article, the scenario typically reflects an ongoing fiscal-level discussions at the federal level. One example is the CNBC IJC article on August 20 2020, and the actual IJC number released earlier that morning was higher than expected:[12]

> *Earlier this week, more than 100* ***House Democrats*** *urged* ***House Speaker*** *Nancy Pelosi, D-Calif., to pass a smaller bill that would reinstated the* ***ex-***

[12] https://www.cnbc.com/2020/08/20/weekly-jobless-claims.html

> ***tra 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."*

A pre-covid example is from January 10 2013 when IJC is again higher than expected:[13]

> *"Many economists feared that the prospect of higher* ***taxes*** *and steep cuts in* ***federal*** *spending would cause a slowdown in job gains. That's a good sign, since more budget showdowns are expected.* ***Congress*** *must vote to raise the* ***government****'s* ***$16.4 trillion*** *borrowing limit by around late February. If not, the government risks defaulting on its debt.* ***Republicans*** *will likely demand deep spending cuts as the price of raising the debt limit."*

The second important topic we need to trace out, given our research objective and hypothesis, is monetary policy. The words we choose are fairly standard, for instance "central bank" "inflation" "Federal Reserve" as well as Fed Chairman and Chairwoman names. The third topic is economic uncertainty, and we follow Baker, Bloom, and Davis (2016); it is noteworthy that we do not use their existing EPU index because we are interested in the mentioning of economic uncertainty particularly from news articles dedicated to discuss IJC news on the announcement days. The fourth topic is coronavirus-related, for validation purpose, as one should expect the topic mentioning to increase dramatically after January 2020. The fifth topic covers normal IJC terms, such as "initial" "jobless" "claim" "unemploy" "Thursday" and so on, and one should expect that this number being stably high.

Second, how does the mentioning of each topic compare to each other, and how does it evolve over time? Given that each IJC article is relatively short (average=237 words), we construct topic mentioning metrics using a group of weeks. For illustration purpose, Figure 4 considers 60-week rolling windows, and shows the rolling topic mentionings, normalized by the "Normal-IJC" mentioning from the same rolling window. The first observation, serving more as a validation, is the time variation in the "Coronavirus" topic, which expectantly starts off as irrelevant but increases 10 times more important during 2020-2021. Next, the two policy mentioning lines – fiscal (black solid) and monetary (red dashed) – show distinctive patterns. Both start with a similar level and trend, remaining

[13] https://www.cnbc.com/2013/01/10/weekly-jobless-claims-edge-higher-to-start-year.html

low during 2015 and 2016; the MP mentioning increases around 2017 and 2018 but has been in decline since until now, whereas the FP mentioning reaches a local peak around 2013-2014 (perhaps amid the fiscal cliff discussion), remains low until April 2020, but has since dramatically increased. Finally, the mentioning of economic uncertainty moves with the MP mentioning around 2013 and 2014, increases around 2016 amid the Brexit referendum and the US election, and increases again in 2018 and 2019 due to the lingering China-US trade war and in the first few months of 2020 due to the initial Covid-19 crisis. The pattern is generally consistent with the narratives of the EPU index by Baker, Bloom, and Davis (2016), and it is important to note that economic uncertainty – interpreted as expected amount of risk in paradigm asset pricing models, an equity risk premium determinant – is weakly correlated with both FP and MP.

Figure 5 complements Figure 4 by constructing "bad" ("good") topic mentioning metrics using articles on bad (good) IJC days from the same 60-week rolling window. For interpretation purpose, we normalize a topic's mentioning using its value during the first 60-week window so that 1.5 means the bad-day mentioning of a particular topic increases by 50% since around 2013-2014, and several key statistical tests are reported in Table 7.[14] From the upper left plot, the increasing mentioning of fiscal policy (FP) on bad IJC days (when initial claims numbers are higher than expected) explains the total pattern from Figure 4, while the FP mentioning on good IJC days remains flat and statistically indifferent from earlier periods (see test results in Table 7). On the other hand, the monetary policy (MP) mentioning during good IJC days exhibits a clear hump around 2017 and 2018, relative to the 2015-2016 period, meaning that monetary policy was much more discussed and speculated when initial claims numbers are lower/better than expected. The bottom left plot of Figure 5 suggests that "bad" uncertainty and "good" uncertainty can move in the same or opposite direction; for instance, uncertainties being referred to prior to 2018 could be different on bad or good news day; after 2018 and through the early months of 2020, both good and bad uncertainties comove strongly and positively, suggesting an overall higher uncertainty, which is consistent with Baker, Bloom, and Davis (2016). This evidence also provides potential direct support to some recent model assumptions in the asset pricing literature where papers model good and bad uncertainties differently, such as Segal, Shaliastovich, and Yaron (2015), Xu (2019), Bekaert, Engstrom, and Xu (2021)). The bottom right plot shows that coronavirus words (e.g. "pandemic" "vaccine" "covid") are mentioned more often when initial claims are worse than expected.

Figure C1 in Appendix C provides a Jackknife exercise which replicates Figure 5, leav-

[14] Table 7 considers 6 equally-spaced subperiods with around 60 weekly articles in each subperiod from the beginning of 2013 so that the last subperiod covers 1/30/2020-3/18/2021.

ing out one keyword at a time from bags of words for Topics FP and MP and recalculates the relative topic mentioning. The bandwidth denoting min and max from the Jackknife exercise is tight and hence indicates that the measurement uncertainty is considerably low.

Summary and link to our hypothesis. With our manually-collected textual analysis data, our hypothesis becomes testable. First, as shown in the diagram at the beginning of Section 3, our hypothesis is that, in a persistent zero-lower-bound, low-interest-rate world, when main street suffers, investors may now expect a more generous federal government support through *fiscal policy*; one SD higher FP expectation and mentioning could drive up the expected future cash flow growth and the aggregate stock return responses on bad IJC days. The rolling textual analysis evidence shows graphically and statistically that (a) FP mentioning fluctuates over time, even before covid-19, but (b) it increases to a high level particularly during bad IJC days and during the covid-19 period. Both observations are consistent with the fact that the covid crisis helps unveil this new fiscal policy mechanism and the "main street pain, wall street gain" phenomenon.

Second, the lower part of the diagram builds on Law, Song, and Yaron (2020), and we predict that, when main street does well, more MP discussions may be expected, hence counteracting the standard "good is good" pricing mechanism. The rolling textual analysis evidence shows that (a) there is a persistent increase in MP mentioning from late 2016 to 2018, which is consistent with the fact that Period 4's return responses are also often weaker as well (see Tables 2 and 3 as discussed in Section 2), and (b) this hump-shape is more salient during good IJC days.

In Sections 3.2 and 3.3, We formalize these two tests next in unified frameworks, respectively, and we separately consider bad and good IJC days to be consistent with our empirical evidence and hypothesis. Our prediction is that, in a persistent zero-lower-bound, low-interest-rate world (past 10 years), "FP expectation" ("MP expectation") is a significant determinant of how asset returns react to bad (good) IJC news.

3.2. Mechanism evidence using rolling windows

In this section, we directly examine the relationship between rolling return responses to the IJC shocks on announcement days with rolling topic mentionings. Panel A (Panel B) in Table 8 reports the results using rolling windows of 40 bad (good) IJC days when computing both return responses and topic mentioning scores. Given the text data availability, the sample starts in around 2014 till March 2021 for both "bad" and "good" analyses. Newey-West standard errors are reported in the parentheses.

We find that the dynamics of return responses on bad IJC days (when initial jobless claims are higher/worse than expected) are mostly explained by the fiscal policy (FP) mentioning variable. From Panel A, during a period with FP mentioning being one SD higher than average, return responses to a 0.1 unit increase in IJC shock could *increase* by 26-34 basis points; in other words, higher FP mentioning often contributes to a more positive / less negative return response to a worse-than-expected "bad" IJC shock on the announcement day. On the other hand, the monetary policy (MP) mentioning explains more variation in the dynamics of return responses on good IJC days (when initial jobless claims are lower/better than expected). During a period when MP mentioning is one SD higher than average, return responses to a 0.1 unit decrease in IJC shock could *decrease* by around 19-22 basis points. Therefore, time-varying fiscal policy mentioning is much more statistically and economically important than monetary policy mentioning in explaining the dynamics of return responses on bad IJC days, whereas the opposite is true in explaining the dynamics of return responses on good IJC days. This evidence supports our core hypothesis.

In addition to the main observation, we also find that higher uncertainty seems to reinforce the "good is good" return response when good news happen (given the significant negative coefficient in Panel B). This is consistent with Andersen, Bollerslev, Diebold, and Vega (2007), Baele, Bekaert, and Inghelbrecht (2010) and Xu (2019); existing work typically finds that return dynamics modeled with time-varying sensitivites to fundamental shocks – spanned by some form of underlying uncertainty or volatility – dominates those without time-varying sensitivities; in times of high economic uncertainty, market returns may show higher sensitivity to macro shocks (e.g., David and Veronesi (2013) explain it using Bayesian updating).

We conduct an array of robustness tests. Columns (2) and (6) of Table 8 use return responses in standard deviations as a return response proxy on the LHS, or "economic magnitude" (SD changes in returns given 1 SD IJC shock). Columns (3) and (7) include uncertainty. Columns (4) and (8) use Dow Jones 65's open-to-close return response as the LHS. Table A6 in the appendix includes three more tests. Robustness test (4) uses all IJC days instead of bad/good split; Test (5) drops 4/9/2021 given the additional Federal Reserve action on that day; Test (6) uses 30-day rolling windows instead of 40-day rolling windows. Results are highly robust. Figure A4 in the appendix shows the scatter plot and pure non-overlapping data points to show that the relationship we document in Table 8 is not driven by the rolling construction.

Finally, we discuss some time series patterns of rolling return response in economic magnitude, which links back to the period-by-period discussion in Section 2. Figure 6 exhibits SD changes in unexpected S&P 500, discount rate news "NDR", and cash flow news "NCF"[15] given 1 SD bad IJC shock in the top plot, and that given 1 SD good IJC shock in the bottom plot. We call it "economic magnitude" in Columns (2) and (6) in Table 8), or "economic significance" in Figure 6. If "bad is bad", risky asset prices should drop given 1 SD bad IJC shock; if "good is good", risky asset prices should increase given 1 SD good IJC shock. During normal time prior to 2020, worse IJC shocks generate more negative returns (coming from lower NCF and higher NDR) most of the time, with exceptions during 2013 and 2014. Given our evidence, this makes sense as the discussion of "fiscal policy" keywords increases around that period (see Figures 4 and 5), which is likely linked to the 2013-14 fiscal cliff debate. Next, during 2020, 1 SD bad IJC shock generates 0.35 SD increases in return, which is 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).[16] This result is consistent with Table 3.

In comparison, the NDR response yields a higher economic magnitude during good IJC days. During 2017-2018, a -1 SD IJC shock surprisingly *increases* discount rate expectation by a magnitude of 0.2 SD (see the dotted line in the bottom plot of Figure 6), which causes overall return response to be negative; good news is not necessarily reflected positively in asset prices, as higher interest rate or risk premium is expected. This period coincides with to the "hump" in MP mentioning (see upper right plot in Figure 5) and higher interest rate expectations (see (4) in Figure 6 which we discuss more later in Section 3.3), consistent with the lower part of our hypothesis. Next, during 2019 and covid period when the MP mentioning appears in straight decline (as we observe in Figure 5), we also observe that "good is good" pricing again. A -1 SD IJC shock *decreases* discount rate expectation by a magnitude of 0.3 SD during 2020, which results in an overall positive return response to a good IJC shock. Figure A3 in the appendix exhibits SD changes in S&P 500, Nasdaq 100, and Dow Jones 65 given 1 SD bad IJC shock in the top plot and 1 SD good IJC shock in the bottom plot. All three series seem to behave similarly, with the Dow Jones 65 exhibiting stronger "main street pain, wall street gain" phenomenon than Nasdaq 100. This is consistent with evidence in Table 4 and our hypothesis through government helping "main street" economy.

3.3. Mechanism evidence using non-overlapping evidence

While the rolling analysis is illustrative and straightforward, there may be econometric concerns given the persistence design. Next, we test our hypothesis using non-overlapping quarterly state variables to identify the time variation in the return coefficient of IJC

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

[16] Notice that 0.45-0.15 does not add up to 0.35; it is because standardization is done separately within return, NCF and NDR projections, and NCF and NDR are correlated.

shocks. Here is the main specification:

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

where t and τ denote weekly and quarterly frequency, respectively, y stock returns (in basis points) on announcement days, and Z a standardized quarterly state variable. The first three state variables we consider are topic mentionings using articles within the same quarter (fiscal policy "FP", monetary policy "MP", uncertainty "UNC"); similarly, we use bad (good) days within the quarter and obtain a quarterly "bad" ("good") topic mentioning measure. Next, we follow Law, Song, and Yaron (2020) and 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 ($\tau - 1$) information set according to the Survey of Professional Forecasters (SPF). Due to availability of the news files as explained by Section 3.1, regression sample runs from January 2013 to March 2021 (end of paper sample). Given our previous results and our hypothesis, we focus on and conduct bad and good IJC day regressions separately.

Figure 7 displays the time series of our quarterly state variables, with the first (last) bar corresponding to 2013Q1 (2021Q1) and bad/good separation for textual variables. The pattern appears less continuous as expected; given that there are only maximum of 12 announcement-day IJC articles in a quarter, sometimes topic words do not appear in the articles at all (which does not mean that state variable drops to zero).[17] That being said, the overall pattern remains quite similar to the rolling version: (a) sooner and higher increases in the FP mentioning on bad IJC days, (b) the hump shape in the MP mentioning on good IJC days from 2016 to 2018, and (c) high uncertainty around 2019 leading into the first quarter of 2020. The last two plots in Figure 7 show the expected changes in future interest rate ($\Delta Tbill3m$) and expected changes in future recession probability ($\Delta Recess$). Investors expected interest rate to climb around 2015 - 2018, which is consistent with the timing of higher MP mentioning particularly when good economy news are released; then, investors started to expect a lower interest rate amid (likely) the China-US trade war in the second half of 2019. Given that covid is unanticipated, the difference between forecast and nowcast interest rates does not show significant revision during 2019Q4 or 2020Q1. Finally, the fifth state variable captures the expectation changes in the probability of future real GNP/GDP declines, or labeled as "recession" by SPF; it has been increasing steadily in the past 10 years but drops significantly when investors stand in 2020Q1 to forecast Q3 compared to Q2. We interpret

[17] In this case, we mark the quarter as missing in our regression analysis.

$\Delta Recess$ as a measure of an overall pessimism about the economy, but it is not directly related to our theoretical hypothesis; as a result, we do not emphasize the $\Delta Recess$ results in the following paragraphs.

Table A7 in the appendix shows correlation matrix of these quarterly state variables (N = 33 non-overlapping quarters). Here are four observations. First, FP and MP mentionings are uncorrelated, regardless during bad or good IJC days. Second, $\Delta Tbill3m$ is highly positively correlated with our MP mentioning during good days ($\rho = 0.46^{***}$), supporting the "contractionary" interpretation of high MP mentioning on good IJC days during the sample period of the paper. Third, FP mentioning during our sample period is particularly associated with bad uncertain environment ($\rho = 0.69^{***}$), suggesting the "expansionary" interpretation of high FP mentioning on bad IJC days during our sample period. Fourth, a higher recession expectation is associated with periods when fiscal policy mentioning on bad IJC days is lower, or when interest rate and monetary policy are expected to be higher and more contractionary on good IJC days.

Next, we discuss the estimation results of Equation (3). Table 9 shows regression results in Equation (3) using one state variable at a time, and Table 10 is our main mechanism table allowing for multiple state variables. In both tables, Panel A (B) reports bad (good) IJC days and topic mentioning state variables extracted from these days' IJC articles:

First, on bad IJC announcement days when fiscal policy mentioning is one SD higher than its average, stock returns could significantly *increase* by 24-26 basis points with a 10% IJC shock, given the significant and positive interaction term (243.349** using Dow Jones 65 and 258.382*** using S&P500). This magnitude is quite consistent with Table 8. The MP mentioning state variable shows insignificant explanatory power, supporting our hypothesis that the "main street pain, wall street gain" phenomenon on bad IJC days is mostly due to when fiscal policy expectation is high.

Second, on good IJC days, fiscal policy mentioning does not explain the time-varying return responses of major stock indices; instead, on announcement days when monetary policy mentioning is one SD higher than its average, stock returns could significantly decrease by 16-30 basis points with a -10% IJC shock, given the positive interaction term (301.688* using Dow Jones 65). This evidence lends supportive evidence to Law, Song, and Yaron (2020) as well as the second half of our hypothesis; that is, increases in monetary policy expectation matters more on good IJC days, counteracting the "good is good" conventional wisdom.

Third, putting several state variables together in Table 10, we find that, on bad IJC days, fiscal policy mentioning dominates monetary policy, uncertainty, and the actual expectation revisions in future interest rate in explaining the time variation in return responses. To explain the return responses on good IJC days, we show evidence that monetary policy mentioning or expectation revisions in future interest rate ($\Delta Tbill3m$) dominate fiscal policy. Note that the single state variable result of $\Delta Tbill3m$ in Table 9 is already borderline significant using Dow Jones 65. From Table A7, MP mentioning on good IJC days "goodMP" and $\Delta Tbill3m$ are significantly and positively correlated at 0.46*** and capture same economic concepts, which motivates the choice of including one at a time in multiple regressions in Table 10. To interpret the coefficient in the last column, when interest rate is expected to increase by 0.09 annual percents (which corresponds to 1 SD of $\Delta Tbill3m$), stock returns could significantly decrease by 50-67 basis points with a -10% IJC shock, given the positive interaction term (671.552** using Dow Jones 65 in Table 10 and 496.752* using S&P 500 in Table A8 in the appendix).

Fourth, we discuss results of the remaining two state variables – recession probability revisions "$\Delta Recess$" and uncertainty "UNC"; both are not our main mechanism variables, but may offer meaningful tests when interpreted as general business cycle variables.[18] From Table 9, results using recession probability revision show that stock returns respond to bad (good) IJC news more negatively (positively) when investors are more pessimistic (optimistic) about future economy.[19] Therefore, the recession channel goes against the policy channels, and in some sense reinforces the conventional "good is good", "bad is bad" pricing. Uncertainty has the same directional implication, with a bit weaker statistical power; in short, stock returns respond to bad (good) IJC news more negatively (positively) when investors expect more (less) uncertainty about future economy.

Fifth, one other concern is that results are driven purely by 2020-2021. In Table A9, we replicate Table 10 using a sample period until December 2019. Results are quite robust. Statistical power drops slightly, given the smaller sample and that the covid period does admittedly help unveil the FP channel in particular, as mentioned in Section 2.

4. Cross Section Evidence

In the last part of the paper, we exploit the Covid period and conduct two more analyses (this section testing our hypothesis in a cross section of S&P500 returns and Section 5 considering monthly macro announcements) to better understand the "main

[18]We do note that the interpretations may be less straightforward given that they correlate with both FP and MP (and each other).

[19]When investors expect a lower chance of future recessions ($\Delta Recess < 0$) on good IJC days, return response coefficient becomes more negative given the positive and significant interaction term (856.51** for S&P500 and 983.78*** for Dow Jones 65), or it is consistent with "good is good" pricing. On the other hand, when investors expect a higher chance of future recessions ($\Delta Recess > 0$) on bad IJC days, worse (i.e., more positive) IJC shocks correspond to even lower stock returns than when $\Delta Recess < 0$.

street pain, wall street gain" phenomenon, given that it maybe hard to find another period (pre-2020) that is long enough with knowingly higher fiscal policy expectation. In the cross section, our hypothesis also predicts that firms/industries that suffer more should exhibit stronger "main street pain, wall street gain" phenomenon, with higher individual stock returns when a bad IJC surprise arrives, compared to those who do not suffer as much.

