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

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Abstract

We propose *fiscal policy* expectation as a new mechanism in stock return responses to macro surprises. When the Main Street suffers more than expected, investors may expect a more generous Federal Government support and drive up expected cash flow growth and hence the aggregate stock prices, leading to a novel "Main Street pain, Wall Street gain" phenomenon. We provide both time series and cross section evidence. *First*, we find that, in the past 10 years, this phenomenon emerges when fiscal policy mentioning in newspapers is high. *Second*, our main cross-sectional identification exploits the Covid period (April 2020 to March 2021), which features an unprecedented fiscal spending in focus. We find that firms/industries that suffer more (unemployment surges, revenue declines) or receive more fiscal support show higher individual stock returns when Initial Jobless Claims are higher than expected. *Lastly*, we solve a conceptual asset pricing framework featuring a simple fiscal rule to reconcile our empirical results (e.g., pricing channel, cross-sectional source).

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

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

1. Introduction

Conventional wisdom and standard theories suggest that bad (good) macro news should drive down (up) stock prices. However, using announcement and high-frequency data from February 2020 to March 2021, we observe that a one standard deviation 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*, providing evidence of the "big disconnect" between the real economy and asset prices. While there is growing literature on the dynamic aspect of return responses to macro announcement surprises, it seems difficult for existing theories to reconcile with our observation. For instance, Boyd, Hu, and Jagannathan (2005) predict that rising unemployment news should be bad news for stocks during economic contractions as it should signal bad future dividend growth; on the other hand, 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 shocks.

We propose *fiscal policy* expectation as a new mechanism in this paper. First, we investigate the dynamic stock return responses to IJC surprises in the recent 20 years. The "bad is good" phenomenon can be observed during several episodes when the interest rate is at or near zero, and is indeed particularly pronounced during the Covid period. Second, to gain insight into the mechanisms, we further dissect the Covid-period result and find that this phenomenon (a) appears only when bad IJC news arrives and the opposite does not hold for good news, (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. Third, using actual IJC news articles written on the IJC announcement days that we manually collect from CNBC (2013-2021), we find that the mentioning of fiscal policy significantly surpasses that of monetary policy since 2019, and peaks mostly during bad IJC surprise days.

In light of these observations, we hypothesize and provide evidence for a fiscal policy expectation channel, which is new to the literature. In a persistent zero-lower-bound, low-interest-rate

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

economy, when the Main Street suffers (e.g., IJC is 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 *are expected to* or *actually* receive more fiscal support show *higher* individual stock returns when bad IJC surprises arrive. We test it during the Covid period and sort firms based on several fundamental firm Covid-impact measures (e.g., labor, revenue) as well as actual fiscal funding. Finally, in the low interest rate sample period we focus on, our evidence continues to support the important role of monetary policy expectation on stock return responses to good IJC news, given its asymmetric potency for interest rate to climb.

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 a daily frequency. While most periods in the past 20 years exhibit "bad is bad", "good is good" pricing, we show that the relation has become mild in recent years; in particular, from February 2020 to March 2021 (end of our sample), the "bad is bad" relation has proven 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, among 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 argue that a fiscal policy expectation channel may be more relevant in explaining dynamic return responses to bad IJC news in a persistent zero-lower-bound (ZLB) world, as the ZLB macro environment has the discount rate constraint.[2]

Our analysis faces an obvious measurement challenge: How to measure expectations of fiscal policy versus monetary policy in a preferably 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 mentions to test the 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," and "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 "Federal Reserve," "bank," and "inflation" and so on. An uncertainty measure, similar to Baker, Bloom, and Davis (2016), is also constructed using IJC articles as a business condition

[2]Such non-montonic asset price reactions to constrained monetary policy are also predicted by a recent Caballero and Simsek (2021)'s model. They do not model fiscal policy.

proxy. Due to text data availability (see more discussions in Section 3.1), we focus on 2013-2021.

The mentioning of two policies – fiscal (FP) and monetary (MP) policy – in IJC news articles exhibits distinctive time series patterns. The MP mentions increased around 2017 and 2018 but have since been in decline till the end of the sample in March 2021, whereas the FP mentions increased around 2013-2014, remained low until April 2020, but have since then increased. In particular, the increased mentions of FP mainly come from bad IJC days, while the hump-shape mentions of MP primarily 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 also suggests that FP (MP) mentions in our low-interest-rate sample can be interpreted as expansionary (contractionary) policy expectation.

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 mentions 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) to span the time variation in return coefficients of IJC shocks. Both tests show not only the 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 mentions are one SD higher than the average, stock returns could significantly *increase* by 24-26 basis points with a 10% IJC shock (higher the IJC 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 mentions do not explain the time variation in return responses to good IJC shocks; instead, on good IJC announcement days when monetary policy mentions are one SD higher than the average, stock returns could significantly decrease by 16-30 basis points with a -10% IJC shock (lower the IJC shock, better the news). This evidence lends support to Law, Song, and Yaron (2020); that is, increases in monetary policy intervention expectation matter 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 mentions on good IJC days are significantly and positively correlated with expectation revisions of future interest rates in our sample: higher MP mentions indeed occur more likely when survey data shows that professionals expect interest rates to increase. Our mechanism tests at the aggregate level support our core hypothesis. The results are also robust using a sample period until December 2019, indicating that the effect exists even before Covid-19.