4.1. Firm covid-impact measures

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

Our first measure considers a novel proprietary dataset provided by LinkUp, a job search engine that aggregates job listings from employer websites (typically an employer's applicant tracking system in real time). LinkUp provides us monthly job postings data by 6-digit NAICS code. We aggregate the number of job postings by 4-digit NAICS code (or 2-digit NAICS code for robustness), and construct our first "firm covid impact" measure using changes in the number of job postings from its 2019 average to its 2020 April-May average. One clear advantage of this measure is its forward-looking nature. Firms increase their job listings when they expect growth in the future. Together, this measure has three clear advantages: (a) forward-looking, (b) can be observed on a monthly or even daily frequency, and (c) more of an out-of-sample measure for our portfolio construction (see later).

Measuring realized impacts is more straightforward. We consider (2) changes in the number of employees from fiscal year (FY) 2019 to fiscal year 2020, (3) quarter-on-quarter growth rate of total revenue between 2019Q2 and 2020Q2 to control for seasonality, and (4) quarter-on-quarter Earning Per Share (basic, excluding extraordinary items) first differences between 2019Q2 and 2020Q2.[20] Data are obtained from Compustat Annual and Compustat Quarter; there is no quarterly data available from employment data. The rule of thumb is that we aim to identify the initial impact of covid on businesses before actual interventions.

We obtain the ticker list of S&P 500 in July 2021 and traced all matched permnos (the CRSP identifier) through our Covid-19 data sample period from February 2020 to March 19 2021.[21]. 491 out of 500 tickers can be found with the number of employees reported in

[20] "2020Q2" refers to 10-Q numbers reported in 2020 July, August, or September from Compustat, and 2019Q2 is the 10-Q report four quarters ahead.

[21] We do not consider the firm added or removed during this period. For example, Tesla entered S&P

Compustat for fiscal years 2019 and 2020. Besides the four main covid-impact measures above, we also use (5) job posting data aggregated at 2-digit NAICS levels, (6) revenue changes and (7) EPS changes from FY 2019 to FY 2020 at the firm level for robustness.

Table A10 in the appendix shows the summary statistics of the seven covid-impact measures. In general, the lower (more negative) the measure is, the more the firm/industry is suffering from covid. Our direct "job posting" measure shows that almost all companies decreased their job listings during the initial impact of covid around, on average, -39%; the distribution is also quite normally distributed and well behaved. Notice that, employment changes calculated using Compustat's fiscal year data in 2019 and 2020 show that some firms indicate positive labor growth, which should include some growth triggered by already one or two rounds of stimulus packages from the federal government in 2020. The third and fourth measures show a wide heterogeneity of changes in firm revenue and EPS, while the latter is a bit more negative skewed (with 5th percentile at about -\$11 and 95th at \$4). Robustness measures (5)-(7) reach similar patterns and conclusions. Due to the skewness in these financial variables, we also consider ranks of these measures in formal analysis.

4.2. Link to our hypothesis

Firms that suffer more should be expected to receive more government support via fiscal policy; hence, their individual stock returns should increase more relative to their historical volatility, when bad IJC surprises arrive. To make individual stock return responses to IJC shocks comparable across firms in a unified framework, our main dependent variable is SD changes in individual stock (open-to-close) returns given 1 SD IJC shock; or econometrically, this is equivalent to "correlation" between individual stock returns and IJC shocks, denoted by $Corr^i$ below. In a "bad is bad" / "good is good" pricing, firm-level correlation should be negative; our "main street pain, wall street gain" phenomenon is consistent with a positive firm-level correlation between firm returns and IJC shocks. The sample period we use to calculate firm-level correlation with IJC shock spans from February 2020 to March 2021 (end of our sample);[22] and three correlations can be calculated for each firm, using all, bad or good IJC days, where the first can be dubbed as unconditional correlation and the other two conditional correlations. Here is

500 in 2020 December. Our analysis includes Tesla for the entire period

[22]In this section, we always drop 03/19/2020, 03/26/2020, 04/02/2020, 04/09/2020 in our analysis, where the first three are identified as IJC outliers as mentioned in Section 2; 04/09 is a day with several unconventional monetary policy announcements. Results are a bit stronger if we include these four days back.

the firm-level specification:[23]

$$Corr^i_{All} = a_{All} + b_{All} CovidImpact^i + \varepsilon^i_{All}; \quad (4)$$

$$Corr^i_{Bad} = a_{Bad} + b_{Bad} CovidImpact^i + \varepsilon^i_{Bad}; \quad (5)$$

$$Corr^i_{Good} = a_{Good} + b_{Good} CovidImpact^i + \varepsilon^i_{Good}. \quad (6)$$

Table 11 reports the regression results with N=491. Here are several main observations. First, from the first two rows, average $Corr^i_{Bad}$ is significant and positive at 0.176 on bad IJC days, whereas average $Corr^i_{Good}$ remains intuitively negative on good IJC days.[24]

Second, results using all IJC days show a strong and consistent takeaway using any of our measures (rank or raw changes): firms that suffer more (i.e., the covid-impact measure is more negative) exhibit a higher $Corr^i$ (i.e., individual stock return would be higher when IJC news are worse). To make sense of the coefficients, firms with job posting changes that are 1 SD below the average change (-0.39-0.21=-0.60, according to summary statistics in Table A10) correspond to a significant 0.02 (0.21×-0.0877) higher-than-average correlation between returns and IJC shocks, i.e., stronger "main street pain, wall street gain" phenomenon. Considering the average correlation is 0.141, 0.02 is a sizable cross-sectional difference (14.2%). For financial variables, a quintile (20% or 0.2) drop in the impact rank (i.e., more suffering) corresponds to around 0.012-0.016 increase in the correlation. This main takeaway is also displayed as negative slopes as depicted in solid lines in Figure 8, where we group firms into 20 bins and each dot represent a bin.

Third, the firm-level correlations on bad or good IJC days only are calculated within these days, respectively, and therefore take out different conditional means in the calculation. We find that the negative slope mainly comes from bad IJC days. This result is consistent with our previous findings that the "main street pain, wall street gain" phenomenon only exists when bad news arrive (see e.g. Table 4). Next, Figure 9 shows that, for the same (ranks of) firms, the good-IJC-day correlations are mostly negative and for sure lower than their bad-IJC-day correlations. If we focus on rank < 50 in subfigures (b)-(d), the relationship between good-IJC-day correlations and impact measures is obsolete – all firm returns go up when IJC shocks are better.

[23]We also use individual return sensitivites to the IJC shock as the left hand side variables, and results are robust. Detailed results are available upon request.

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

4.3. Which industries suffer more? Do bills help them more?

Who are the firms that we identify as "being impacted by covid"? Are they indeed those who receive more support from the government? Although these questions move beyond our research question, we document several useful facts below for future research. Table A11 in the appendix reports the average covid-impact measures by 2-digit NAICS industries. The top 3 damaged industries in S&P500[25] are *Mining* (Naics:21), *Transportation and Warehouse* (Naics: 48-49), and *Accommodation and Food Services* (Naics: 72). The average *Mining* industry YoY employment change has a low rank (lower=more decreases in employment) at 20th, and job postings lose by 64% from 2019 to April/May of 2020. The QoQ revenue and EPS changes also rank low at 19th and 23th, respectively. Similarly for *Transportation and Warehouse* and *Accommodation and Food Services*, YoY employment changes rank at 27th and 36th, and job postings decrease by 53% and 34%, respectively. Similarly, revenue and earnings changes all rank in the lowest 1/3 bins. On the other hand, *Healthcare and Social Assistance* industry shows both positive financial growth and high YoY employment rank at 66th; even job postings during early period of covid only drop by 2.3%. *Retail Trade*, *Information*, and *Professional Scientific and Technical Services* also remain intact under Covid-19 shocks.

We also construct a likelihood ratio for each fundamental variable, for each 2-digit Naics code, such that a higher ratio represents that this industry of interest falls in the most damaged 15% tail with exceptionally high probability compared to its normal presence:

$$Ratio = \frac{Prob(\#\text{Firm in the most damaged 15\%})}{Prob(\#\text{Firm in the least damaged 50\%})}$$

Table A12 presents the ratios for each industry. All ratios agree on the top three damaged industries: *Mining*, *Transportation and Warehousing*, and *Accommodation and Food Services*.

The American Rescue Plan Act (ARP) of 2021 also confirms that these damaged industries do get substantial fiscal policy support. One significant example is the transportation industry. At least five sub-sections in ARP are dedicated to rescue the transportation-related business: *Continued Assistance to Rail Workers*, *Public Transportation*, *Transportation and Infrastructure*, and *Aviation Manufacturing Jobs Protection,Airlines*. From our Figure 8, the Transportation and Warehouse industry also shows an industry-average correlation (between stock returns and IJC shock) that is 0.186 (p=0.092) higher correlation than the S&P500 average (0.141). Overall, our finding is consistent with Gourinchas, Kalemli-Özcan, Penciakova, and Sander (2021) who conclude that "fiscal support in 2020

[25]We only include industries with more than five firms in S&P 500 ticker list. In total, 14 Naics 2-digit industries meet our criterion.

achieved important macroeconomic results...preventing many firm failures"; like a "battlefield surgery", one can observe some degree of poor targeting, but these firms represent a very small share of the funds disbursed by fiscal policy.

Other fiscal channels are also plausible: *Agriculture* and *Healthcare* industries also receive considerable fiscal help by the nature of the pandemic crisis. Although we do not find huge job loss in these two industries, the industry-level correlations between stock returns and IJC shocks are also significantly higher than the S&P 500 average by 0.108 (p=0.016). Such crisis-specific fiscal channels are not our focus.

4.4. Investment strategies

Finally, we form a portfolio sorted by our "firm covid impact" or "suffering" measures, and examine its properties on bad IJC announcement days, good IJC announcement days, and any other days during this period without IJC announcements.

In the first step, we sort the 491 out of S&P500 firms (that we can identify with our four main "impact" measures) into 5 bins based on these measures, one at a time. In the second step, we call the 1st (5th) quintle the "Most-Suffering" ("Least-Suffering") quintle, and obtain value-weighted daily open-to-close returns of these individual stock returns within the two bins. Third, the portfolio takes the return differences between the Most-Suffering and the Least-Suffering quintile bins. As mentioned before, within each quintile bin, average returns can be calculated using bad IJC days (when actual IJC number is higher/worse than expected), good IJC days (when actual IJC number is lower/better than expected), and non-IJC days. Sample period is the same as before (February 2020 – March 2021), excluding outlier days 03/19, 03/26, 04/02/2020 and a major unconventional monetary policy announcement day 04/09/2020.

From Figure 10, using any of our aforementioned impact measures, we find that the average daily open-to-close portfolio returns on bad IJC days are positive, and importantly, higher than those on good IJC or non IJC days. The bad-IJC-day average ranges from 5 to 12 basis points, with our labor measure (changes in online job postings from 2019 to April/May of 2020) giving the largest portfolio return compared to our financial measures (revenue or EPS changes). The average good-IJC or non-IJC days returns are often negative or statistically close to zero, meaning that firms that suffer more from covid are expectantly earning less returns. Figure A5 in the appendix shows a series robustness results using equal weights, using alternative covid-impact proxies or including back the outlier dates that we take out.

Lastly, we examine the performance of size, book-to-market (BM) and earnings-price (EP) portfolios. We similarly sort our 491 firms into 5 quintiles based on the firms' end-of-

2019 data from low to high (one at a time), and construct value-weighted quintile returns on bad-, good-, and non-IJC days from February 2020 to March 2021 excluding 03/19, 03/26, 04/02, 04/09/2020 (as above). Figure 11 shows the return difference between the 1st and the 5th quintile. We find that small (low size) and value (high B/M, high E/P) firms outperform when IJC numbers are higher/worse than expected, according to the solid bars indicating "bad IJC days." This finding is consistent with the cash flow pricing channel in Section 2 using aggregate return decomposition; as Campbell and Vuolteenaho (2004) put, small and value firms exhibit considerably higher cash-flow betas. The fact that small firms outperform large firms on bad IJC days also provide suggestive evidence *against* an alternative mechanism to the "bad is good" aggregate result during 2020-2021: that is, big firms may show higher stock returns when bad IJC news come out, given their stronger lobbying capabilities and capacities. We in fact find the opposite. On the other hand, on good IJC days (shaded bars) or non-announcement days (hollow bars), small and values firms perform worse than large and growth firms. This is consistent with the general observation of this prolong weakening performance of size and value factors since early 2000 (see recent evidence and discussions in Blitz (2020), Asness, Frazzini, Israel, Moskowitz, and Pedersen (2018), Arnott, Harvey, Kalesnik, and Linnainmaa (2021), Fama and French (2021) and so on).

While it may be hard to find another long-enough period – pre-2020 – with knowingly higher fiscal policy expectation to conduct a decent cross-section exercise, our cross-section evidence indicates that, when bad main street news come out, investors believe that more help is going to firms/industries that suffer more.

5. External validation: Monthly macro announcement surprises

For our analysis, the advantage of focusing on weekly initial jobless claims announcements is two fold: First, it is the most timely-released data on the economy's health, and there are 54 weekly announcement data points from February 2020 to March 2021 (end of our sample) after teasing out outliers and FOMC overlaps; second, the "main street" interpretation of IJC shocks is unambiguous, whereas it may not be the case for inflation surprises or industrial production surprises for instance. In this section, we put the "main street pain, wall street gain" phenomenon to test using monthly macro announcement surprises. There is also a unique cross-macro-variable perspective that can help us test our hypothesis. Our theory would predict that this phenomenon should be more pronounced when bad news about how the main street is doing arrive.

Table 12 shows the correlation coefficients between seven mainstream monthly macro surprises (constructed from their respective announcement days) and daily open-to-close S&P500 returns,[26] during a "normal" benchmark period (or "Period 3", 2009/06-2016/12, as motivated in Section 2 and used in Tables 1-6) and during the covid period (or "Period 5", 2020/02-2021/03). Appendix D provides the corresponding scatter plots. From Panel A, when bad monthly labor news arrive (i.e., higher-than-expected unemployment rate and/or lower-than-expected changes in non-farm payrolls), daily stock return response is significantly less negative and more positive during covid period than during normal period. For instance, the correlation between unemployment surprises and stock returns during covid is significant and positive (0.793***), which is striking 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 around zero, partially due to the rounding numbers forecasters typically enter for unemployment rates (causing too many zeros in the unemployment rate surprises). Similarly, lower-than-expected changes in non-farm payroll normally corresponds to lower stock returns, but during covid could correspond to higher stock returns. From Panel B, bad news about manufacturing, consumption or consumer confidence indicators normally would significantly decrease stock returns, but appear as good news to the stock market during covid, in particular the manufacturing news (-0.569*). As a result, evidence from these two panels – which consider macro announcements that plausibly paint a health report on the 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 variable such as CPI changes and industrial production growth. Although the correlation coefficients are all statistically insignificant, these two variables draw an opposite effect: bad news about the economy decreases stock returns, and the effect is quite strong in terms of economic magnitude during covid period.

[26] Given that different macro variables may be released at different times of a day, we simply use daily open-to-close return in this external validation exercise instead of complicating it. Here are some examples: at 8:30AM EST or before market opens such as non-farm payrolls (Bureau of Labor Statistics, BLS), unemployment rate (BLS), CPI (BLS), retail sales (Bureau of the Census, BC), industrial production (Federal Reserve Board) etc.; at 10:00AM EST such as manufacturing index (Institute of Supply Management), consumer confidence index (Conference Board) etc.)

6. Conclusion

Our paper starts with a surprising observation during the Covid period (2020/02-2021/03): a one standard deviation increase in the initial jobless claims (IJC) surprise (8.7%) significantly predicts higher daily major stock index returns of 26-38 basis points (where IJC shock is defined as the relative change of actual and expected IJC numbers). The phenomenon (a) appears only when bad news arrive, (b) is stronger for Dow Jones industrial or transportation index, (c) prices through the cash flow channel, and (d) builds up through noon. We coin this phenomenon "main street pain, wall street gain." We argue that existing theories may have a hard time explaining this phenomenon that we observe during covid. The business-cycle based explanation by Boyd, Hu, and Jagannathan (2005) predicts that rising unemployment news should be bad news for stocks during economic contractions as it signals bad future dividend growth; on the other hand, the monetary-policy-expectation based explanation by Law, Song, and Yaron (2020) predicts that rising unemployment news could be good news if further lower interest rates are expected, but interest rate during the majority period of 2020-2021 is at the zero lower bound.

We document an increasingly important role of *fiscal policy* expectation through examining stock return responses to macro surprises in the past 10 years, using high-frequency and daily data, textual analysis, and cross section evidence. Using actual IJC news articles manually collected from CNBC (2013-2021), we find that topic mentioning of fiscal policy significantly surpasses that of monetary policy since 2019, and peaks mostly on bad IJC surprise days. Then, we construct and obtain state variables from textual and survey data to explain time-varying stock return responses to IJC shocks. We find that, in a persistent zero-lower-bound, low-interest-rate economy, when the main street suffers (e.g., worse number of IJC than expected), investors may expect a more generous federal government support through fiscal policy, *driving up* the expected future cash flow growth and the aggregate stock return responses. In a unified framework, our evidence also supports the important role of monetary policy expectation in explaining return responses to macro surprises on good IJC days, consistent with Law, Song, and Yaron (2020). Crucially, our aggregate result is robust using sample with or without 2020-2021.

The covid crisis triggered an unprecedented adverse shock to the labor market, which helps unveil this phenomenon. We conduct two more exercises zeroing in the covid period, for identification advantage, that use cross section data and external validations to provide more direct evidence of our proposed mechanism through fiscal policy expectation.

Our cross-section evidence shows that firms/industries that suffer more exhibit stronger "main street pain, wall street gain" phenomenon, with *higher* individual stock returns on bad IJC days, than those who suffer less. To measure to what extent the a firm is impacted negatively by covid during the initial shock, we use changes in the number of firm job postings from 2019 to 2020 April-May, changes in employment, revenue and EPS. Both direct damage data and a likelihood ratio measure agree that the top 3 damaged industries in S&P500 are *Mining*, *Transportation and Warehouse*, and *Accommodation and Food Services*. Through textual analyzing the actual stimulus bills, our evidence agrees with Gourinchas, Kalemli-Özcan, Penciakova, and Sander (2021) that this round of fiscal support appears to indeed effectively support industries who need support. This evidence ties up the story that firms that suffer more have higher stocks returns when bad macro news are announced, as investors expect that they will receive more government support. This appears to be rational pricing. Our external validations examine stock return responses to seven mainstream monthly macro announcement surprises. Not all macro news trigger the "main street pain, wall street gain" phenomenon. In fact, those plausibly paint a health report on main street households – employment, manufacturing and consumption/consumer confidence news – show such phenomenon.

Moving forward, in a post-covid era, interest rate will likely stay at its zero-lower bound for a while. As Mr. Powell said in his October 6 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." Our paper is among the first to document that investors may have already been putting fiscal policy expectation into pricing with a unprecedented weight, and the covid period helps unveil this phenomenon. Future research should further examine the role of fiscal policy expectation in financial market, which may be a novel form of *federal government* intervening the market.

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Table 1: Summary statistics of Initial Jobless Claims (IJC) shock

This table shows summary statistics of IJC shocks in five subsamples from 2002 to 2021, grouped by general macro environment (NBER business cycle and monetary policy indicator):

Period 1	*2002/02-2007/11*		*Contractionary-High interest rate*
Period 2	*2007/12-2009/06*	*Global Financial Crisis*	*Expansionary-ZLB*
Period 3	*2009/07-2016/12*		*Expansionary-ZLB*
Period 4	*2017/01-2020/01*		*Contractionary-Low interest rate*
Period 5	*2020/02-2021/03*	*Covid, during & post*	*Expansionary-ZLB*

Our main IJC shock is defined as $\frac{IJC_t - E_{t-\Delta}(IJC_t)}{E_{t-\Delta}(IJC_t)}$, where y_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 survey forecasts submitted until shortly before the announcement at time $t - \Delta$. Both actual and expected claims are from Bloomberg. Summary statistics using $IJC_t - E_{t-\Delta}(IJC_t)$ are reported in Appendix A. 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.

	Period 1	**Period 2**	**Period 3**	**Period 4**	**Period 5**	**All periods**
Min	-0.148	-0.143	-0.117	-0.141	-0.153	-0.153
1st	-0.096	-0.138	-0.091	-0.115	-0.152	-0.117
5th	-0.073	-0.082	-0.067	-0.074	-0.112	-0.075
10th	-0.056	-0.053	-0.053	-0.062	-0.083	-0.061
25th	-0.027	-0.014	-0.026	-0.036	-0.038	-0.028
50th	0.000	0.008	-0.003	-0.008	0.005	-0.002
75th	0.031	0.042	0.025	0.020	0.058	0.030
90th	0.059	0.072	0.054	0.050	0.131	0.062
95th	0.079	0.094	0.079	0.065	0.190	0.087
99th	0.145	0.166	0.144	0.178	0.223	0.171
Max	0.211	0.176	0.203	0.216	0.224	0.224
Mean	0.003	0.011	0.000	-0.004	0.019	0.002
Mean-Bad	0.040	0.043	0.036	0.036	0.083	0.041
Mean-Good	-0.033	-0.035	-0.030	-0.039	-0.049	-0.035
SD	0.048	0.053	0.044	0.051	0.087	0.052
SD-Bad	0.034	0.038	0.033	0.041	0.068	0.039
SD-Good	0.027	0.037	0.024	0.027	0.040	0.029
Skewness	0.456	0.002	0.672	0.990	0.550	0.603
Skewness-Bad	1.894	1.411	1.930	2.576	0.738	1.964
Skewness-Good	-1.395	-1.364	-1.023	-1.108	-0.946	-1.291
N	292	79	379	156	54	960
N-Bad	144	47	175	72	28	466
N-Good	148	32	204	84	26	494

Table 2: How do asset prices respond to macro shocks, now and then?

This table uses daily-level evidence to examine the responses of various asset prices and risk variables to IJC shocks on the announcement days. Definition of the left-hand-side (LHS) variables: (1) **S&P500**, open-to-close log daily returns (unit: basis points); (2) **GovBond10yr**, daily log changes in the US 10-year Government bond total return index (unit: basis points); (3) **TBond10yr**, daily changes in 10-year Treasury yield (unit: annual rate); (4) **TBill3m**, daily changes in 3-month Treasury bill secondary market rate (unit: annual rate); (5) **GrowthUnc**, daily changes in a financial proxy to real economic growth uncertainty (unit: annualized variance in percentage-squared); (6) **RV1m**, daily changes in 1-month realized variance in S&P500 (unit: annualized variance in percentage-squared); (7) **EPU**, daily changes in the Economic Policy Uncertainty; (8) **VIX**, open-to-close changes in the volatility index; (9) **RiskAversion**, daily changes in a financial proxy to aggregate relative risk aversion. Data sources are Datastream; FRED; CBOE; Baker, Bloom, and Davis (2016); Bekaert, Engstrom, and Xu (2021). "IJC shock" shows the coefficients of LHS variable on IJC shocks on announcement days, with robust standard error, t-statistics and R-squared displayed in respective rows; "SD chngs per 1SD shock" shows the standard deviation (SD) changes in the LHS variable given 1 SD IJC shock. See details of the periods in Table 1. ***, p-value <1%; **, <5%; *, <10%.

		S&P500	**GovBond10yr**	**Yield10yr**	**TBill3m**	**GrowthUnc**	**RV1m**	**EPU**	**VIX**	**RiskAversion**
Period 1	IJC shock	-81.249	**161.770*** **	**-0.204*** **	**-0.095** **	**0.372** **	**-84.707** **	52.975	1.505	**0.279** **
	(SE)	(104.369)	**(47.465)**	**(0.061)**	**(0.045)**	**(0.161)**	**(36.018)**	(69.492)	(1.343)	**(0.135)**
	[t]	[-0.778]	**[3.408]**	**[-3.372]**	**[-2.111]**	**[2.308]**	**[-2.352]**	[0.762]	[1.120]	**[2.073]**
	SD chngs per 1SD shock	-0.040	**0.170**	**-0.167**	**-0.109**	**0.116**	**-0.117**	0.042	0.063	**0.123**
	R2%	0.16%	**2.88%**	**2.78%**	**1.18%**	**1.35%**	**1.38%**	0.18%	0.40%	**1.51%**
Period 2	IJC shock	-112.247	**338.714** **	**-0.373***	-0.025	0.844	**502.223** **	141.265	-1.745	1.242
	(SE)	(442.666)	**(153.774)**	**(0.206)**	(0.236)	(0.653)	**(238.875)**	(137.769)	(4.327)	(3.286)
	[t]	[-0.254]	**[2.203]**	**[-1.813]**	[-0.108]	[1.292]	**[2.102]**	[1.025]	[-0.403]	[0.378]
	SD chngs per 1SD shock	-0.026	**0.230**	**-0.198**	-0.017	0.092	**0.178**	0.104	-0.037	0.040
	R2%	0.07%	**5.29%**	**3.92%**	0.03%	0.85%	**3.17%**	1.08%	0.13%	0.16%
Period 3	IJC shock	-97.163	**174.551*** **	**-0.207*** **	-0.012	0.332	20.161	47.554	2.167	0.337
	(SE)	(107.303)	**(52.324)**	**(0.060)**	(0.014)	(0.205)	(36.495)	(50.701)	(1.901)	(0.209)
	[t]	[-0.905]	**[3.336]**	**[-3.460]**	[-0.871]	[1.621]	[0.552]	[0.938]	[1.140]	[1.615]
	SD chngs per 1SD shock	-0.042	**0.168**	**-0.167**	-0.040	0.083	0.019	0.041	0.057	0.089
	R2%	0.18%	**2.81%**	**2.78%**	0.16%	0.68%	0.04%	0.17%	0.33%	0.79%
Period 4	IJC shock	109.978	36.716	-0.039	-0.036	0.104	-6.037	-125.070	-0.280	-0.010
	(SE)	(85.849)	(70.305)	(0.079)	(0.024)	(0.155)	(42.777)	(76.130)	(1.505)	(0.078)
	[t]	[1.281]	[0.522]	[-0.493]	[-1.522]	[0.668]	[-0.141]	[-1.643]	[-0.186]	[-0.126]
	SD chngs per 1SD shock	0.085	0.053	-0.050	-0.098	0.051	-0.011	-0.138	-0.012	-0.008
	R2%	0.72%	0.29%	0.25%	0.95%	0.26%	0.01%	1.91%	0.01%	0.01%
Period 5	IJC shock	**307.916***	60.588	-0.087	0.017	-1.007	-185.712	-59.092	-6.774	-2.811
	(SE)	**(186.945)**	(61.521)	(0.066)	(0.025)	(0.667)	(396.830)	(99.012)	(4.977)	(2.485)
	[t]	**[1.647]**	[0.985]	[-1.310]	[0.675]	[-1.510]	[-0.468]	[-0.597]	[-1.361]	[-1.131]
	SD chngs per 1SD shock	**0.197**	0.132	-0.177	0.067	-0.145	-0.048	-0.083	-0.135	-0.111
	R2%	**3.90%**	1.75%	3.13%	0.45%	2.10%	0.23%	0.70%	1.82%	1.24%

Table 3: How do pricing channels change?

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). We use monthly parameter estimates of a Campbell and Vuolteenaho (2004) framework, in a long sample, to impute daily measures; see our methodology in Appendix B. By design, NCF minus NDR is the total unexpected return (with expected rounding differences) See other notation details in Table 2.

		Unexpected return	**NCF**	**NDR**
Period 1	IJC shock	-63.460	-64.453	-0.993
	(SE)	(104.387)	(87.948)	(55.696)
	[t]	[-0.608]	[-0.733]	[-0.018]
	SD chngs per 1SD shock	-0.032	-0.023	0.000
	R2%	0.11%	0.17%	0.00%
Period 2	IJC shock	-62.158	-115.558	-53.400
	(SE)	(435.723)	(334.331)	(152.290)
	[t]	[-0.143]	[-0.346]	[-0.351]
	SD chngs per 1SD shock	-0.014	-0.029	-0.012
	R2%	0.02%	0.11%	0.11%
Period 3	IJC shock	-86.736	-3.993	**82.743***
	(SE)	(106.271)	(79.224)	**(48.330)**
	[t]	[-0.816]	[-0.050]	**[1.712]**
	SD chngs per 1SD shock	-0.037	-0.002	**0.037**
	R2%	0.15%	0.00%	**0.55%**
Period 4	IJC shock	111.454	60.276	-51.178
	(SE)	(86.420)	(62.499)	(52.804)
	[t]	[1.290]	[0.964]	[-0.969]
	SD chngs per 1SD shock	0.086	0.037	-0.040
	R2%	0.74%	0.40%	0.57%
Period 5	IJC shock	299.961	**298.903****	-1.058
	(SE)	(186.761)	**(133.464)**	(103.733)
	[t]	[1.606]	**[2.240]**	[-0.010]
	SD chngs per 1SD shock	0.192	**0.197**	-0.001
	R2%	3.68%	**7.56%**	0.00%

Table 4: "Bad is good": What assets, and When?

This table focuses on the Period 5 (2020/02-2021/03, end of our sample) and provides further evidence on the source of this "main street pain, wall street gain" phenomenon: cash flow or discount rate return components, Nasdaq or Dow Jones index returns, and bad or good IJC shock announcement days. The first three columns use the same LHS variables as in Table 3; the next six columns use open-to-close log returns, and are expressed in basis points as before; Nasdaq and Dow Jones indices are downloaded from Datastream. The coefficient in row "IJC shock" 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 2

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	**585.113****	**479.568****	-105.545	**591.829****	498.523	**575.072****	**589.960****	**549.662***	498.755
(SE)	**(262.050)**	**(224.735)**	(154.879)	**(264.162)**	(324.814)	**(263.722)**	**(291.756)**	**(312.686)**	(468.282)
[t]	**[2.233]**	**[2.134]**	[-0.681]	**[2.240]**	[1.535]	**[2.181]**	**[2.022]**	**[1.758]**	[1.065]
SD chngs per 1SD shock	**0.395**	**0.265**	-0.072	**0.400**	0.275	**0.392**	**0.387**	**0.321**	0.231
R2%	**15.68%**	**17.40%**	1.97%	**15.97%**	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)

	Unexpected return	**NCF**	**NDR**	**S&P500**	**Nasdaq100**	**DowJones65**	**DowJones30 Indus.**	**DowJones20 Transp.**	**DowJones15 Util.**
IJC shock	-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 5: High-frequency evidence using E-mini S&P 500 futures

This table examines the coefficient of intradaily returns of E-mini S&P 500 futures on IJC shocks. Intradaily returns (in basis points) are calculated using the same start time of 8AM Eastern Time and an end time that is commonly 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 3, which is a relatively normal with the majority of the time during this period having zero-lower-bound interest rates; the right four columns use Period 5, dubbed as "Covid" in this table. Period dates are listed in Table 1. Row "Closeness (covid-normal)?" provides t-statistics of whether the "covid" coefficient is higher than the "normal" coefficient, with bold indicating significance. High-frequency futures data is obtained from TickData. See most notation details in Table 2.

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 3)***				***"Covid" (Period 5)***			
Panel A. All IJC days								
IJC shock	-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	-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	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 6: High-frequency evidence using E-mini Dow futures

This table examines the coefficient of intradaily returns of E-mini Dow futures on IJC shocks. See tables notes in Table 6.

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 3)***				***"Covid" (Period 5)***			
Panel A. All IJC days								
IJC shock	-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	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	-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 7: What people talk about in CNBC IJC news articles: Non-overlapping 60-week windows

This table creates six non-overlapping subsamples of available CNBC IJC news articles on IJC days (60 weeks each). **Panel A** reports text mentioning relative to the first subsample in 2013-2014 (e.g., $\frac{X_2}{X_1}$ is reported if the textual mentioning score is X_1 (X_2) in subsample 1 (2)). Five bags of topics are considered; standard errors are reported in parentheses, and closeness is conduct to test whether this value equals 1 (***, p-value <1%; **, <5%; *, <10%). Similarly, relative mentioning is computed using bad-IJC-days only or using good-IJC-days only. A continuous version of bad and good relative mentioning is shown in Figure 5. **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 (higher the t, higher relative mentioning in bad bays). **Textual data:** The original news articles are scraped 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 mentionings 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 8: Relationship between return responses and topic mentioning from rolling windows

This table examines the relationship between return responses to IJC shocks and topic mentioning using rolling windows of 40 bad IJC days in Panel A and 40 good IJC days in Panel B. For instance, for Panel A (B), the rolling return responses uses 40 consecutive bad (good) IJC days per rolling window, and the topic mentioning variables consider news articles from the same rolling window. **Left-hand-side variables:** Three return responses are considered – rolling S&P 500 return coefficient, rolling S&P 500 economic magnitude (in standard deviations), and rolling Dow Jones return coefficient. In mutlivariate regressions, each topic mentioning variable is standardized for interpretation purpose; Newey-West standard error (Newey and West (1987)) and the number of SD changes in return responses given 1 SD topic mentioning are reported as well. ***, 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 9: Mechanism and state variables

This table reports the following regression:

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

where t and τ denote weekly and quarterly frequency, y stock returns (in basis points) and Z a standardized state variable of interest. The first three state variables are textual mentionings 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 follow Law, Song, and Yaron (2020) and 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 according to the Survey of Professional Forecasters (SPF). Time series of all quarterly state variables are shown in Figure 7; due to news file availability, sample runs from 2013Q1 to 2021Q1. ***, p-value <1%; **, <5%; *, <10%.

	Panel A. Bad IJC days					Panel B. Good IJC days				
▶ **Quarterly state variable (standardized):**	**FP**	**MP**	**UNC**	**$\Delta Tbill3m$**	**$\Delta Recess$**	**FP**	**MP**	**UNC**	**$\Delta Tbill3m$**	**$\Delta Recess$**
▶ *Source:*	*CNBC textual analysis*			*SPF*		*CNBC textual analysis*			*SPF*	
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 10: Mechanism comparisons

This table builds on Table 9 and includes multiple state variables and their interactions in one framework. Drop quarters when textual UNC mentioning is missing. Appendix provides two more robustness: complete results using S&P500 (Table A8), and this table but using pre-2020 data only (Table A9). ***, 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 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)**
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)**

Table 11: Cross section evidence: Relationship between firm stock return responses to IJC shocks and firm covid impact measures

Dependent variable uses return response's economic magnitude so that it can be used to compare across firms; sample uses February 2020 to March 2021; we are able to identify 491 out of SP500 with our covid impact measures. **Covid impact measures:** (1) changes in number of all-internet job posting, e.g. -0.8 would mean that firm job posting decreases by 80% between 2019 and April/May of 2020; (2) employment changes from fiscal year (FY) 2019 to FY 2020; (3) revenue changes from 2019Q2 to 2020Q2; (4) Earnings per share (EPS) first difference between 2019Q2 and 2020Q2; (5) is (1) but the data uses 2-digit NAICS sorting; (6) revenue changes from FY 2019 to FY 2020; (7) EPS first difference between FY 2019 and FY 2020; sources for (1) and (5) are from a proprietary source, LinkUp, and the rest are from Compustat Annual and Compustat Quarter. Overall, the lower the measure, the larger the impact and suffering. **Left and right blocks:** In the first three columns, we consider ranks of changes for (2)-(4), due to potential skewness for these change variables, as shown in Table A10 in the appendix; in the rightest three columns, we also show results using raw changes. The t statistics are shown 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**	**All-IJC**	**Bad-IJC**	**Good-IJC**
	DV Mean:	0.141	0.176	-0.075	0.141	0.176	-0.075
	DV SD:	0.114	0.153	0.155	0.114	0.153	0.155
	Right-hand-side:	**Rank of changes**			**Raw changes**		
		Panel A. Four main covid-impact measures					
1	Job Postings Change; 2019 Average-2020 April&May Average , 4-digit NAICS				**-0.0877*** (-3.81)**	**-0.114*** (-3.63)**	0.0275 (0.74)
2	Employment Change; FY 2019-2020	**-0.0601*** (-3.46)**	**-0.0535** (-2.19)**	**0.100*** (4.29)**	**-0.0518** (-2.47)**	-0.028 (-0.82)	**0.101* (1.95)**
3	Revenue Change; 2019Q2-2020Q2	**-0.0815*** (-4.63)**	**-0.0652*** (-2.72)**	**0.102*** (4.38)**	**-0.0390*** (-2.99)**	-0.0278 (-1.15)	**0.0413** (2.55)**
4	EPS Change; 2019Q2-2020Q2	**-0.0812*** (-4.76)**	**-0.0726*** (-2.99)**	0.021 (0.90)	**-0.00233*** (-3.28)**	**-0.00215** (-2.02)**	4.56E-04 (0.64)
		Panel B. Robustness					
5	Job Postings Change; 2019 Average-2020 April&May Average , 2-digit NAICS				**-0.167*** (-3.50)**	-0.13 (-1.71)	**-0.187** (-2.53)**
6	Revenue Change FY2019-2020	**-0.106*** (-6.20)**	**-0.0732*** (-3.02)**	**0.0863*** (3.6)**	**-0.0273** (-2.45)**	-0.0137 (-0.88)	**0.0247** (2.32)**
7	EPS Change FY 2019-2020	**-0.0566** (-3.14)**	-0.0378 (-1.51)	**0.0435* (1.87)**	-0.00129 (-1.64)	-0.00118 (-1.37)	**0.0011* (1.90)**

Table 12: External validation: Relationship between monthly macro announcement surprises and daily open-to-close S&P500 returns

This table shows the correlation coefficients between monthly macro announcement surprises and daily open-to-close S&P500 returns, during a "normal" benchmark period (or "Period 3", 2009/06-2016/12, as used in Tables 1-6) and during the covid period (or "Period 5", 2020/02-2021/3). The table focuses on 7 mainstream macro announcements: Panel A, employment; Panel B, manufacturing, consumption/consumer confidence; Panel C, other general economy indicators. All actual and forecast median data are obtained from Bloomberg. Discussions are included in Section 5. Corresponding figures are shown in the Appendix D. Note that we drop macro data corresponding to March 2020 (abnormal underestimates of the covid impact) and May 2020 (abnormal underestimates of the rebounce) – both can be identified as outliers using box plot analysis. **From left to right:** Column (1) shows the sign of a bad news for the macro variable in the same row; Columns (2) and (3) show the correlation coefficients (***, p-value <1%; **, <5%; *, <10%); Column (4) shows whether the correlation patterns comparing normal and covid fits the "main street pain, wall street gain" phenomenon (X=Yes; Reject=correlation difference is statistically different from 0).