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 these 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 the 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 cross-section, our theory predicts that firms should exhibit a stronger "Main Street pain, Wall Street gain" effect when they are expected to gain more support from fiscal spending. The Covid-19 crisis renders an ideal context to test our theory in the cross-section of stock returns for two reasons: One, our textual analysis shows an unprecedented and persistently high fiscal policy mentioning since April 2020 until the end of the sample (March 2021); two, the cross section is market-wide and fiscal spending during Covid-19 is more likely to help the companies which experience distress triggered by non-financial risks. First, in a *cross-section analysis* using firms of S&P500, we find that firms/industries that suffer more – measured by 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 the three most damaged industries, controlling for the total number of firms in the universe of S&P500, and they are getting heavily mentioned in the text of stimulus bills. To formally quantify the magnitude of the cross-sectional effect, we form a value-weighted portfolio — long the "Most-Suffering" quintileshort the "Least-Suffering" quintile — and evaluate its performance on IJC announcement days from February 2020 to March 2021 (excluding IJC outlier and FOMC overlapping days). We find that the average daily portfolio returns on bad IJC days are positive, ranging from 10 to 13 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, appears to generate the largest portfolio return compared to financial suffering measures. Using pre-Covid firm characteristics, small, value or low operational cash flow firms show significantly higher returns on bad IJC days; high leverage firms do not, which potentially rules out the effect of unconventional monetary policy.

As our external validation analysis, we evaluate the co-movement 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).

Finally, we provide and solve in closed-form a conceptual asset pricing framework to reconcile our empirical results (particularly on the pricing channels, and cross-sectional results). This model builds on Bansal and Yaron (2004) (henceforth, BY2004) but differs from it by introducing a simple fiscal policy rule — government spending is expected to go up when bad shocks arrive. When a bad economic shock arrives, fiscal policy could counteract the conventional positive relationship between expected growth state variable and price-dividend ratio; as a result, fiscal policy could alter the sign of return loadings on macro shocks, potentially resulting in "bad is good" scenario. In that world, our calibration shows that risk premium could still increase as fiscal rule introduces volatility. The model focuses on the pricing channel, and leaves more precise modeling of expectations and high-frequency macro announcement dynamics to future research. To rationalize the empirical evidence that we document in the paper, the expected growth channel as we document is likely the dominant channel.

In the cross section, we focus on one particular heterogeneity source: there may be different firm-level pass-through of the fiscal rule. Higher sensitivity to the country fiscal rule should exhibit a higher chance to offset the standard (positive) dividend growth and long-run risk effects of macro news on their stock prices, hence resulting in a less positive or more negative coefficient in response to macro news.

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 macro-finance 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 dominates. Then, recent theories (Law, Song, and Yaron (2020), Yang and Zhu (Forthcoming), Caballero and Simsek (2021)) argue that time-varying return responses to macro news likely depend on monetary policy intervention expectations. Law, Song, and Yaron (2020) provide evidence using a sample from 1998 to 2017 with revisions in future interest rates that do not necessarily move with the business cycle in empirical evidence or in theory. As a theoretical contribution, our paper points out that, in a persistent zero-lower-bound, low-interest-rate modern world, neither existing explanation seems to dovetail with the novel "Main Street pain, Wall Street gain" phenomenon during the Covid period (February 2020 to March 2021) that we document at both daily and high frequencies. One may point out that investors could still expect more unconventional monetary policy (UMP), which is potentially picked up by our main MP mentioning measure already (e.g., in a context of UMP, keywords such as "Federal Reserve" and "monetary policy" are still likely mentioned somewhere and are hence picked up). In addition, most programs were forcefully announced with expectations set and communicated before the end of April 2020, whereas the "Main Street pain, Wall Street gain" phenomenon stayed in the data even when we moved into 2021, and in fact appeared stronger from May to October 2020. Our cross-sectional evidence also shows that highly-leveraged firms do not show significantly higher returns on bad IJC days. In general, our evidence 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 generally 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 to good news. We show consistent evidence, using samples *with or without 2020-2021*, that different policy expectation channels may matter differently to dynamic return responses to bad or good macro surprises, in this persistent zero-lower-bound economy. The Covid crisis triggered an unprecedented adverse shock to the labor market, the "Main Street", which helps unveil this new fiscal policy mechanism. Our evidence – with the interplay of both fiscal policy and monetary policy – lends immediate support to predictions made in Caballero and Simsek (2021).[3]

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 the stock market. Among the few papers written, the focus is mostly on examining the long-term or short-term effects of tax policies and public deficit on capital markets within an equilibrium framework, or uses 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)). Using trained human readers and a wide range of major newspapers, Baker, Bloom, Davis, and Sammon (2021) show evidence of the rising importance of monetary and fiscal policy in driving positive stock market jumps, which aligns with one of our big-picture takeaways despite our different research questions and approaches. To answer our research question, instead of using model-implied fiscal policy expectations or reading all possible newspapers outlets, we circumvent this measurement challenge and create our own measure by only looking at news articles dedicated to discussing this particular macro announcement *on* its announcement day in real time (to capture potential fiscal policy (spending) expectations). The idea that "news mentions" reflecting "expectation" and "beliefs" has been widely used; for instance, Da, Engelberg, and Gao (2015) measure beliefs on recessions using internet search volumes, while Baker, Bloom, and Davis (2016) measure economic uncertainty using news articles. Our methodology of measuring fiscal policy expectation and connecting it to asset prices is new to the literature, as Brunnermeier, Farhi, Koijen, Krishnamurthy, Ludvigson, Lustig, Nagel, and Piazzesi (2021) call for more research on measuring beliefs about macro conditions.