	(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	

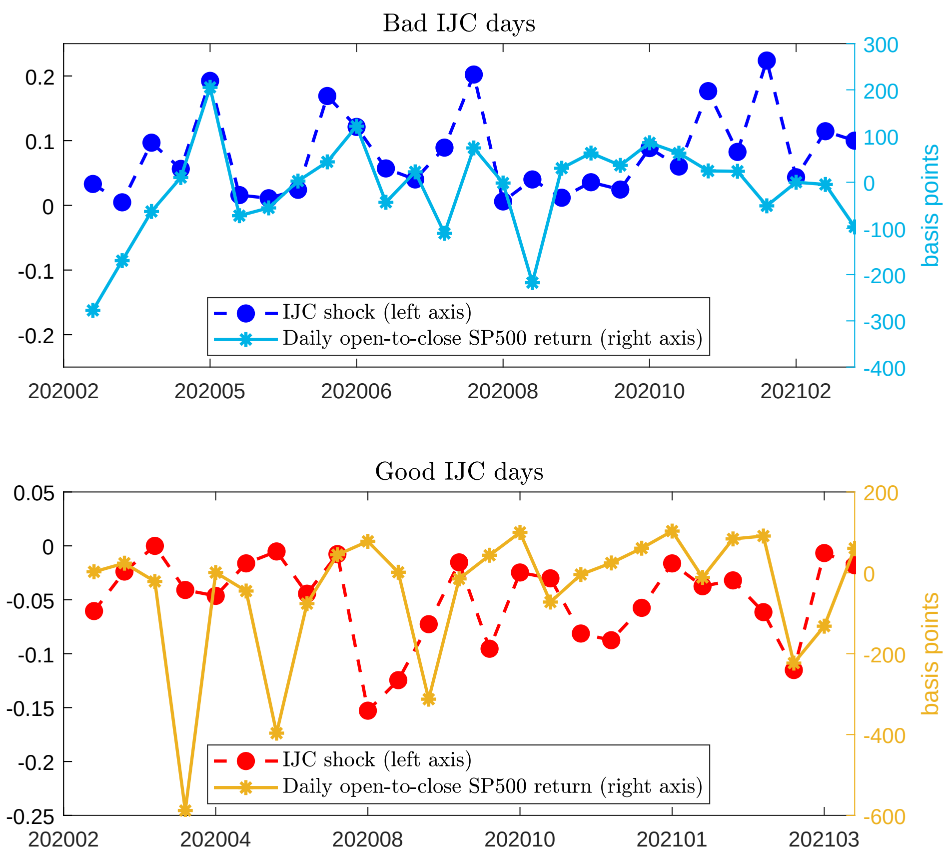


Figure 1: Relation between daily open-to-close S&P500 returns and IJC shocks during Covid (period 5). Excluding IJC shock outliers (2020/3/19, 3/26, 4/2), FOMC days, and other major Federal Reserve announcement (2020/4/9).

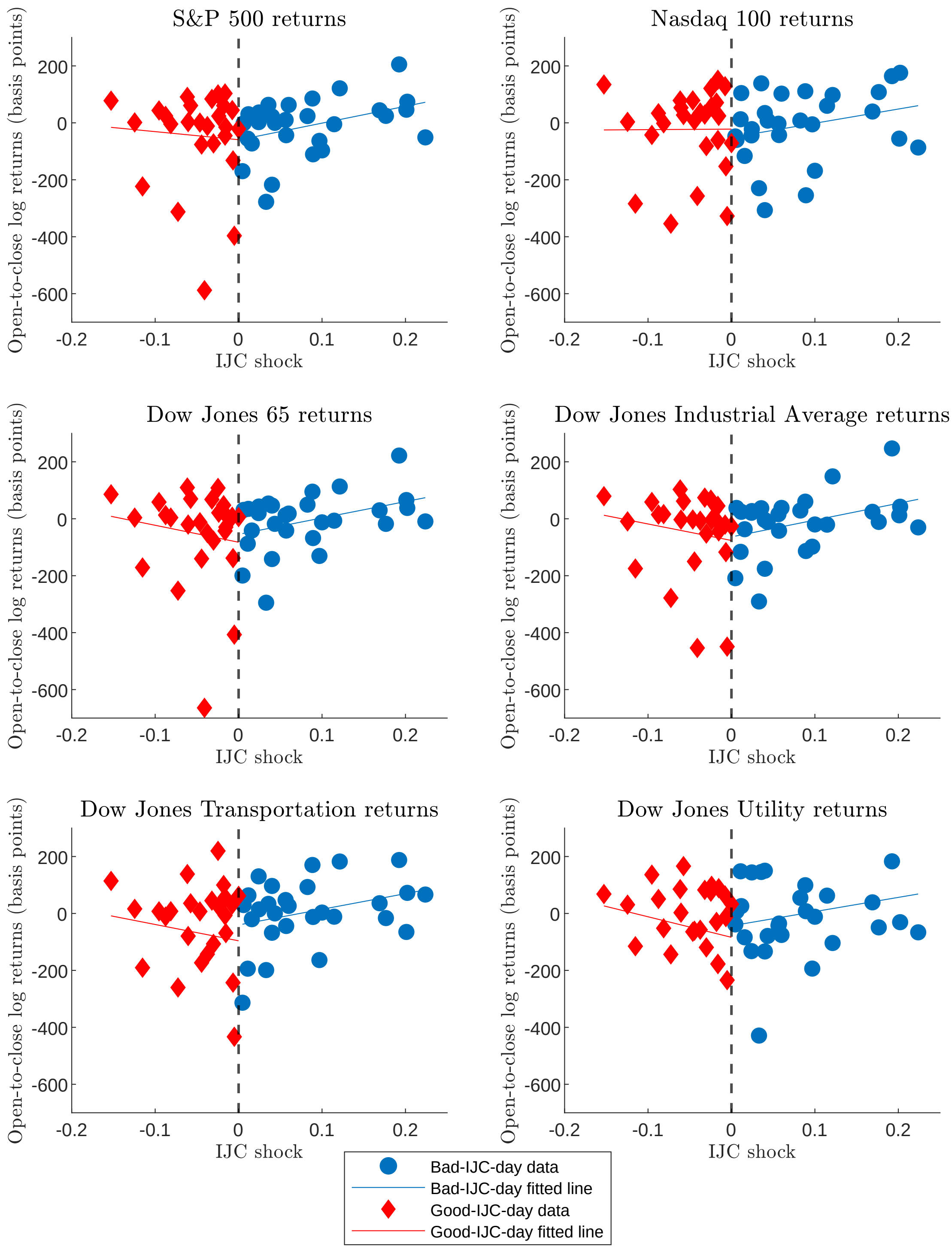
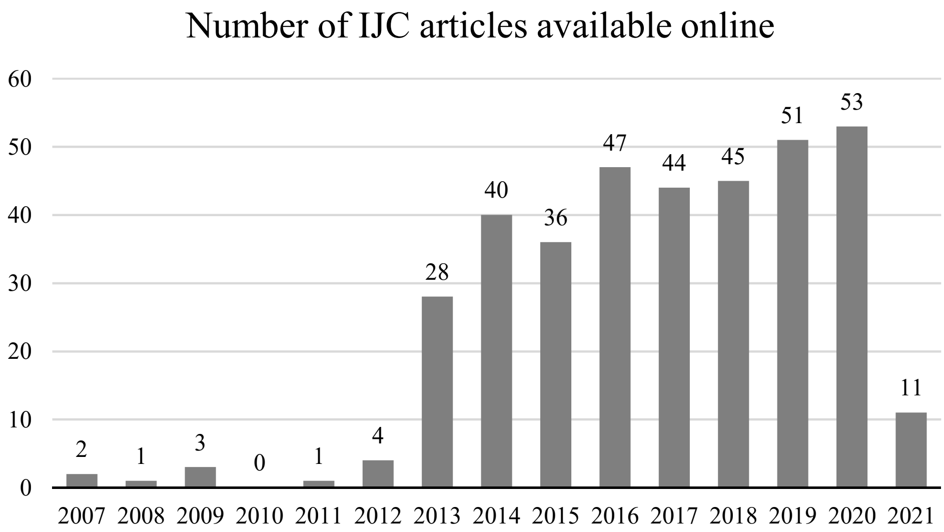


Figure 2: Relation between various daily open-to-close stock returns and IJC shocks during Covid (period 5). Excluding IJC shock outliers (2020/3/19, 3/26, 4/2), FOMC days, and other major Federal Reserve announcement (2020/4/9).



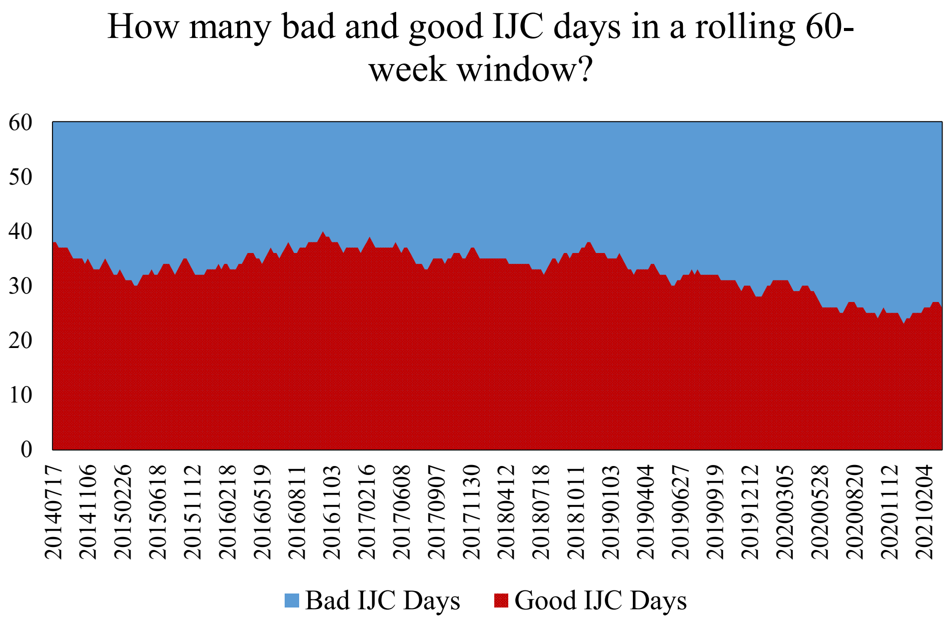


Figure 3: Summary of CNBC jobless claim articles, until the IJC announcement date on 2021/3/18; source: https://www.cnbc.com/jobless-claims/. Data collection process is described in Appendix C. Top plot: number of articles each year; bottom plot: take a rolling 60-week window (time stamp=last day of the rolling window) and show 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).

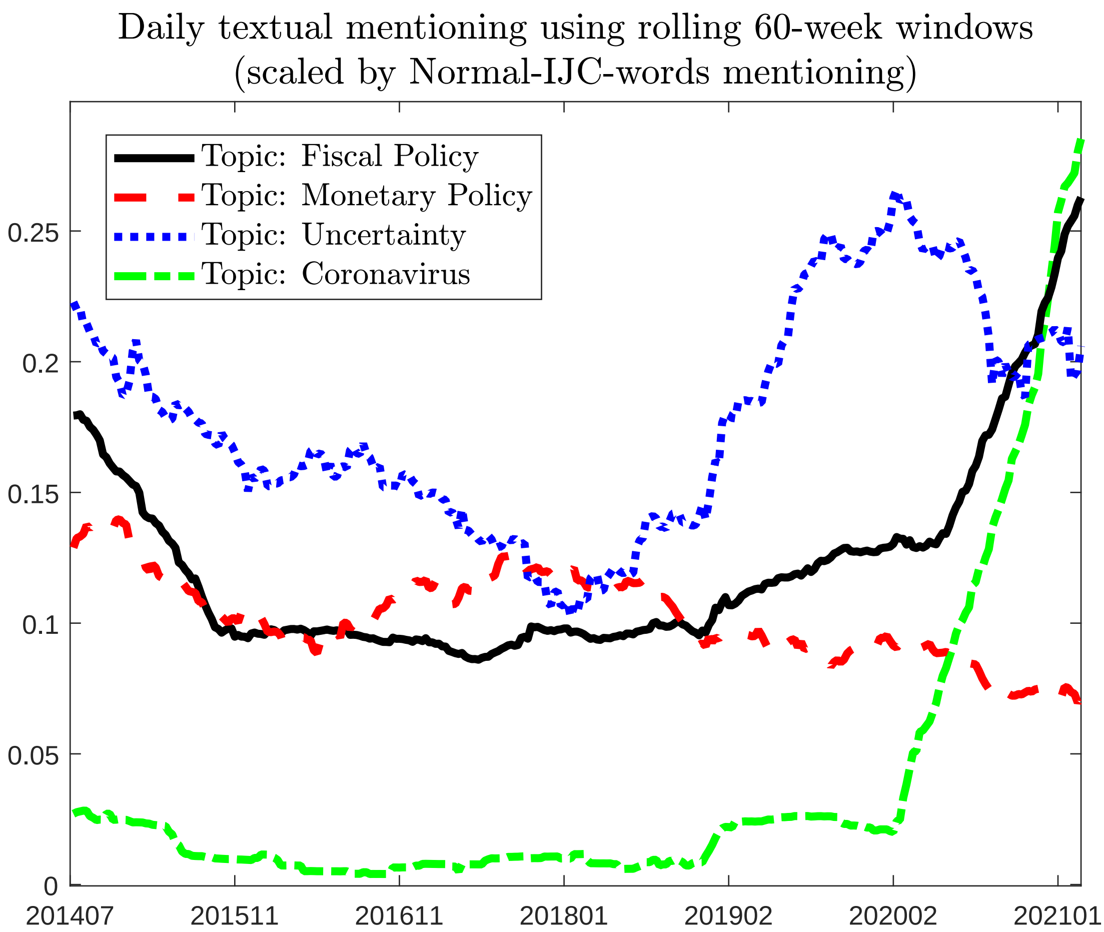


Figure 4: What do people talk about on IJC announcement days?

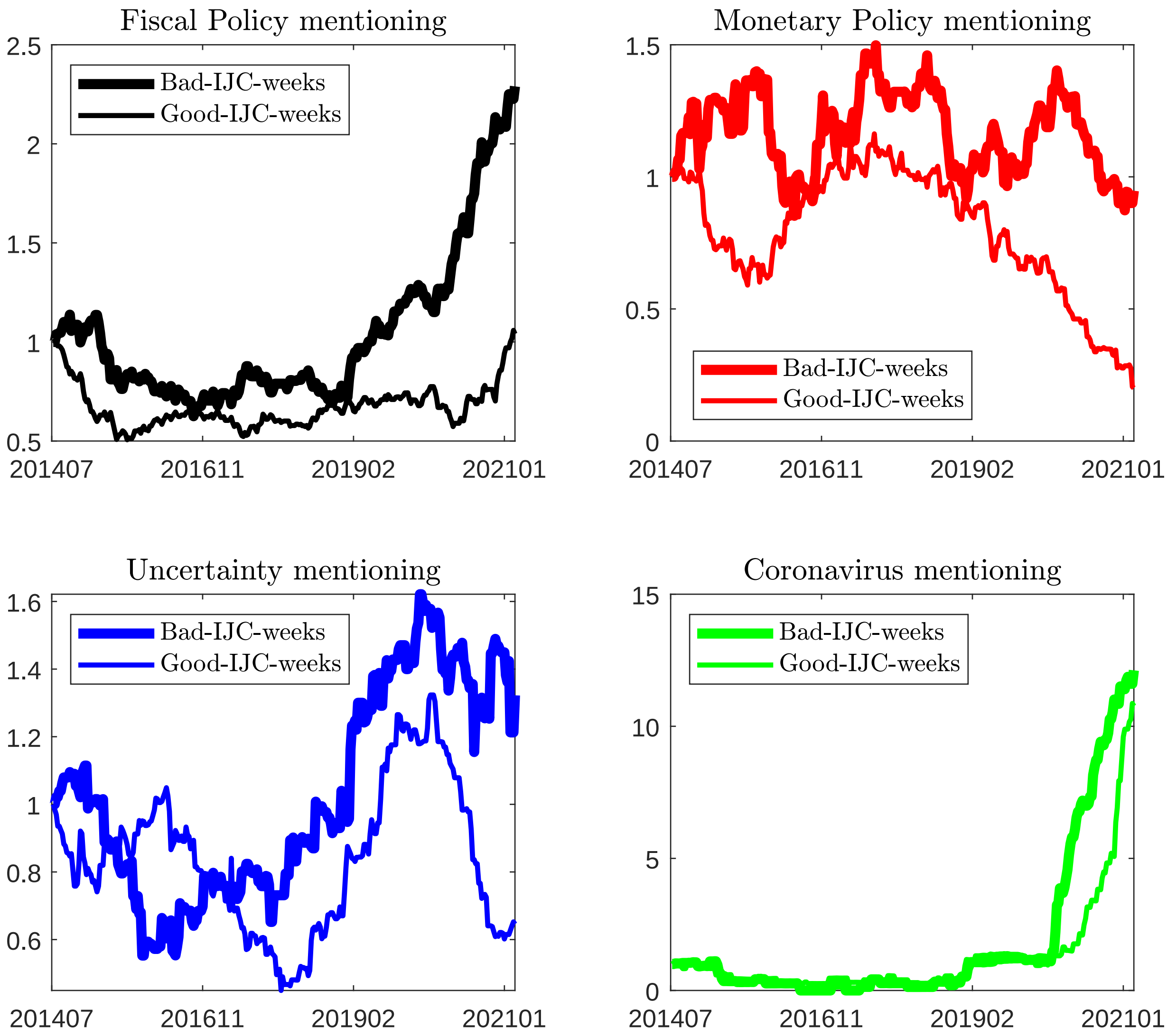


Figure 5: What do people talk about on "bad" and "good" IJC announcement days?

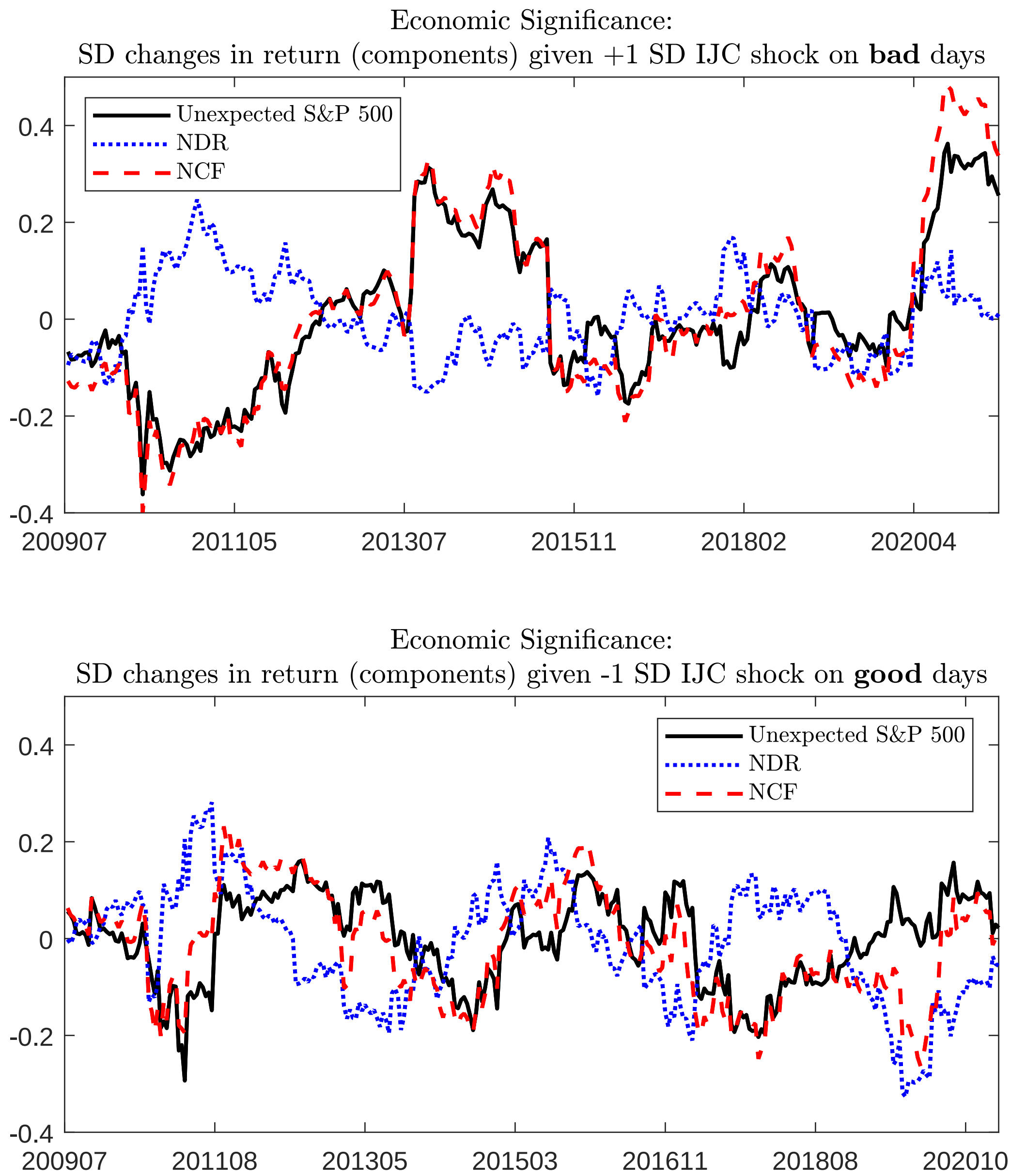


Figure 6: Depicting the economic significance of the rolling return (component) coefficients on IJC shocks, on bad and good days, respectively. Top plot: if "bad is bad", risky asset prices should drop given +1SD IJC shock (jobless claims are higher than expected); bottom plot: if "good is good", risky asset prices should increase given -1SD IJC shock (jobless claims are lower than expected).

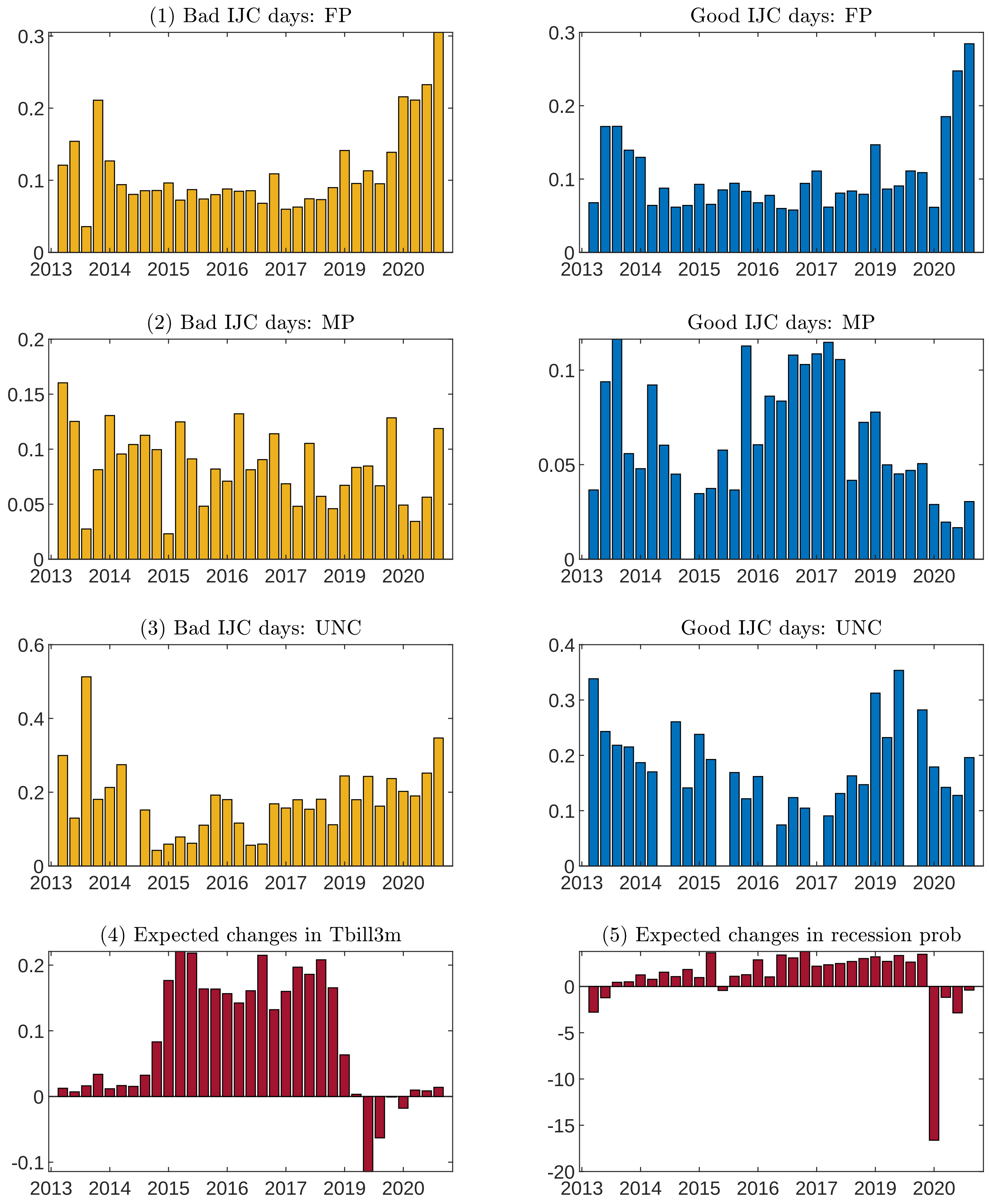
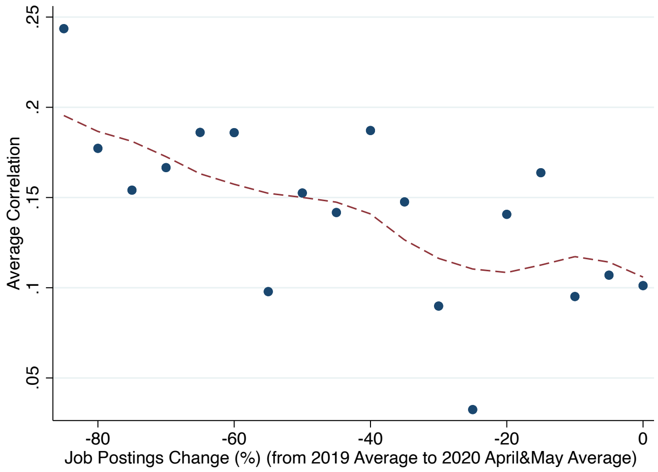
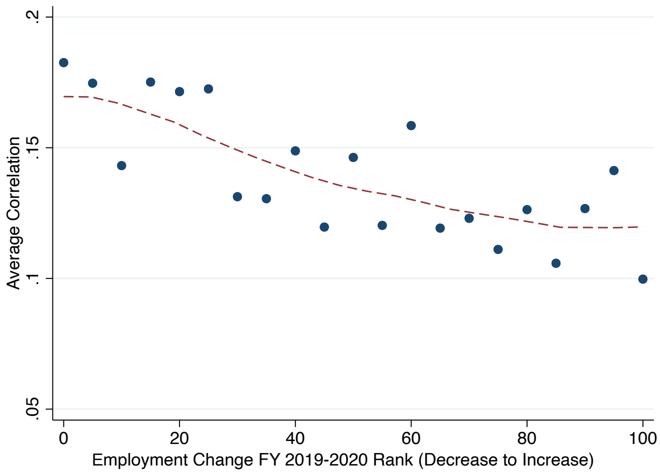


Figure 7: Quarterly state variables.

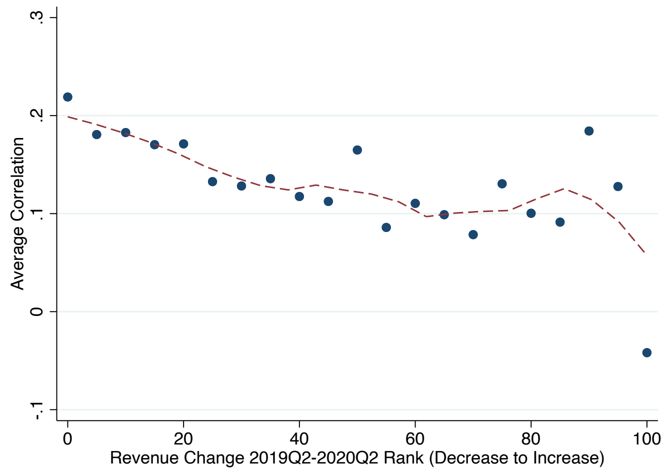
Non-overlapping quarterly topic mentioning, scaled by by score of normal IJC words, in (1)-(3), and expected changes in T-bill rates and recession probability, in (4)-(5). Sources are CNBC and author calculation for the top six plots (first three rows), and the Survey of Professional Forecaster for the bottom two plots (last row).



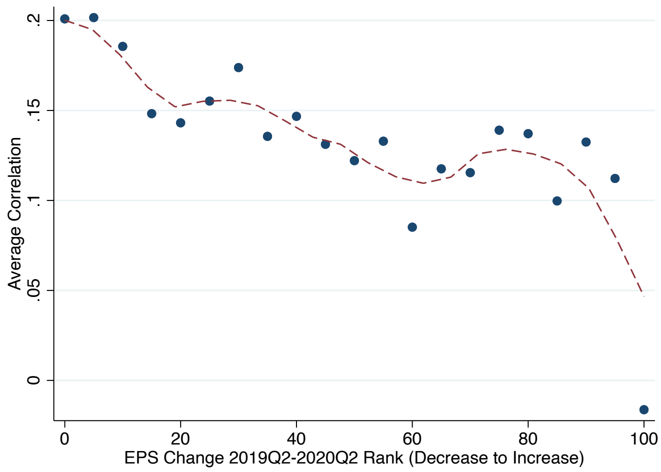
(a)



(b)



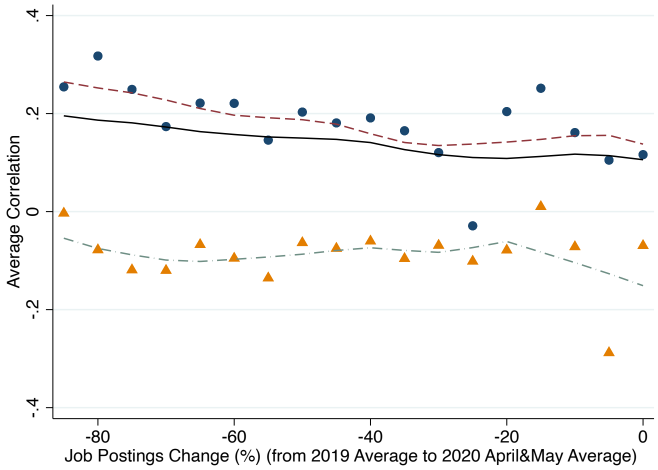
(c)



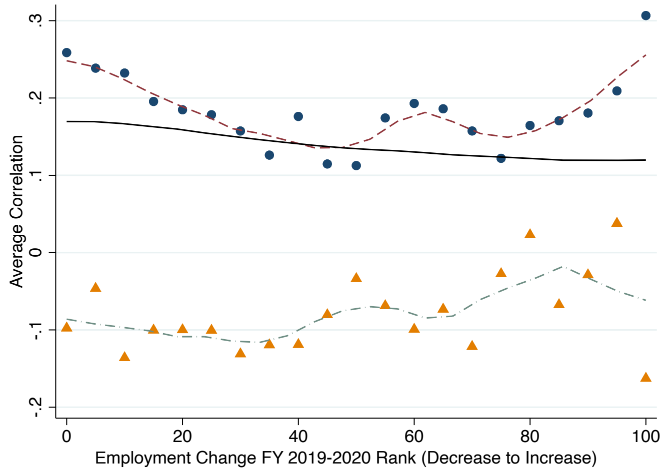
(d)

Figure 8: Cross-section evidence

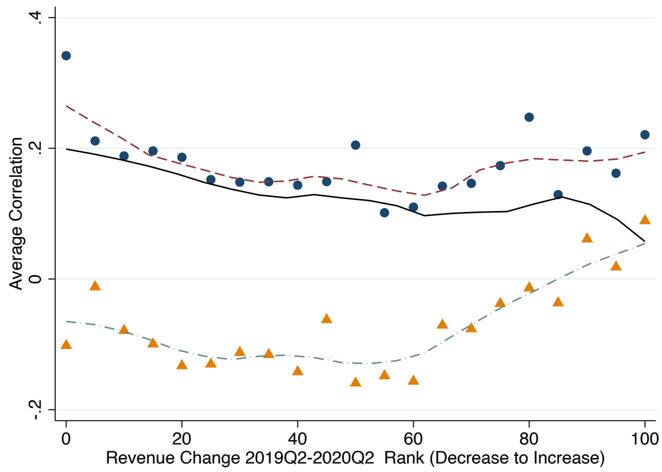
This figures shows the relationship between four "firm covid impact" measures (x-axis) and firm return reactions to IJC shocks (y-axis). Firms that suffer more show stronger "main street pain, wall street gain" phenomenon (which is captured by SD changes in individual stock returns given 1 SD IJC shock, or "correlation" in the y-axis above; higher the correlation, stronger the phenomenon). We group all firms (491 out of 500 S&P 500 firms) into 20 bins (5% each). The x variable in Figure (a) is the changes in number of all-internet job posting, where "-80" indicates that for job posting decreases by 80% between 2019 and April/May of 2020. The x variables in Figures (b)-(d) are ranks of employment change, revenue change, and Earnings per share (EPS) change, respectively; employment change compars 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. The y variable is the bin-level correlation or SD changes as mentioned above. Dashed lines are kernel trends.



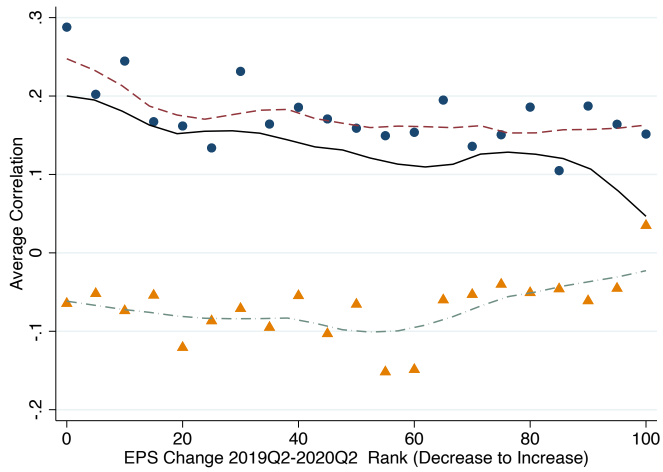
(a)



(b)



(c)



(d)

Figure 9: Cross-section evidence: Bad (circles) vs Good (triangles) IJC days

This figure complements Figure 8 and shows the relationship between the 4 "firm covid impact" measures (x-axis) and firm return reactions to IJC shocks (y-axis) calculated using bad (blue circles) and good (orange triangles) IJC days. Solid black lines are kernel trends from Figure 8, where the y variables are computed using all IJC days. See other variable details in Figure 8.

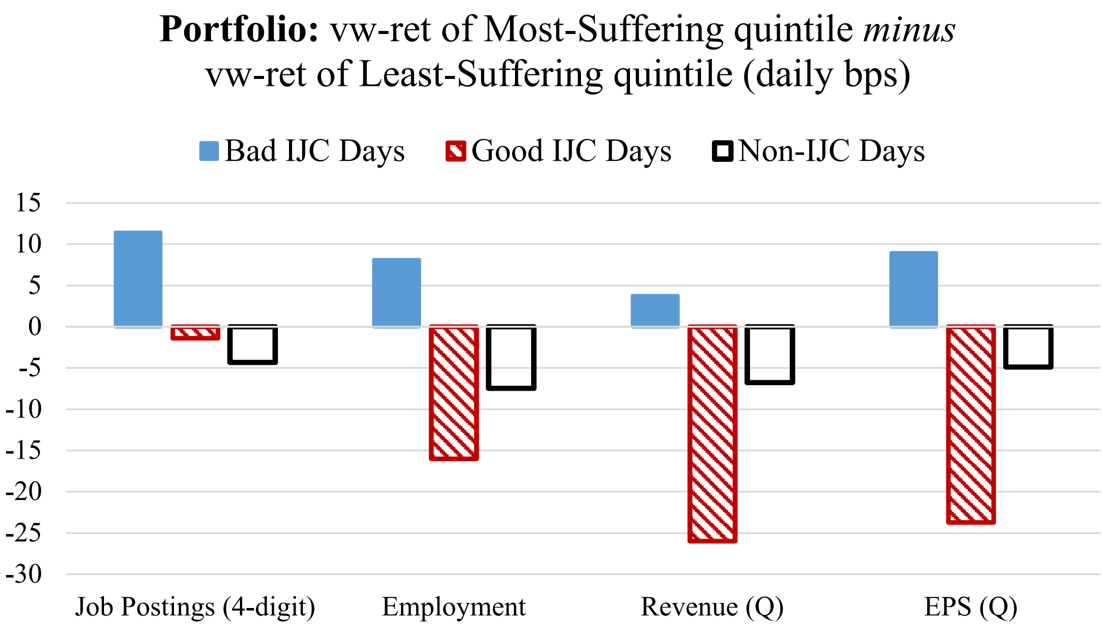


Figure 10: Investment strategy

Step 1: We sort S&P500 firms into 5 bins based on our four main "firm covid impact" measures as in Figure 8 and Table 11: (1) changes in number of all-internet job posting (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) quintle the "Most-Suffering" ("Least-Suffering") quintle, and obtain value-weighted daily open-to-close returns of these individual stock returns. 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 actual IJC number is higher/worse than expected), good IJC days (when actual IJC number is lower/better than expected), and non-IJC days. Returns refer to daily open-to-close stock returns in basis points; sample period runs from February 2020 to March 2021 (end of the sample). Returns exclude 03/19, 03/26, 04/02, 04/09 of 2020. Robustness using equal weights, using alternative covid-impact proxies and including these four dates are shown in Figure A5 in the appendix.

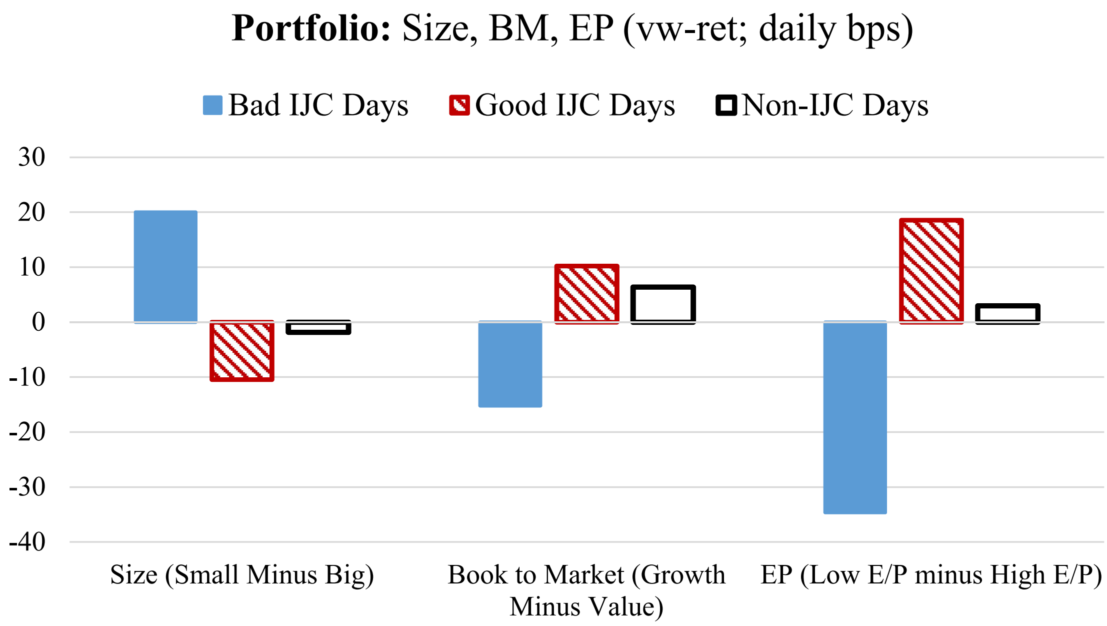


Figure 11: How do standard size, BM, EP portfolios perform?