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

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 with a 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. We hypothesize *fiscal policy* expectation as a new mechanism to reconcile these facts, and provide both aggregate and cross-sectional evidence. Section 3 investigates plausible mechanisms using textual analysis and professional survey data. Section 4 tests our hypothesis in the context of the Covid period. Section 5 solves a conceptual asset pricing model with a simple fiscal rule to to reconcile our empirical results (particularly on the pricing channels, and cross-sectional results). Sections 6 and 7 provide external validation and our final remarks, respectively.

2. Dynamic Stock Return Responses to Labor News

In this section, we examine how stock 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 reasons. First, economically, jobless numbers closely reflect how the "Main Street" is doing and should matter to policymakers. 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 a 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 6. Here, Section 2.1 establishes main empirical results at the aggregate level, and 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,

$$IJCShock_t = \frac{IJC_t - E_{t-\Delta}(IJC_t)}{E_{t-\Delta}(IJC_t)},$$

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

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. It should be noted that a simple level difference, $IJC_t - E_{t-\Delta}(IJC_t)$, is another intuitive way to construct macro shocks, as is used in several papers with pre-2020 sample (e.g., Balduzzi, Elton, and Green (2001), Kurov, Sancetta, Strasser, and Wolfe (2019) and so on). 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 a substantial difference in economic magnitude before and after 2020 (see statistics in Table A1 in the appendix), which may cause difficulty with interpreting the results.

Table 1 shows the summary statistics of our main IJC shock. To better summarize, 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*

We discuss 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 during the peak of the Global Financial Crisis in 2009), our shock proxy (after dropping the three outliers) appears to have 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.

[5]Boxplot outlier analysis using the ×2 interquartile range rule suggests that 2021/3/19 (actual: 281K; expected: 200K; shock=27.7%), 3/26 (actual: 3.28M; expected: 1.70M; shock=93.1%) and 4/2 (actual: 6.65M; expected: 3.76M; shock=76.7%) constitute three, unrepresentative shock outliers.

[6]It is worth pointing out that the period classification here does not enter our main mechanism analysis in Section 3, and it is a simple way of sorting 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 for now.

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

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

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 the 10-year Treasury yield, (4) daily changes in the 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 financial proxies of uncertainty and risk aversion are provided by Bekaert, Engstrom, and Xu (2021a), and daily text-based economic policy uncertainty is provided by Baker, Bloom, and Davis (2016).

Since the turn of the century, as IJC shocks increase 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 a 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. As expected, VIX seems to have mixed reactions, as 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 rather 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 Covid-19 recession period, February 2020, to the end of our sample, March 2021. That covers 54 weeks after excluding 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 1 SD IJC shock (8.7% from Table 1). In terms of economic magnitude in standard deviations, a 1 SD IJC shock corresponds to a 0.2 SD increase in daily open-to-close stock returns. We coin this observation the "Main Street pain, Wall Street gain" phenomenon in this paper.

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

The last few rows of Table 2 also show that asset or risk variables that typically move with discount rates 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.

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 daily frequency, whereas the NCF-NDR decomposition is typically estimated at a lower frequency (i.e., monthly) in a VAR system. Estimating this VAR system at a daily frequency is not trivial. First, the choice of ρ at a daily frequency is not as straightforward as $0.95^{1/252}$.[8] Second, some variables in the state vector simply cannot be constructed at a 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,

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

24, 46 ...; and so on.[10] Appendix B provides (a) more estimation details, (b) replication to Campbell and Vuolteenaho (2004), and (c) 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 good real economic shock can decrease discount rate (and risk variables) while also increasing expected future cash flow growth. In our modern sample (1982/01-2021/04), we find that NDR (NCF) now explains 31% (34%) with a positive covariance between NDR and NCF. Results are robust using open-to-close or daily stock market returns. Hence, one useful takeaway, from the long-term time series perspective, is that 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 therefore are potentially comparable from the perspective of an 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 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 the reactions of several more discount-rate-driven asset prices and risk variables to IJC shocks; 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 the actual IJC number is higher than expected). As shown in Table 4, all statistically significant return responses come from

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

bad IJC days, with economically meaningful magnitudes. When bad IJC news arrives, 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. In fact, from the top plot of Figure 1, the time between April 2020 and November 2020 and then again after February 2021 exhibits rather strong positive comovement between bad IJC shocks and good stock returns.

High-frequency evidence For identification purpose, the literature has been tracing out stock and bond market reactions to macro shocks using high-frequency data (e.g., Balduzzi, Elton, and Green (2001), Andersen, Bollerslev, Diebold, and Vega (2007) 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.

Tables 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 "Covid", given the similar ZLB monetary policy environment. All high-frequency data is 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 most time stamps 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 also motivates our textual analysis in Section 3, which obtains direct evidence on what people discuss after the IJC announcements, while looking for

[11]We relegate results using E-mini Nasdaq-100 Futures to Table A2 in the appendix.

new mechanisms.