We sort S&P500 firms into 5 bins based on firms' end of 2019 size, B/M and E/P values. The portfolio takes the return difference between the lowest-size (BM or EP) and the highest-size (BM or EP) quintile bins. Within each quintile, average returns can be calculated using bad IJC days (when actual IJC number is higher/worse than expected), good IJC days (when actual IJC number is lower/better than expected), and non-IJC days. Returns refer to daily open-to-close stock returns in basis points; sample period runs from February 2020 to March 2021 (end of the sample). Returns exclude 03/19, 03/26, 04/02, 04/09. Robustness using equal weights are shown in Figure A5 in the appendix.

Appendices

A. Additional Tables and Figures

Table A1: Summary statistics of alternative IJC shock (actual-expected)

	Period 1	Period 2	Period 3	Period 4	Period 5	All periods
Min	-62	-78	-38	-43	-255	-255
1st	-34	-70	-33	-29	-254	-63
5th	-25	-34	-25	-18	-131	-29
10th	-19	-23	-18	-14	-78	-20
25th	-9	-8	-10	-8	-30	-10
50th	0	4	-1	-2	1	-1
75th	11	19	8	5	68	10
90th	22	38	19	12	171	23
95th	29	45	25	15	213	35
99th	48	56	49	38	477	81
Max	80	56	64	53	481	481
Mean	1.091	4.911	0.209	-1.158	43.954	2.721
Mean-Bad	13.969	19.053	12.949	8.147	135.482	20.011
Mean-Good	-11.439	-15.859	-10.720	-9.133	-54.615	-13.838
SD	16.860	23.746	15.766	11.845	188.383	46.286
SD-Bad	12.344	15.610	12.187	9.264	218.860	58.299
SD-Good	9.694	17.568	8.696	7.008	63.375	19.534
Skewness	0.478	-0.419	0.701	0.735	3.577	14.144
Skewness-Bad	2.025	0.814	1.876	2.697	3.401	13.956
Skewness-Good	-1.622	-1.820	-0.990	-1.778	-1.872	-6.591
N-Total	292	79	379	156	54	960
N-Bad	144	47	175	72	28	466
N-Good	148	32	204	84	26	494

Table A2: How do asset prices respond to macro shocks, now and then?

This table complements Table 2 and uses the alternative IJC shock ($IJC_t - E_{t-\Delta}(IJC_t)$; see Table A1). See other table details in Table 2. ***, p-value <1%; **, <5%; *, <10%.

		S&P500	**GovBond10yr**	**Yield10yr**	**TBill3m**	**GrowthUnc**	**RV1m**	**EPU**	**VIX**	**RiskAversion**
Period 1	IJC shock	-0.254	**0.442*** **	**-5.60E-04*** **	**-2.53E-04** **	**0.0011** **	**-0.251** **	0.151	0.005	**0.001** **
	(SE)	(0.309)	**(0.138)**	**(1.75E-04)**	**(1.20E-04)**	**(0.0005)**	**(0.109)**	(0.206)	(0.004)	**(0.000)**
	[t]	[-0.822]	**[3.197]**	**[-3.210]**	**[-2.105]**	**[2.219]**	**[-2.300]**	[0.732]	[1.167]	**[2.039]**
	SD chngs per 1SD shock	-0.045	**0.164**	**-0.162**	**-0.102**	**0.119**	**-0.123**	0.042	0.067	**0.134**
	R2%	0.20%	**2.69%**	**2.62%**	**1.05%**	**1.41%**	**1.51%**	0.18%	0.44%	**1.81%**
Period 2	IJC shock	-0.379	**0.656***	-7.27E-04	4.96E-05	0.0020	**1.300** **	0.275	-0.004	0.003
	(SE)	(1.037)	**(0.363)**	(5.00E-04)	(4.38E-04)	(0.0015)	**(0.568)**	(0.348)	(0.010)	(0.008)
	[t]	[-0.365]	**[1.804]**	[-1.453]	[0.113]	[1.333]	**[2.289]**	[0.788]	[-0.357]	[0.399]
	SD chngs per 1SD shock	-0.038	**0.198**	-0.172	0.015	0.099	**0.205**	0.090	-0.033	0.049
	R2%	0.15%	**3.92%**	2.95%	0.02%	0.98%	**4.20%**	0.81%	0.11%	0.24%
Period 3	IJC shock	-0.338	**0.540*** **	**-6.46E-04*** **	-3.73E-05	**0.0010***	0.086	0.149	0.007	0.001
	(SE)	(0.310)	**(0.146)**	**(1.68E-04)**	(3.69E-05)	**(0.0006)**	(0.113)	(0.145)	(0.006)	(0.001)
	[t]	[-1.088]	**[3.699]**	**[-3.837]**	[-1.010]	**[1.681]**	[0.763]	[1.032]	[1.299]	[1.622]
	SD chngs per 1SD shock	-0.052	**0.186**	**-0.187**	-0.043	**0.091**	0.029	0.046	0.070	0.104
	R2%	0.27%	**3.45%**	**3.48%**	0.18%	**0.83%**	0.09%	0.21%	0.49%	1.08%
Period 4	IJC shock	0.482	0.157	-1.68E-04	-1.65E-04	0.0004	-0.024	**-0.560***	-0.001	-3.40E-05
	(SE)	(0.359)	(0.289)	(3.25E-04)	(1.01E-04)	(0.0006)	(0.177)	**(0.326)**	(0.006)	(3.23E-04)
	[t]	[1.341]	[0.543]	[-0.517]	[-1.645]	[0.701]	[-0.135]	**[-1.718]**	[-0.144]	[-0.105]
	SD chngs per 1SD shock	0.087	0.053	-0.050	-0.104	0.051	-0.010	**-0.144**	-0.009	-0.006
	R2%	0.75%	0.28%	0.25%	1.08%	0.26%	0.01%	**2.08%**	0.01%	0.00%
Period 5	IJC shock	**0.125***	**0.033** **	**-4.27E-05** **	**2.22E-05** **	**-0.0004** **	0.026	**-0.078*** **	**-0.003** **	-0.001
	(SE)	**(0.069)**	**(0.015)**	**(1.68E-05)**	**(1.12E-05)**	**(0.0002)**	(0.350)	**(0.020)**	**(0.001)**	(0.001)
	[t]	**[1.801]**	**[2.228]**	**[-2.543]**	**[1.988]**	**[-2.565]**	[0.073]	**[-3.927]**	**[-2.052]**	[-1.367]
	SD chngs per 1SD shock	**0.174**	**0.157**	**-0.189**	**0.190**	**-0.131**	0.015	**-0.239**	**-0.128**	-0.061
	R2%	**3.03%**	**2.47%**	**3.57%**	**3.62%**	**1.72%**	0.02%	**5.69%**	**1.65%**	0.37%

Table A3: How do pricing channels change?

This table complements Table 3 and uses the alternative IJC shock ($IJC_t - E_{t-\Delta}(IJC_t)$; see Table A1) & paper's sample in the left panel, and paper's main shock & a sample without 2020/4/9 in the right panel. See other table details in Table 3. ***, 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	-0.195	-0.219	-0.024	-63.460	-64.453	-0.993
	(SE)	(0.308)	(0.265)	(0.162)	(104.387)	(87.948)	(55.696)
	[t]	[-0.634]	[-0.828]	[-0.148]	[-0.608]	[-0.733]	[-0.018]
	SD chngs per 1SD shock	-0.034	-0.028	-0.004	-0.032	-0.023	0.000
	R2%	0.13%	0.25%	0.01%	0.11%	0.17%	0.00%
Period 2	IJC shock	-0.232	-0.362	-0.130	-62.158	-115.558	-53.400
	(SE)	(1.016)	(0.776)	(0.380)	(435.723)	(334.331)	(152.290)
	[t]	[-0.228]	[-0.467]	[-0.343]	[-0.143]	[-0.346]	[-0.351]
	SD chngs per 1SD shock	-0.024	-0.041	-0.013	-0.014	-0.029	-0.012
	R2%	0.06%	0.21%	0.13%	0.02%	0.11%	0.11%
Period 3	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 4	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 5	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 A4: "Bad is good": What assets, and When?

This table complements Table 4 and further drops the 2020/4/9 (Thursday) given. See other table details in Table 4. ***, 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	**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	-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 A5: High-frequency evidence using E-mini Nasdaq futures

This table complements Tables 5 and 6 and further drops the 2020/4/9 (Thursday) given a series of additional Federal Reserve action announcements to support the economy (https://www.federalreserve.gov/newsevents/pressreleases/monetary20200409a.htm). See other table details in Table 4. ***, 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 3)**				**Covid (Period 5)**			
Panel A. All IJC days								
IJC shock	-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	-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	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: Relationship between return responses and topic mentioning from rolling windows – More robustness results

This table complements Table 8 and shows 3 more robustness results, Robustness (4)-(6). To summarize:

- Robustness (1), (2), (3) in Table 8: using economic magnitude (in standard deviation rather than in basis points); including uncertainty mentioning; using Dow Jones 65 open-to-close returns (rather than the default S&P500 open-to-close returns).
- Robustness (4): using all IJC days.
- Robustness (5): drops the 2020/4/9.
- Robustness (6): 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 mentioning (RHS). Table format follows Table 8.

See other table details in Table 8. ***, p-value <1%; **, <5%; *, <10%.

	Robustness (4). Using all IJC days				Robustness (5). Without 4/9/2020		
Rolling sample:	All IJC days				Bad IJC	Good IJC	All IJC
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**	
Constant	**59.984*****	**0.044*****	**59.984*****	**82.621*****	**23.363**	-28.104**	**58.887*****
(SE)	(19.733)	(0.012)	(19.825)	(18.678)	(38.104)	(14.202)	(19.777)
FP (standardized)	**197.735*****	**0.116*****	**197.993*****	**161.616*****	**266.987*****	**80.747*****	**196.988*****
(SE)	(26.342)	(0.015)	(25.522)	(17.990)	(40.847)	(17.666)	(26.419)
SD chngs	1.278	1.256	1.280	1.213	1.060	0.329	1.277
MP (standardized)	**110.275*****	**0.065*****	**109.519*****	**125.082*****	86.098	**223.482*****	**110.794*****
(SE)	(23.606)	(0.015)	(30.270)	(15.908)	(55.953)	(13.943)	(23.765)
SD chngs	0.713	0.708	0.708	0.939	0.342	0.911	0.718
UNC (standardized)			-1.468				
(SE)			(26.867)				
SD chngs			-0.009				
R2 Ordinary	63.9%	61.2%	63.9%	47.4%	63.1%	56.3%	61.2%
R2 Adjusted	63.6%	60.9%	63.5%	47.0%	62.5%	55.7%	60.9%
N	271	271	271	271	115	155	270

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 A7: Correlation among quarterly state variables in Tables 9 and 10.

Correlation (N=33)	badFP	badMP	badUNC	goodFP	goodMP	goodUNC	$\Delta Tbill3m$	$\Delta Recess$
badFP	1	0.21	**0.69*****	0.25	**-0.44*****	0.02	**-0.43****	**-0.55*****
badMP		1.00	**0.36****	**-0.29***	0.04	-0.10	-0.05	0.16
badUNC			1.00	0.26	-0.09	**0.33***	**-0.50*****	-0.24
goodFP				1.00	-0.05	0.22	-0.25	0.08
goodMP					1.00	-0.07	**0.46*****	**0.43****
goodUNC						1.00	-0.24	0.20
$\Delta Tbill3m$							1.00	**0.31***
$\Delta Recess$								1.00

Table A8: Robustness to mechanism results: complete results for S&P500 returns

This table complements Columns (1) and (5) of Table 10. Sample is the same, from January 2013 to March 2021. See other table details in Table 10. ***, 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 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)**
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)**

Table A9: Robustness to mechanism results: pre-2020 results

This table replicates Table 10 using pre-covid sample, from January 2013 to December 2019. See other table details in Table 10. ***, 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	4.651	6.956	6.231	6.575	5.706	7.100	5.742	5.729
(SE)	(8.934)	(8.845)	(8.928)	(8.436)	(9.378)	(9.647)	(9.377)	(8.170)
IJC shock	56.860	10.944	18.043	7.265	-22.809	-41.915	-111.428	45.972
(SE)	(172.568)	(170.836)	(172.136)	(163.215)	(197.038)	(216.164)	(205.028)	(161.241)
Quarterly FP (standardized)	-11.121	-19.204	**-26.338***	**-26.355***	**20.928***	17.992	8.896	20.483
(SE)	(13.392)	(13.258)	**(15.686)**	**(15.005)**	**(12.003)**	(12.167)	(13.709)	(13.657)
IJC shock*Quarterly FP (standardized)	297.860	**318.041***	**391.789***	**373.602***	199.703	119.307	-166.861	349.523
(SE)	(184.004)	**(182.158)**	**(214.750)**	**(215.830)**	(247.473)	(248.223)	(290.234)	(259.581)
Quarterly MP (standardized)	-1.789	1.150	-0.762		-6.009	0.558	4.364	
(SE)	(9.179)	(9.087)	(9.452)		(7.442)	(7.920)	(7.927)	
IJC shock*Quarterly MP (standardized)	-104.347	-33.355	1.341		171.781	**307.397***	**435.025****	
(SE)	(200.126)	(198.117)	(212.869)		(163.171)	**(177.556)**	**(176.547)**	
Quarterly UNC (standardized)			9.242	8.133			14.119	10.919
(SE)			(10.651)	(10.997)			(10.372)	(9.951)
IJC shock*Quarterly UNC (standardized)			-124.231	-134.177			**414.955***	246.376
(SE)			(214.286)	(207.299)			**(216.806)**	(198.200)
Quarterly $\Delta Tbill3m$ (standardized)				-0.836				13.583
(SE)				(8.497)				(9.194)
IJC shock*Quarterly $\Delta Tbill3m$ (standardized)				-81.286				**420.827****
(SE)				(191.704)				**(209.817)**

Table A10: 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)	Job Post Change (2-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 A11: Two-digit NAICS industry average covid-impact measures (rank measures: from decreases to increases; job posting change is percentage change from 2019 average to 2020 April/May average)

NAICS Code	NAICS Industry Name	Employment Rank	Job Posting Change	Revenue Rank	EPS Rank	Revenue Rank (Q)	EPS Rank (Q)	# Firms
21	Mining	20.2th	-64%	20th	27.3th	19th	22.8th	16
48	Transportation and Warehousing	26.8th	-53%	31.2th	30.8th	29.9th	27.9th	22
72	Accommodation and Food Services	35.5th	-34.1%	30th	31.2th	33.9th	34.7th	10
42	Wholesale Trade	39.9th	-43.4%	52.6th	47.3th	53.4th	53.4th	22
22	Utilities	40.8th	-33.6%	39.7th	49.9th	45.5th	56.2th	30
53	Real Estate Rental and Leasing	44.7th	-24.4%	42.8th	47.7th	39.7th	50.2th	22
23	Construction	49th	-38.4%	60.9th	84.3th	58.8th	64.8th	5
56	Administrative and Support and Waste Management and Remediation Services	49th	-39.4%	48.4th	47.3th	44.1th	49.2th	13
52	Finance and Insurance	54.1th	-39.2%	51.2th	49.9th	54.2th	50.5th	72
31	Manufacturing	54.2th	-41.1%	50.6th	50.1th	51.9th	49.6th	181
54	Professional Scientific and Technical Services	54.7th	-28.9%	59.9th	56.7th	55.1th	60.6th	20
51	Information	59.2th	-42%	67.2th	57.8th	62.2th	57th	42
44	Retail Trade	60.7th	-25.6%	65.1th	63th	62.9th	62.8th	22
62	Health Care and Social Assistance	66.1th	-2.4%	72.5th	74.5th	76.9th	66.5th	6

Table A12: Likelihood ratio: 15% most damaged firms relative to 50% least damaged firms

NAICS Code	NAICS Industry Name	Employment Rank	Job Posting Change	Revenue Rank	EPS Rank	Revenue Rank (Q)	EPS Rank (Q)	# Firms
21	Mining	25.53	19.09	18.53	8.41	20.23	16.78	16
48	Transportation and Warehousing	8.51	4.45	5.05	6.05	5.06	6.04	22
72	Accommodation and Food Services	3.99	2.12	4.49	6.72	5.62	5.03	10
42	Wholesale Trade	2.55	0	0.26	1.68	0.28	1.03	22
53	Real Estate Rental and Leasing	1.37	0.32	1.93	0.37	1.93	0.31	22
22	Utilities	1.28	0	1.68	0.4	0	0	30
23	Construction	1.06	0	0	0	0	0.84	5
56	Administrative and Support and Waste Management and Remediation Services	1.06	1.06	1.35	0.48	1.69	0.56	13
31	Manufacturing	0.72	1.55	0.9	0.8	0.78	0.81	181
44	Retail Trade	0.64	0.37	0.79	0.72	0.79	0.89	22
51	Information	0.61	0.24	0	0.15	0.23	0.52	42
52	Finance and Insurance	0.41	0	0.66	1.26	0.65	1.12	72
54	Professional Scientific and Technical Services	0.32	0.19	0	0.28	0	0	20
62	Health Care and Social Assistance	0	0	0	0.67	0	0.67	6