While Dow futures show stronger effect than Nasdaq futures, suggesting a plausible channel through cash flow expectations, we also directly examine price movement of three traded discount-rate-related futures markets around *bad* IJC days: the 30-day Fed Fund futures, the 10-year Treasury note futures, and the VIX futures. We relegate detailed results to Appendix Table A3. In general, we find no significant difference between the normal- and the Covid-period price responses from these three futures markets on bad IJC days. We document that investors do not appear to speculate future Federal Reserve monetary policy to be more expansionary (i.e., a lower interest rate and hence a higher 30-day Fed Fund futures price) during both periods. Long-term Treasury note futures price increases significantly with a bad IJC shock 5 minutes after the announcement time during the normal period, which is expected as it may signal a weakening economy (see similar result also in Kurov, Sancetta, Strasser, and Wolfe (2019)). The Covid-period responses also share an overall positive response. In addition, we find insignificant VIX future price responses to IJC shocks on bad IJC days.[12]

Lastly, the intradaily evidence shows that there is no statistical difference between normal and Covid periods regarding how a futures market responds to *good* IJC surprises. From Panel C of Tables 5 and 6, 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, A4 and A5 in the appendix). Notedly, 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, with the last one being a Thursday. Evidence from Tables A4, A6 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 the relationship has become mild, and in the recent period since 2020 (even entering 2021), the relationship has

[12] In unreported results, using all IJC days, we find that VIX future prices significantly increase in a short window (e.g., 5 minutes) when the actual IJC numbers are higher/worse than expected.

turned significantly opposite, and we coin it the "Main Street pain, Wall Street gain" phenomenon. The phenomenon (a) appears only when bad news arrives, (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.

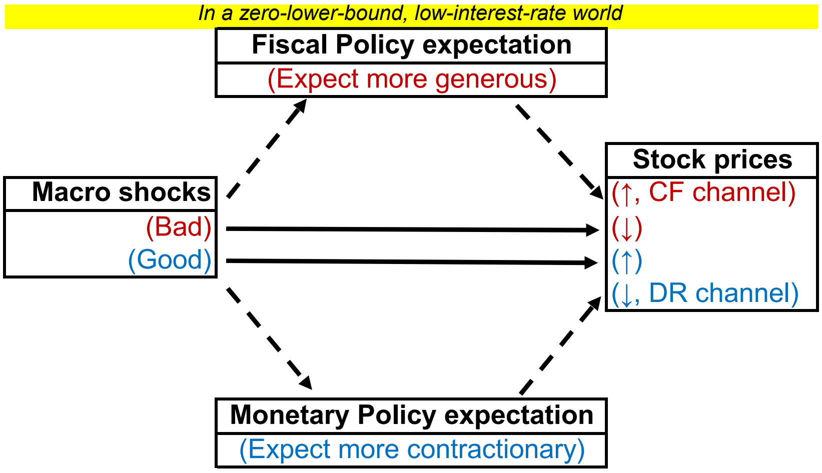
3. Mechanism

This particular period post-2020 (even into 2021) 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. 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.

In the existing literature, 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 (Forthcoming) and our own work. 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 arrives at a low-interest-rate environment, as there is a clear potency for interest rates to increase and for monetary policy to exert. A representative example may be 2017 to 2019, or our Period 4. However, it may be hard for this channel to continue explaining the "Main Street pain, Wall Street gain" phenomenon on bad IJC days from February 2020 to March 2021. The interest rate already dropped to 0-0.25% on March 15, 2020 and remains at zero since then. It is less likely that investors expect the interest rate to go further down, and in fact, the Survey of Professional Forecasters (SPF) shows that investors expected the annual rate to change by 0-0.01% during the remainder of 2020. Most unconventional monetary policies were announced before mid-April 2020 (and scheduled to operate around March-May 2020), while our results mainly come from May 2020 until March

2021. It is less likely that investors expect the Fed emergency lending facilities to be laxer.

The Covid-19 crisis triggers an unprecedented adverse shock to the labor market, which helps unveil the new *fiscal policy expectation* mechanism. The diagram below illustrates our hypothesis, building on the existing monetary policy-focused explanation. In this low-interest-rate economic environment (which is likely to sustain in the foreseeable future post Covid), one policy expectation channel may become more relevant, depending on bad or good IJC surprises:



At the aggregate, our hypothesis predicts that fiscal (monetary) policy expectation may be a more important driver for return responses to bad (good) IJC shocks. In the cross section, firms/industries that are expected to receive more fiscal support should exhibit stronger "Main Street pain, Wall Street gain" phenomenon in their respective stock prices. We test our hypothesis predictions using both longitudinal textual analysis (this section) and cross-sectional evidence (Section 4).

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 mentions as testable mechanisms. We relegate technical details to Appendix C and describe our 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, such articles typically get finalized around noon. However, news on this website is 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 manually parse and examine this website in a systematic way.

We use Python and then manually verify CNBC IJC news articles on announcement days for as far back as 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 can 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 can 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. These articles have an average of 327 words (see Appendix C for more details).

Construct topic mentioning scores. To retrieve the relative importance of words by topic in 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 mentions, 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, to capture fiscal policy mentions. For instance, when words such as "aid," "extend," "benefit," "congress," "lawmaker," and "Federal Government" appear in one article, the scenario typically reflects an ongoing fiscal-level discussion 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:[13]

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

A pre-Covid example is from January 10, 2013 when IJC is again higher than expected:[14]

> *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 and general, for instance "central bank," "inflation," and "Federal Reserve" as well as Federal Reserve Chairpersons' 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 discussing IJC news on the announcement days, for identification purposes. The fourth topic is coronavirus-related, for validation purposes, as one should expect the topic mentions to increase dramatically after January 2020. The fifth topic covers normal IJC terms, such as "initial," "jobless," "claim," "unemployment," "Thursday" and so on, and one should expect that this number remains stably high.