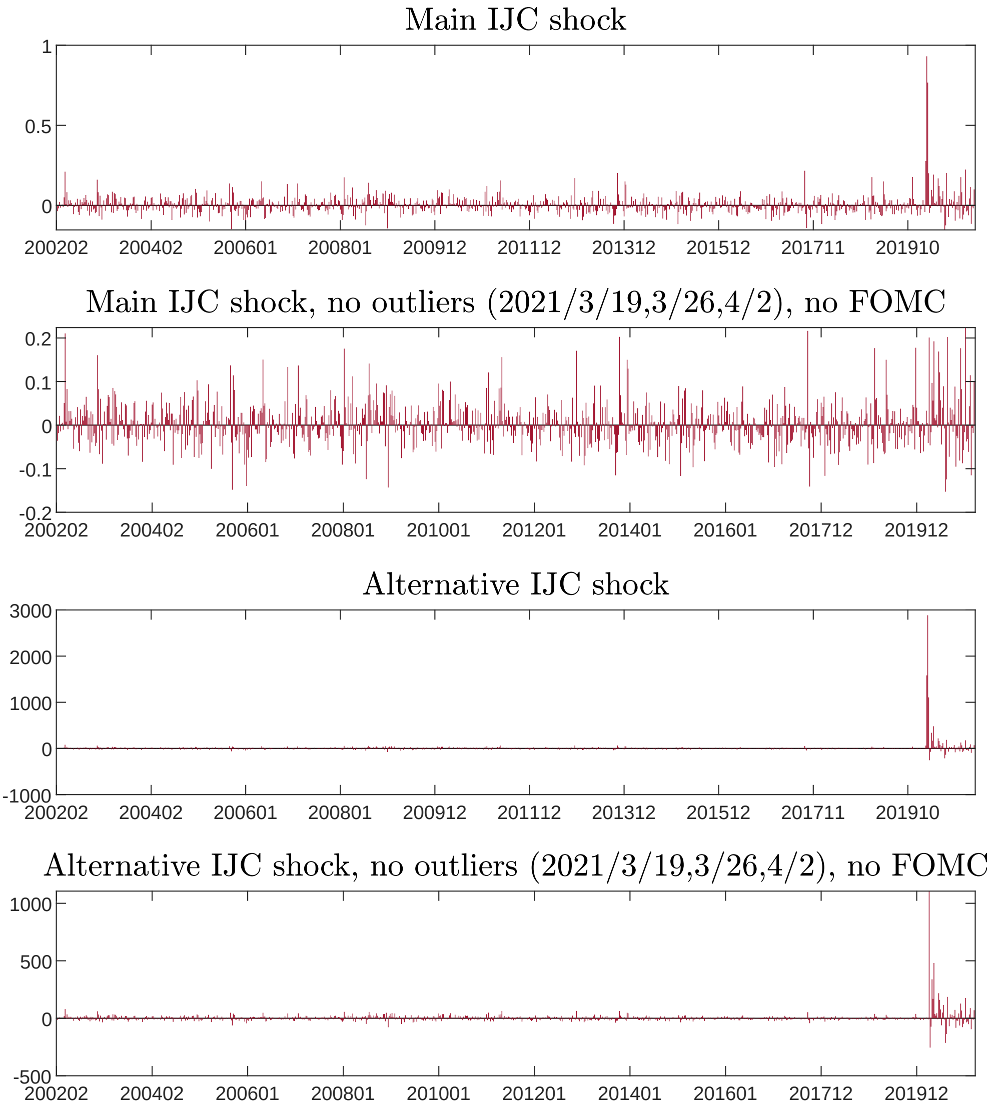


Figure A1: Time series of main IJC shocks ($\frac{IJC_t - E_{t-\Delta}(IJC_t)}{E_{t-\Delta}(IJC_t)}$) and alternative IJC shocks ($IJC_t - E_{t-\Delta}(IJC_t)$), with or without identified outliers and FOMC days

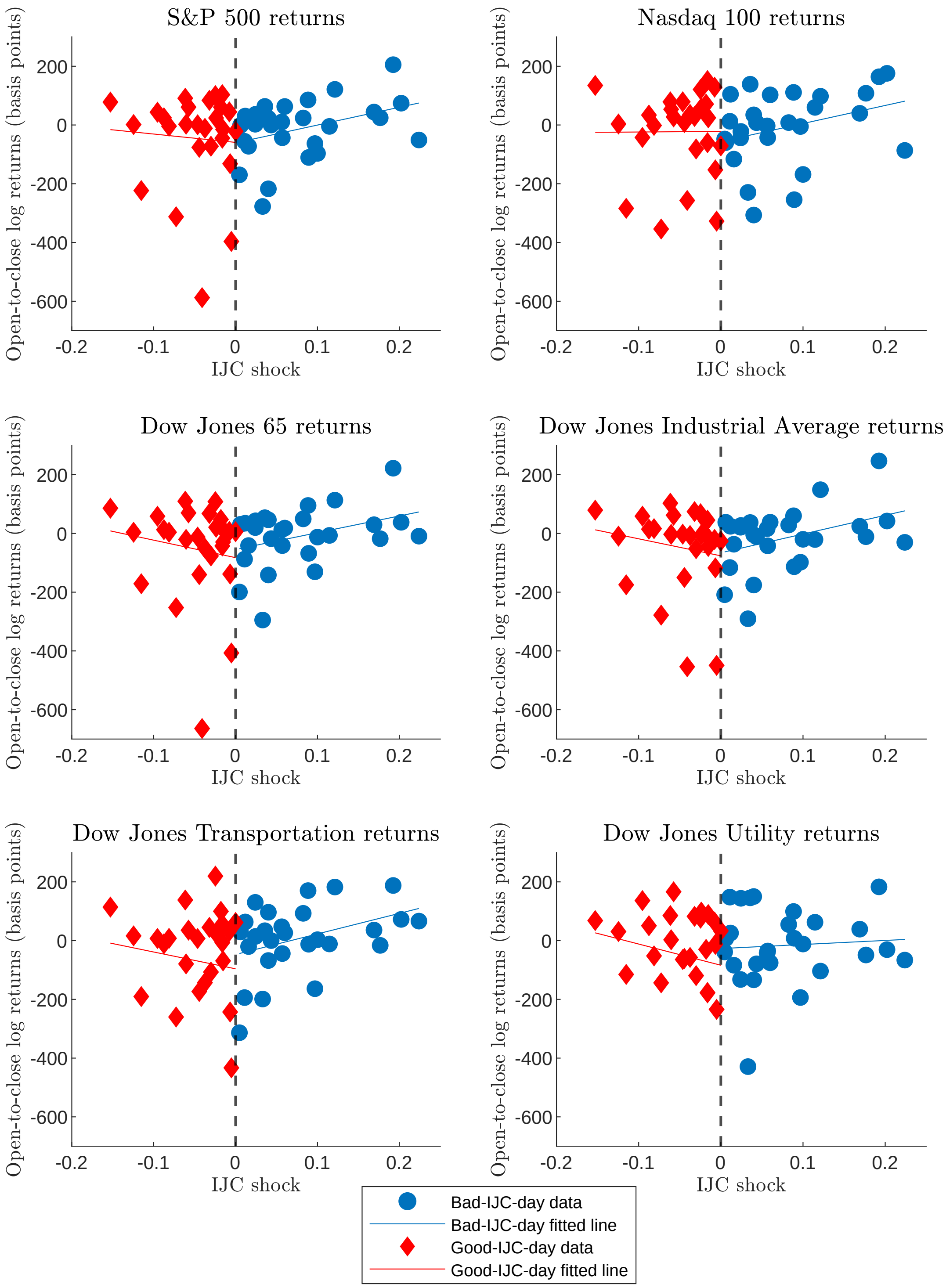
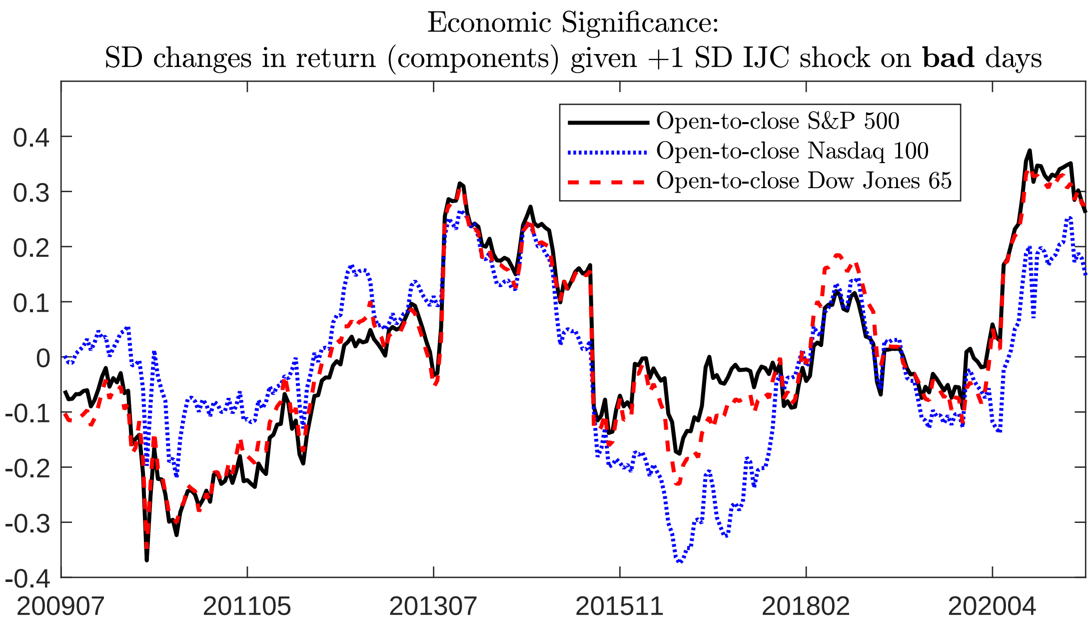


Figure A2: Robustness: Relation between stock returns and IJC shocks during Covid (period 5); without 2020/4/9



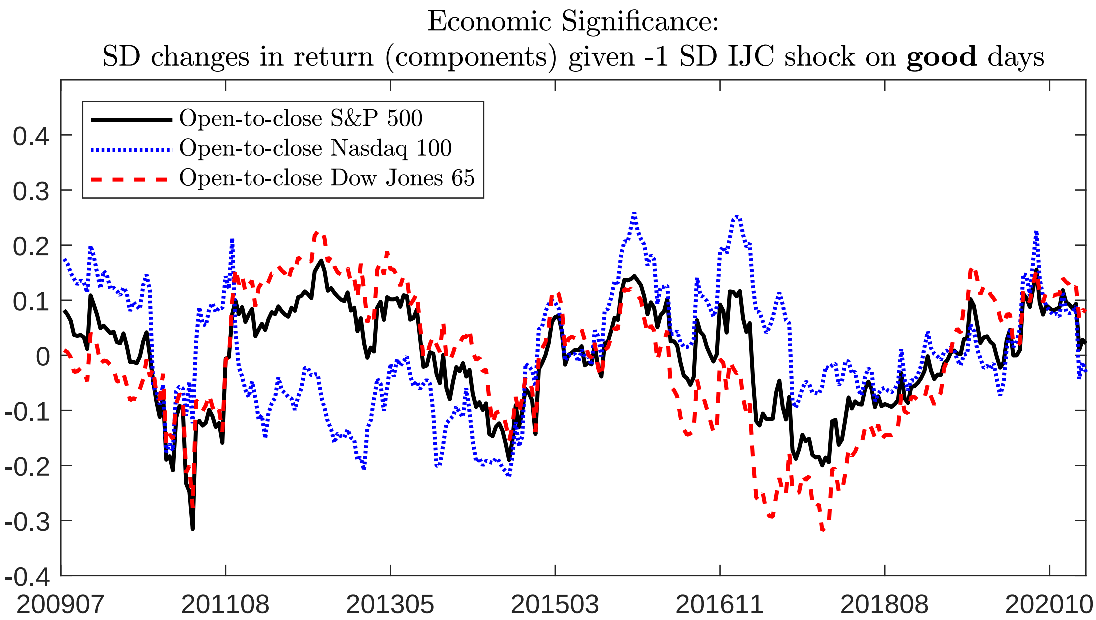


Figure A3: Depicting the economic significance of the rolling return (component) coefficients on IJC shocks, on bad and good days, respectively. Top plot: if "bad is bad", risky asset prices should drop given +1SD IJC shock (jobless claims are higher than expected); bottom plot: if "good is good", risky asset prices should increase given -1SD IJC shock (jobless claims are lower than expected).

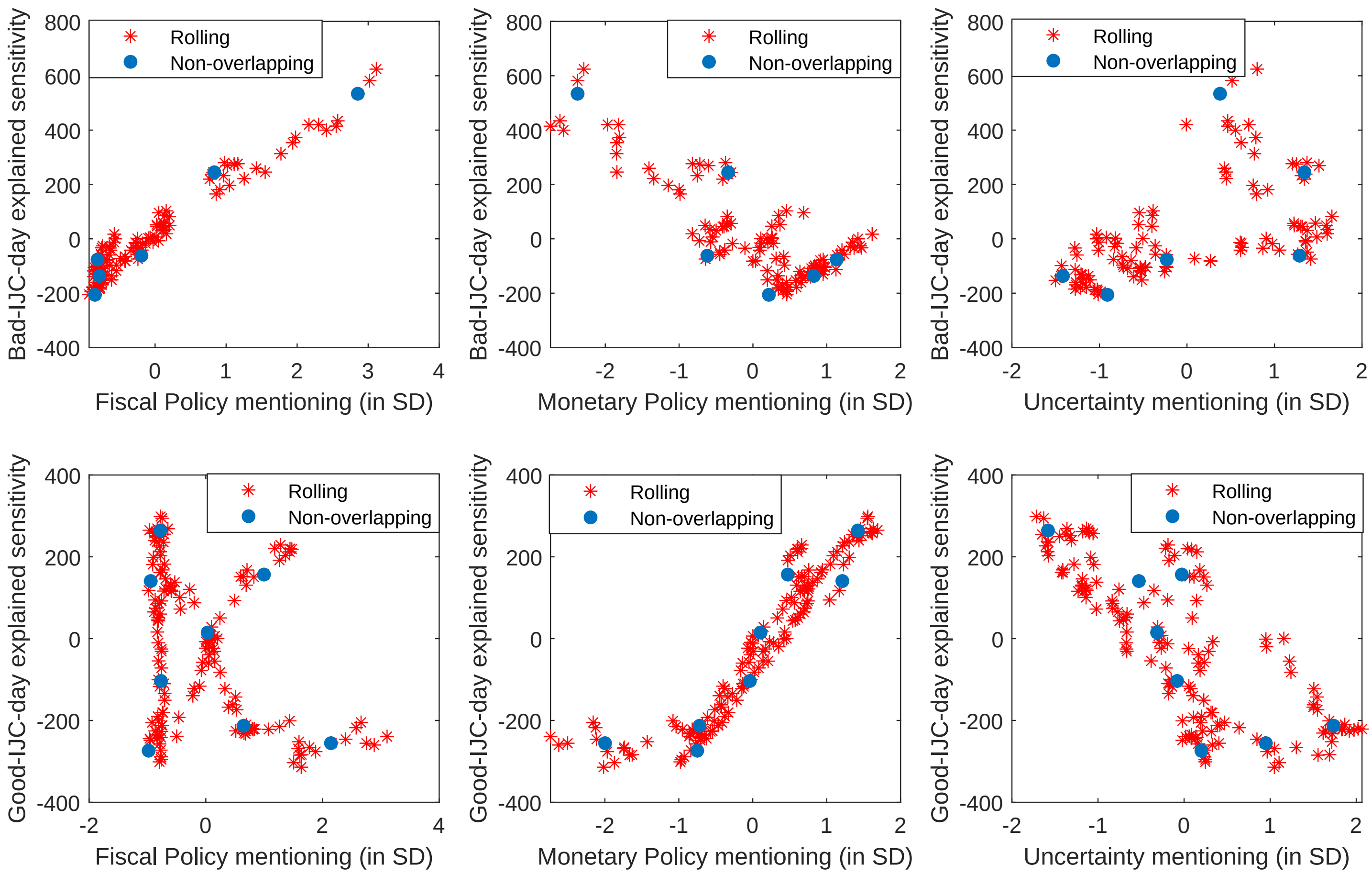


Figure A4: Rolling S&P500 return coefficient (on IJC shocks), explained by rolling textual topic mentioning (measured in standard deviations within each topic).

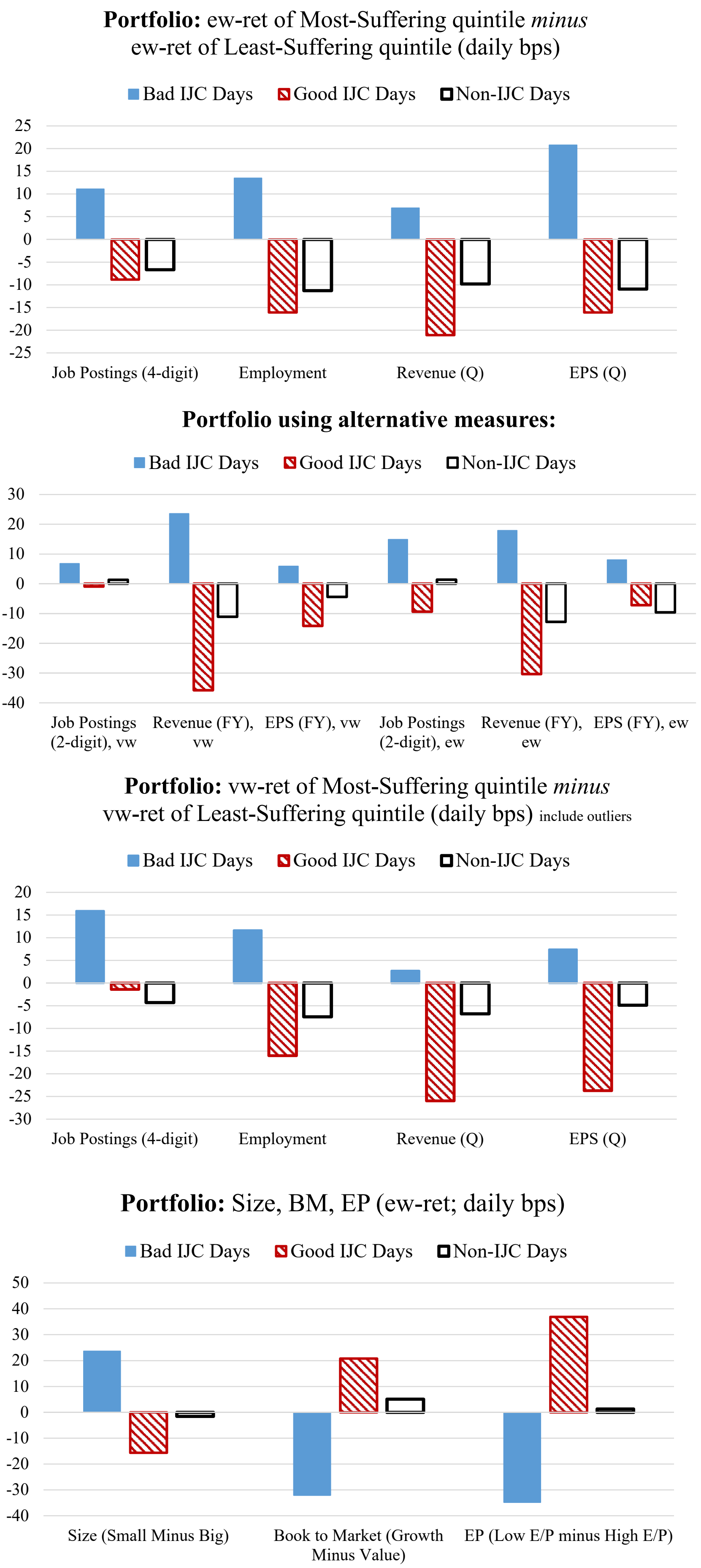


Figure A5: Robustness: Investment strategy

This table complements Figure 10 and provides robustness results using equal weights (plot 1), using alternative (less accurate) covid-impact measure at the firm level (plot 2), and including back 03/19, 03/26, 04/02, 04/09 of 2020 (plot 3). Plot 4 complements Figure 11 using equal weights. See other details in Figures 10 and 11.

B. Imputing daily cash flow and discount rate shocks using monthly Campbell and Vuolteenaho (2004) decomposition

B.1. Estimate monthly parameters; Validation

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 part 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 negative of 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).

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

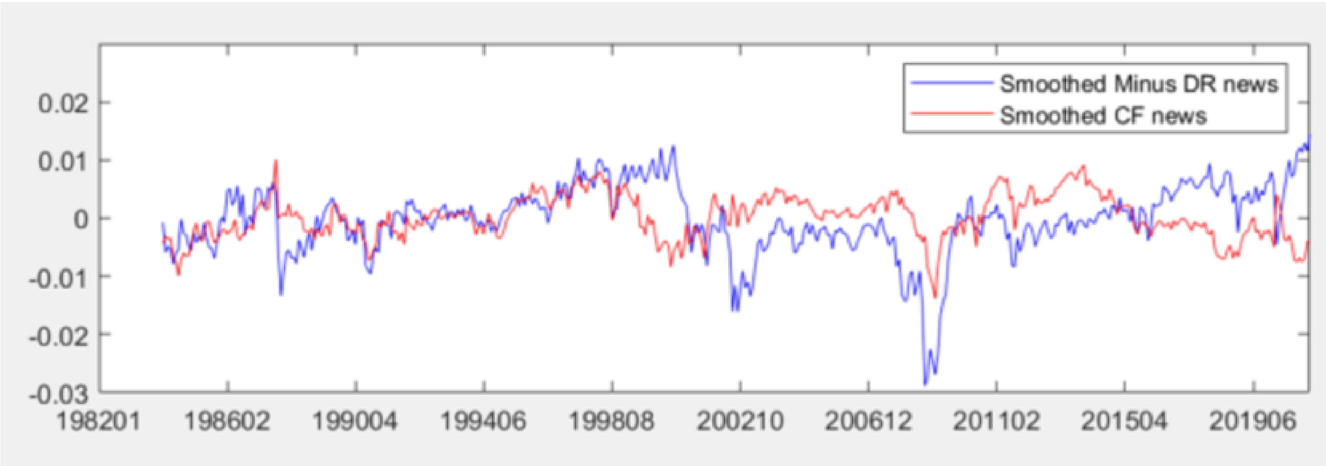


Figure B1: Replicate Figure 1 of Campbell and Vuolteenaho (2004) using our Sample 4: Cash flow and the negative of discount rate news, smoothed with a trailing exponentially weighted moving average and estimated from Sample 4. The decay parameter is set of 0.08 per month. Estimation details are in Table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

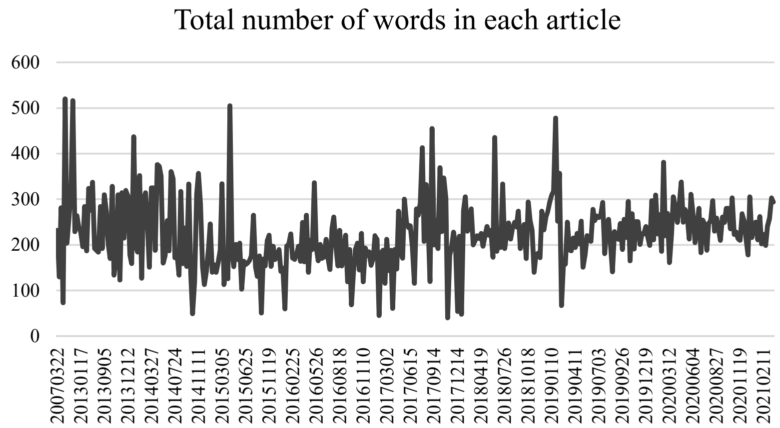
	Sample 1			Sample 2		
	NCF	NDR	NCF,NDR	NCF	NDR	NCF,NDR
Std/Corr	0.02412	0.05298	0.13237	0.02571	0.04340	-0.12449
	(0.00095)	(0.00244)	(0.06036)	(0.00101)	(0.00174)	(0.05281)
Var/Cov	0.00058	0.00281	0.00017	0.00066	0.00188	-0.00014
	(0.00005)	(0.00025)	(0.00008)	(0.00005)	(0.00015)	(0.00006)
r^e shock 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 date, 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 for the same dates — some entirely related to 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. Available articles on the CNBC website

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 key words for each of the five topics; their variants are also considered in the search (see details above). The time variation in the topic mentioning (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 5, we standardize the series with its first data value for interpretation purpose (that is, 1.5 means that mentioning is 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.

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
tax				
trillion				
washington				
white house				

C.3. TF-IDF scores to identify relative topic mentioning

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

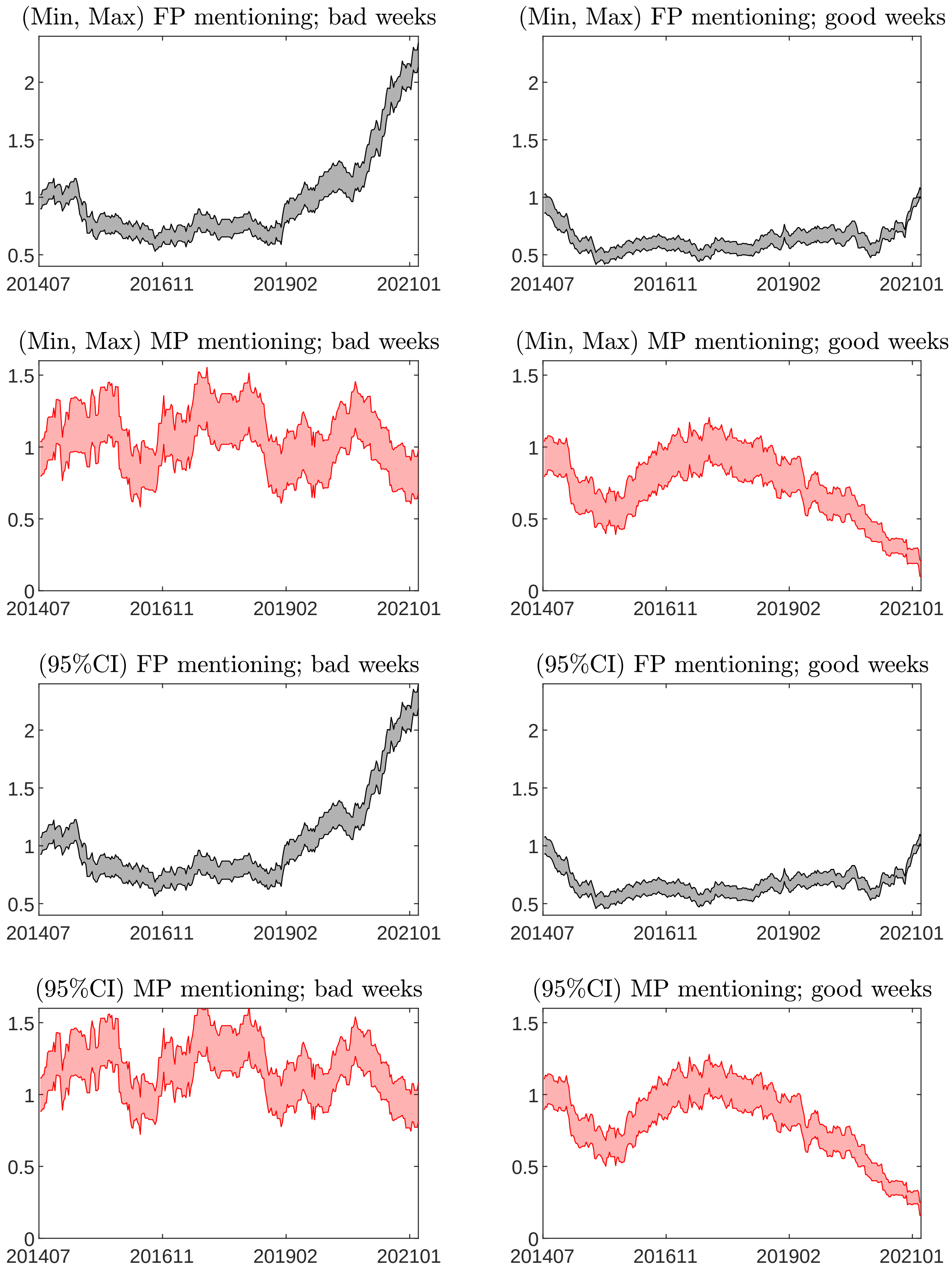


Figure C1: Jackknife exercise of the scaled rolling topic mentioning values. This table complements Figure 5 in the main text and provides measurement uncertainty. In this plot, we drop one keyword at a time and recalculate the bad and good rolling topic mentioning scores using all bad and good IJC announcement 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 standard deviation of the recalculated mentioning score (omitting one at a time).

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 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 and get a tf-idf matrix for each period.

C.4. Word clouds: visualizing relative mentioning among fiscal policy, monetary policy and uncertainty, before and after 2020

The two plots below use simple word clouds to show that, from 2013-2019 (left) to 2020-2021 (right), the relative mentioning of monetary policy (red) has dropped while that of fiscal policy has increased.

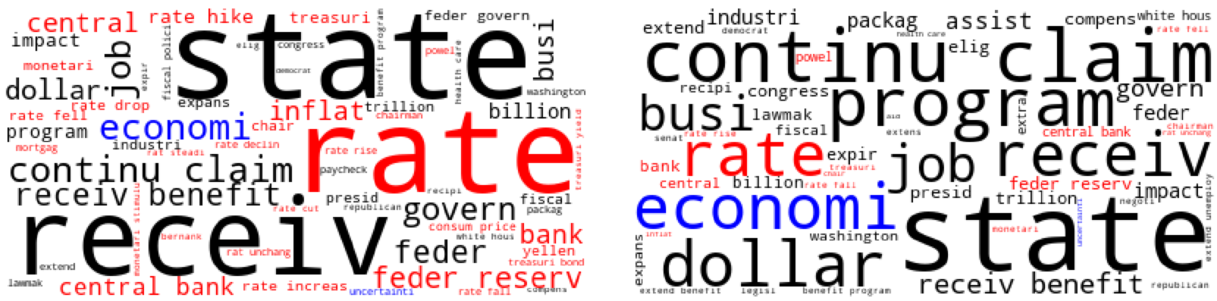


Figure C2: Left: Pre 2020; right: Post 2020 (black: FP; red: MP; blue: UNC)

D. Relationship between monthly macro announcement surprises and daily open-to-close returns

This appendix section complements Table 12 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 12, we display return relationships with macro news about the labor market, manufacturing, consumption, and some other economy variables (which are likely priced through monetary policy and risk channels) in three subsequent figures below.

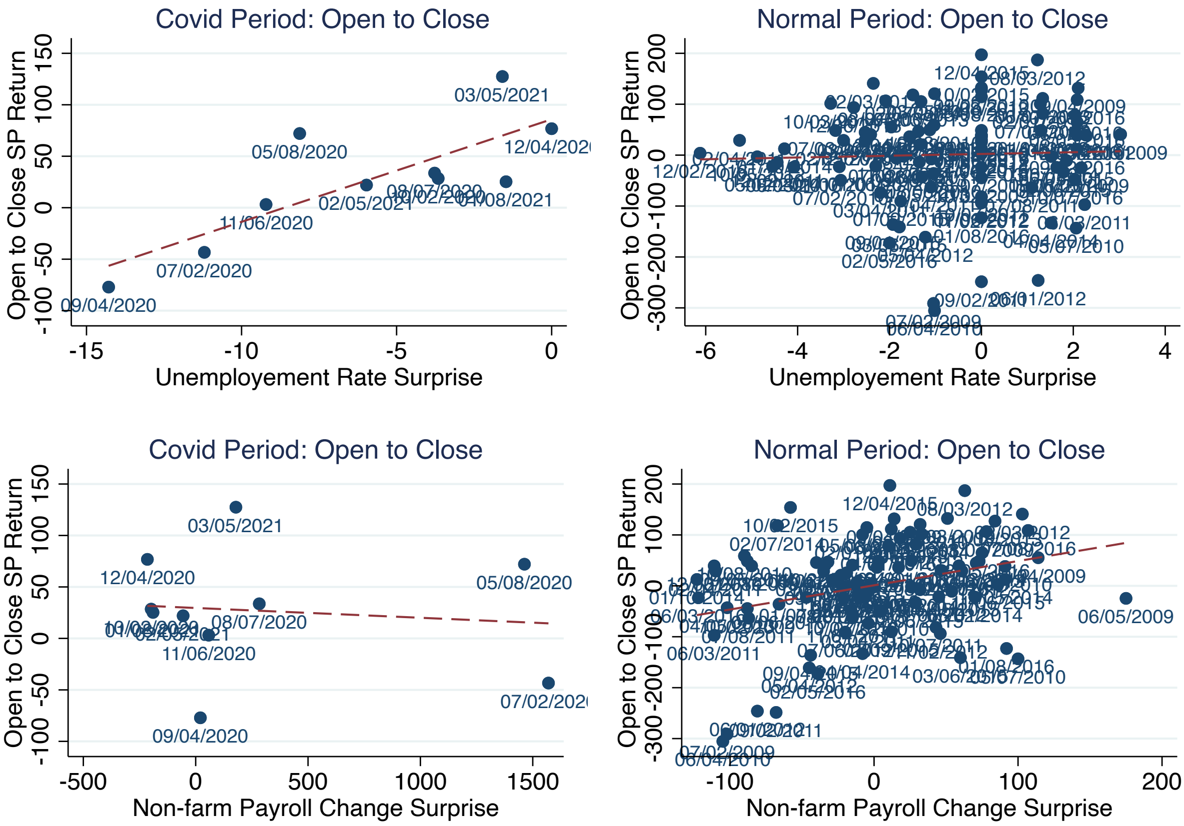


Figure D1: Employment news and daily open-to-close returns

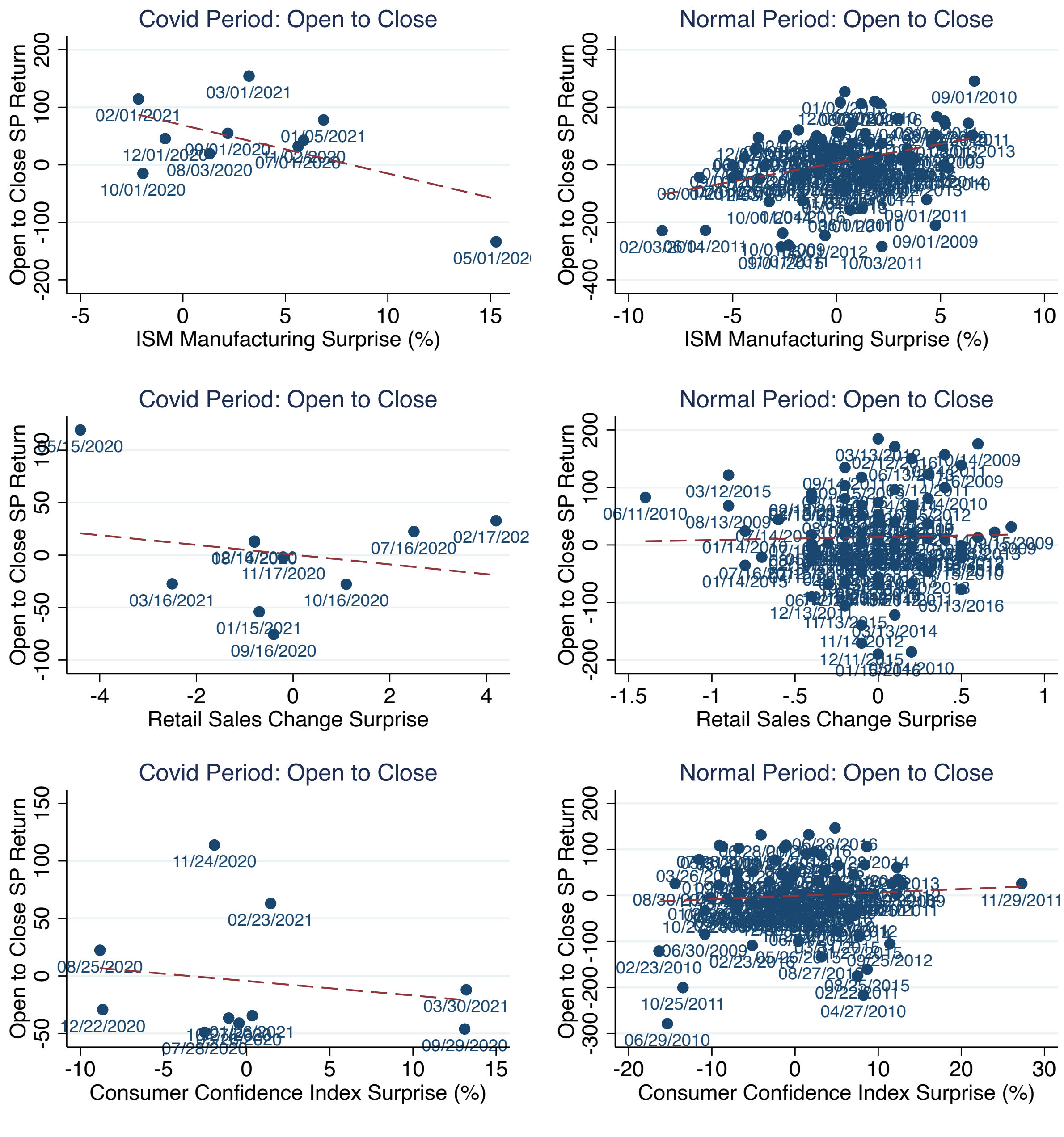


Figure D2: Manufacturing, consumption/consumer news and daily open-to-close returns

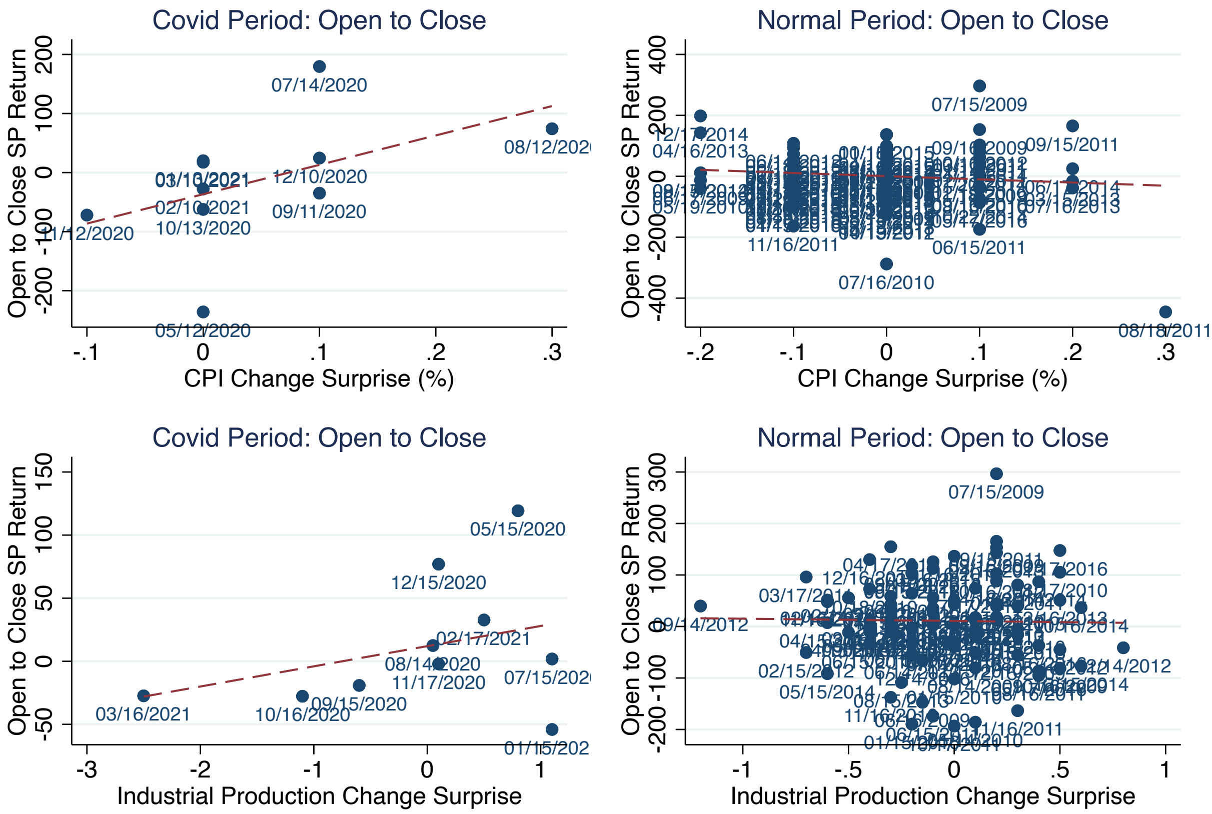


Figure D3: Other economy news and daily open-to-close returns