Second, how does the mentioning of each topic compare with each other, and how does it evolve over time? Given that each IJC article is relatively short (average=327 words), we construct topic mentions metrics using a group of weeks. For illustration purposes, Figure 4 considers 60-week rolling windows, and shows the rolling topic mentions, normalized by the "Normal-IJC" mentions from the same rolling window. The first observation, serving more as a validation, is the time variation in the "Coronavirus" topic, which expectantly starts off as irrelevant but increases 10 times more during 2020-2021.[15] Next, the two policy mentions

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

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

[15] Earlier values are not exactly at zero because of some words in this topic, such as "virus," and "case."

lines – fiscal (black solid) and monetary (red dashed) – show distinctive patterns. Both start with a similar level and trend, remaining low during 2015 and 2016; the MP mentions on IJC announcement days increased around 2017 and 2018 but have been declining until now, whereas the FP mentions reached a local peak around 2013-2014 (perhaps amid the fiscal cliff discussion), remained low until April 2020, but have since dramatically increased. Finally, the mentions of economic uncertainty moved with the MP mentions around 2013 and 2014, increased around 2016 amid the Brexit referendum and the US election, increased again in 2018 and 2019 due to the lingering China-US trade war as well as 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 an expected amount of risk in paradigm asset pricing models, an equity risk premium determinant – is weakly correlated with our FP and MP measures.

Figure 5 complements Figure 4 by constructing "bad" ("good") topic mentions metrics using articles on bad (good) IJC days from the same 60-week rolling window. For interpretation purposes, we normalize a topic's mentions using its value during the first 60-week window so that "1.5" means that the bad-day mentions of a particular topic increases by 50% since the beginning of the sample, and several key statistical tests are reported in Table 7.[16] 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 mentions 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) mentions 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 were lower/better than expected. Both observations suggest that FP (MP) mentions in our low-interest-rate sample can be interpreted as expansionary (contractionary) policy expectation.

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 (2021a)). The bottom right plot shows that Coronavirus words (e.g. "pandemic," "vaccine," "Covid") are mentioned slightly more often when initial claims are worse than expected.

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

[16]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.

out one keyword at a time from bags of words, for Topics "FP" and "MP", and recalculates the relative topic mentions. The bandwidth denoting the minimum and maximum from the Jackknife exercise is tight and 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 would predict that one SD higher FP expectation and mentioning could drive up aggregate stock return responses to IJC shocks, particularly on bad IJC days. The rolling textual analysis evidence shows graphically and statistically that (a) FP mentions fluctuate over time, even before Covid-19, but (b) it increases to a persistently high level, particularly on bad IJC days and during the Covid-19 period. 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 mentions 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.

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

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 mentions. 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 around 2014 untill 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 mentions 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 mentions often contribute 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) mentions explain 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 mentions are 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 mentions are much more statistically and economically important than monetary policy mentions 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 happens (given the significantly 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 sensitivities to fundamental shocks – spanned by some form of underlying uncertainty or volatility – dominate 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 A7 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"[17] given 1 SD bad IJC shock in the top plot, and 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 mentioning 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).[18] This result is consistent with Table 3.

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

[18]Notice that 0.45-0.15 does not add up to 0.35. It is because standardization is done separately within return,

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 the 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 the "hump" in MP mentions (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 the Covid period when the MP mentions appear 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 a 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".

3.3. Mechanism evidence using non-overlapping evidence

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

NCF and NDR projections; and NCF and NDR are correlated.

corresponding to 2013Q1 (2021Q1) and bad/good separation for textual variables. The pattern appears less continuous as expected; given that there are only a 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).[19] That being said, the overall pattern remains quite similar to the rolling version: (a) sooner and higher increases in the FP mentions on bad IJC days, (b) the hump shape in the MP mentions 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 the interest rate to climb around 2015 - 2018, which is consistent with the timing of higher MP mentions particularly when good economy news is 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, 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 than to forecast Q2 (i.e., the -16.62% drop in future recession probability corresponds to $\tau = 2020Q2$). We interpret $\Delta Recess$ as a measure of an overall pessimism about the economy, but it is not directly related to our theoretical hypothesis. As a result, we discuss the $\Delta Recess$ results as a separate case in the following paragraphs.

Table A8 in the appendix shows a correlation matrix of these quarterly state variables (N = 33 non-overlapping quarters). We discuss four observations next. First, FP and MP mentions are uncorrelated, regardless of bad or good IJC days. Second, $\Delta Tbill3m$ is highly positively correlated with our MP mentions during good days ($\rho = 0.46^{***}$), supporting the "contractionary" interpretation of high MP mentions on good IJC days during the sample period of the paper. Third, FP mentions during our sample period are particularly associated with a bad uncertain environment ($\rho = 0.69^{***}$), suggesting the "expansionary" interpretation of high FP mentions on bad IJC days during our sample period. Fourth, a higher recession expectation is associated with periods when fiscal policy mentions on bad IJC days are 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 mentions is one SD higher than the average, stock returns could significantly *increase* by 24-26 basis points with a 10% IJC

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

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 high fiscal policy expectation.

Second, on good IJC days, fiscal policy mentions do not explain the time-varying return responses of major stock indices. Instead, on announcement days when monetary policy mentions are one SD higher than the 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 support 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 mentions dominate 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 mentions or expectation revisions in future interest rate ($\Delta Tbill3m$) dominate fiscal policy. Notedly, the single state variable result of $\Delta Tbill3m$ in Table 9 is already borderline significant using Dow Jones 65. From Table A8, our MP mentions on good IJC days "goodMP" and $\Delta Tbill3m$ are significantly and positively correlated at 0.46*** and capture the same economic concepts. This motivates the choice of including one at a time in multiple regressions in Table 10. To interpret the coefficient in the last column, when the 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 A9 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.[20] 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.[21] Therefore, the recession channel goes against the policy channels, and in some senses 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

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

[21] When investors expect a lower chance of future recessions ($\Delta Recess < 0$) on good IJC days, the 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 $\Delta Recess < 0$.

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 11, we replicate Table 10 using a sample period until December 2019. Results are quite robust. Statistical power drops slightly as expected, given that the sample becomes smaller and the Covid period should help with the FP effect identification, as mentioned in Section 2.

4. Cross-Sectional Evidence

Different firms can benefit from fiscal spending differently. Our theory predicts that firms should exhibit a stronger "Main Street pain, Wall Street gain" effect when they are expected to gain more support from fiscal spending. The Covid-19 crisis renders an ideal context to test our theory in the cross-section stock returns for two reasons. First, our textual analysis shows unprecedented, persistently high fiscal policy mentions when news professionals discuss bad Main Street news. In reality, the government deploys a total of 5 trillion USD of fiscal spending to rescue the economy over a slow course of 10 months from May 2020 to March 2021. Second, fiscal spending during Covid-19 is more likely to help the companies which experience distress triggered by Covid health/non-financial risks. For example, American Airlines is more likely to benefit from stimulus bills as air transportation dramatically declines; thus, stock prices can boost more when bad labor news arrives. Meanwhile, Microsoft is unlikely to get government help as its business thrives; therefore, the "Main Street pain, Wall Street gain" phenomenon should be relatively minimal.

In this section, we test whether firms with more severe Covid-19 damages show higher individual stock returns on the bad IJC days, as they are expected to benefit from a more generous fiscal bill. Section 4.1 explains our Covid-impact measures at the firm/industry level (e.g., labor, finance). Section 4.2 tests our hypothesis using all firms, and Section 4.3 uses portfolio sorting. To interpret our result more directly, we make links to the actual bills in Section 4.4.

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 the firm universe of S&P 500 to be consistent with our aggregate analysis.

Our first measure considers a novel 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 a 6-digit NAICS code. We aggregate the number of job postings by a 4-digit NAICS code, 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) observable 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 Earnings Per Share (basic, excluding extraordinary items) first differences between 2019Q2 and 2020Q2.[22] Data is obtained from Compustat Annual and Compustat Quarter, and we use number of employees from 10-K as the employment data is not available in 10-Q.

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.[23] 491 out of 500 tickers can be found with the number of employees reported in 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 when the initial impact of Covid arrived, on average, -39%. The distribution is also quite normal and well-behaved. Notedly, employment changes calculated using Compustat's fiscal year data in 2019 and 2020 show that some firms indicated positive labor growth, which should include some growth triggered by 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 negatively skewed (with the 5^{th} percentile at about -\$11 and the 95^{th} at \$4). Robustness measures (5)-(7) reach similar patterns and conclusions. Due to the skewness in these financial variables, we take the percentile rank of these measures in our cross-sectional analysis (e.g., lower rank=more damage).

4.2. Cross-sectional evidence: All-firm analysis

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

[22] "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.

[23] We do not consider the firms added or removed during this period. For example, Tesla entered S&P 500 in 2020 December. Our analysis includes Tesla for the entire period

changes in individual open-to-close stock returns given 1 SD IJC shock; or econometrically, this is equivalent to the "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 between firm returns and IJC shocks should be *negative*; on the other hand, our "Main Street pain, Wall Street gain" phenomenon should be consistent with a *positive* firm-level correlation. The sample period we use to calculate firm-level correlation with IJC shock spans from February 2020 to March 2021 (end of our sample);[24] and three correlations can be calculated for each firm, using all, bad or good IJC days, where the first can be dubbed as an unconditional correlation and the other two as conditional correlations.[25] Here is the firm-level specification:[26]

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

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

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

Table 12 reports the regression results with N=491 (e.g., number of firms that we can identify with all four main "Covid-impact" measures). We discuss several main observations next. 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.[27]

Second, results using all IJC days show a strong and consistent takeaway using any of our measures (rank or raw changes). The negative coefficients mean that 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 is 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 — that is, a 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 "suffering" rank corresponds to around 0.012-0.016 increase in the correlation. This main takeaway is also displayed as negative slopes in solid lines in Figure 8, where we group firms into 20 bins and each dot represent a bin.

Third, results using conditional correlations (calculated using only bad or good IJC days) show 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

[24]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 cautiously stronger if we include these four days.

[25]These two conditional correlations take out different conditional means for both types of IJC shocks.

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

[27]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, econometrically.

bad news arrives (see e.g. Table 4). Next, Figure 8 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 the bottom 50 percent firms 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.

4.3. Cross-sectional evidence: Portfolio formation and returns

Then, we quantify the average daily investment returns by exploiting the “Main Street pain, Wall Street gain” effect. We form portfolios sorted by the aforementioned “Covid impact” measures and evaluate its performances on bad IJC announcement days, good IJC announcement days, and any other days without IJC announcements from February 2020 to March 2021 (excluding outlier days 03/19, 03/26, 04/02/2020 and a major unconventional monetary policy announcement day 04/09/2020, as before).

In the first step, we sort the 491 out of S&P 500 firms into 5 bins based on these Covid-impact measures, one at a time. Then, we call the 1^{st} (5^{th}) 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. Finally, the portfolio takes the return differences between the “Most-Suffering” and the “Least-Suffering” quintile bins. Average portfolio returns can be calculated using bad IJC days (when the actual IJC number is higher/worse than expected), good IJC days (when the actual IJC number is lower/better than expected), and non-IJC days. Our theory predicts that the portfolio should outperform on bad IJC days, compared to good IJC and non-IJC days.

From Figure 9, using any of our Covid-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 10 to 13 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 robust results using equal weights or using alternative Covid-impact proxies.

Lastly, we extend our firm sorting to their pre-Covid (end-of-2019) reported characteristics, which link to various kinds of firms that “social planner” may actively monitor during Covid-19 and hence tilt their support towards given their pre-existing financial health. This may help us further rule out alternative mechanisms. We focus on three groups of firm characteristics: (1) firm size and valuation measures (using both Book-to-Market and Earnings-to-Price ratio); (2) free cash flows (FCF=operating cash flow (OANCF)-gross capital expenditures (CAPX)); (3) risk (leverage=(long-term debt+short-term debt)/shareholder equity). The portfolio takes the return difference between the lowest (lowest-size, lowest-BM, lowest-EP, lowest-FCF, lowest-leverage) and the highest quintile bins. Within each quintile, average returns can be calculated on bad-, good-, and non-IJC days. Figure 10 shows that small 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 sensitivities to cash flow. 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: big firms may show higher stock returns when bad IJC news come out, given their stronger financial resilience or lobbying capabilities to get government funding. 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, indicating intuitively that they experience more adverse Covid shocks on average. Next, we also find that firms with low free cash flow in 2019 show higher returns on bad IJC days during Covid. This is consistent with the view that companies already in cash shortage tend to be more reactive to government support. Finally, we find that high-minus-low leverage portfolios[28] using pre-Covid leverage show minimal positive returns (which can be tested as insignificant) on bad IJC days, suggesting that the risk and Monetary Policy channel when IJC news comes out may still be there, but is statistically and economically weak.

4.4. Which industries suffered more? Did bills also help them more?

Who are the firms damaged more by Covid? Are they indeed the ones who receive more support from the government? We cross-validate that most damaged industries are particularly highlighted in the stimulus bills. Table A11 in the appendix reports the average Covid-impact measures by 2-digit NAICS industries. The top 3 damaged industries in S&P 500[29] 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 average rank (lower=more decreases in employment) at the 20th percentile, and job postings lose by 64% from 2019 to April/May of 2020. The QoQ revenue and EPS changes also rank at the 19th and 23rd percentile, 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 bracket. On the other hand, the *Healthcare and Social Assistance* industry shows both positive financial growth and high YoY employment rank at 66th; even job postings during the 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.

[28]Our leverage and FCF variables are correlated at -0.01 in the S&P 500 universe.

[29]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.

Alternatively, we can measure industry-level Covid impact by the fraction of firms from this industry that fall in the topmost damaged bins, relative to the industry's general presence in the S&P 500 universe. We 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 compared to its presence in the least damaged 50%:

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

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 rescuing the transportation-related business: *Continued Assistance to Rail Workers*, *Public Transportation*, *Transportation and Infrastructure*, and *Aviation Manufacturing Jobs Protection*. 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 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 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.

5. A conceptual asset pricing framework: Long-run risk, uncertainty, and fiscal rule

In this section, we provide a conceptual asset pricing framework to reconcile our empirical results (particularly on the pricing channels, and cross-sectional results). This model builds on Bansal and Yaron (2004) (henceforth, BY2004) but differs from it by introducing a simple fiscal policy rule. To be specific, we build a dynamic model with the Epstein-Zin recursive preferences, stochastic volatility, long-run risk, and a real macroeconomic factor affecting the discount rate and the equity cash flows process. Finally, we derive the model in closed-form.

5.1. Setup

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

$$m_{t+1} = \theta \log \beta - \frac{\theta}{\psi} g_{t+1} + (\theta - 1) r_{m,t+1}, \tag{7}$$

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

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

5.2. Dynamic processes

The dynamics of log real growth from period t to $t+1$ (g_{t+1}), growth uncertainty (v_{t+1}), expected growth (x_{t+1}), fiscal policy conceptualized as government expenditure here (FP_{t+1}), and finally, log dividend growth from period t to $t+1$ (Δd_{t+1}) are given as follows, respectively:

$$g_{t+1} = \mu_g + x_t + \sqrt{v_t}\varepsilon_{g,t+1}, \tag{8}$$

$$v_{t+1} = \mu_v + \rho_v v_t + \sigma_v \varepsilon_{v,t+1}, \tag{9}$$

$$\text{[New]} \quad x_{t+1} = \rho_x x_t + \sigma_{xg}\sqrt{v_t}\varepsilon_{g,t+1} + \sigma_{xFP} FP_{t+1} + \sigma_x \varepsilon_{x,t+1}, \tag{10}$$

$$\text{[New]} \quad FP_{t+1} = \underbrace{\sigma_{FPg}}_{<0} \sqrt{v_t}\varepsilon_{g,t+1} + \sigma_{FP}\varepsilon_{FP,t+1}, \tag{11}$$

$$\Delta d_{t+1} = \mu_d + \rho_{dx} x_t + \sigma_{dg}\sqrt{v_t}\varepsilon_{g,t+1} + \sigma_d \varepsilon_{d,t+1}, \tag{12}$$

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

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

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

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

5.3. Price-dividend ratio

We derive asset prices using the SDF mentioned in Equation (7) and the standard asset pricing condition $E_t[M_{t+1}R_{i,t+1}] = 1$, for any asset $R_{i,t+1}$ (log return: $r_{i,t+1}$) including the market return $R_{m,t+1}$ (log return: $r_{m,t+1}$). Given all shocks in the system are conditionally normal, the Euler equation can be rewritten as follow:

$$E_t\left[\exp\left(\theta \log\beta - \frac{\theta}{\psi}g_{t+1} + (\theta-1)r_{m,t+1} + r_{i,t+1}\right)\right] = 1 \Leftrightarrow \tag{13}$$

$$E_t\left(\theta \log\beta - \frac{\theta}{\psi}g_{t+1} + (\theta-1)r_{m,t+1} + r_{i,t+1}\right) + \frac{1}{2}V_t\left(\theta \log\beta - \frac{\theta}{\psi}g_{t+1} + (\theta-1)r_{m,t+1} + r_{i,t+1}\right) = 0. \tag{14}$$

The relevant state variables in solving for the equilibrium price-dividend ratio are x_t and v_t. We follow Bansal and Yaron (2004)'s approximate solution method (in order to derive closed-form solution) and conjecture the logarithm of the price-dividend ratio, $z_t = A_0 + A_1x_t + A_2v_t$. We substitute this conjecture into the log market return equation, $r_{m,t+1} = \Delta d_{t+1} + k_0 + k_1z_{t+1} - z_t$, and then to the Euler equation equivalent expression in Equation (14). As the Euler condition must hold for all values of the state variables, it follows that all terms involving x_t

and v_t must satisfy these two conditions, respectively:

$$-\frac{\theta}{\psi} + \theta\left[\rho_{dx} + k_1 A_1 \rho_x - A_1\right] = 0, \tag{15}$$

$$\theta(k_1 A_2 \rho_v - A_2) + \frac{1}{2}\left[-\frac{\theta}{\psi} + \theta\sigma_{dg} + \theta\, k_1 A_1\left(\sigma_{xg} + \sigma_{xFP}\sigma_{FPg}\right)\right]^2 = 0. \tag{16}$$

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

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

$$A_1 = \frac{\rho_{dx} - \frac{1}{\psi}}{1 - k_1\rho_x} = 33.3576 > 0. \tag{17}$$

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

$$A_2 = \theta\frac{\frac{1}{2}\left[-\frac{1}{\psi} + \sigma_{dg} + k_1 A_1\left(\sigma_{xg} + \sigma_{xFP}\sigma_{FPg}\right)\right]^2}{1 - k_1\rho_v} < 0. \tag{18}$$

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

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

Lastly, A_0 is implicitly defined in closed-form.

5.4. Equity risk premium and contemporaneous log market returns

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

$$
\begin{aligned}
E_t\left(r_{m,t+1} - rf_t\right) + \frac{1}{2}V_t(r_{m,t+1}) &= -Cov_t(m_{t+1}, r_{m,t+1}) \\
&= \underbrace{\left[\frac{\theta}{\psi}\left(\sigma_{dg} + k_1 A_1(\sigma_{xg} + \sigma_{xFP}\sigma_{FPg})\right) + (1-\theta)\left(\sigma_{dg} + k_1 A_1(\sigma_{xg} + \sigma_{xFP}\sigma_{FPg})\right)^2\right]}_{\equiv B_{erp}(\sigma_{FPg})} v_t \\
&\quad + (1-\theta)\left[\sigma_d^2 + (k_1 A_1 \sigma_x)^2 + (k_1 A_1 \sigma_{xFP}\sigma_{FP})^2 + (k_1 A_2 \sigma_v)^2\right]. \qquad (19)
\end{aligned}
$$

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

$$
\begin{aligned}
r_{m,t} &= \Delta d_t + k_1 z_t - z_{t-1} + k_0, \\
&= constant + \left[\rho_{dx} + k_1 A_1 \rho_x - A_1\right] x_{t-1} + \left[k_1 A_2 \rho_v - A_2\right] v_{t-1} \\
&\quad + \underbrace{\left[\sigma_{dg} + k_1 A_1\left(\sigma_{xg} + \sigma_{xFP}\sigma_{FPg}\right)\right]}_{\equiv B_r(\sigma_{FPg})\ ①} \sqrt{v_{t-1}}\varepsilon_{g,t} \\
&\quad + \sigma_d \varepsilon_{d,t} + k_1 A_1 \sigma_x \varepsilon_{x,t} + \underbrace{k_1 A_1 \sigma_{xFP}\sigma_{FP}}_{③} \varepsilon_{FP,t} + \underbrace{k_1 A_2 \sigma_v}_{②} \varepsilon_{v,t}. \qquad (20)
\end{aligned}
$$

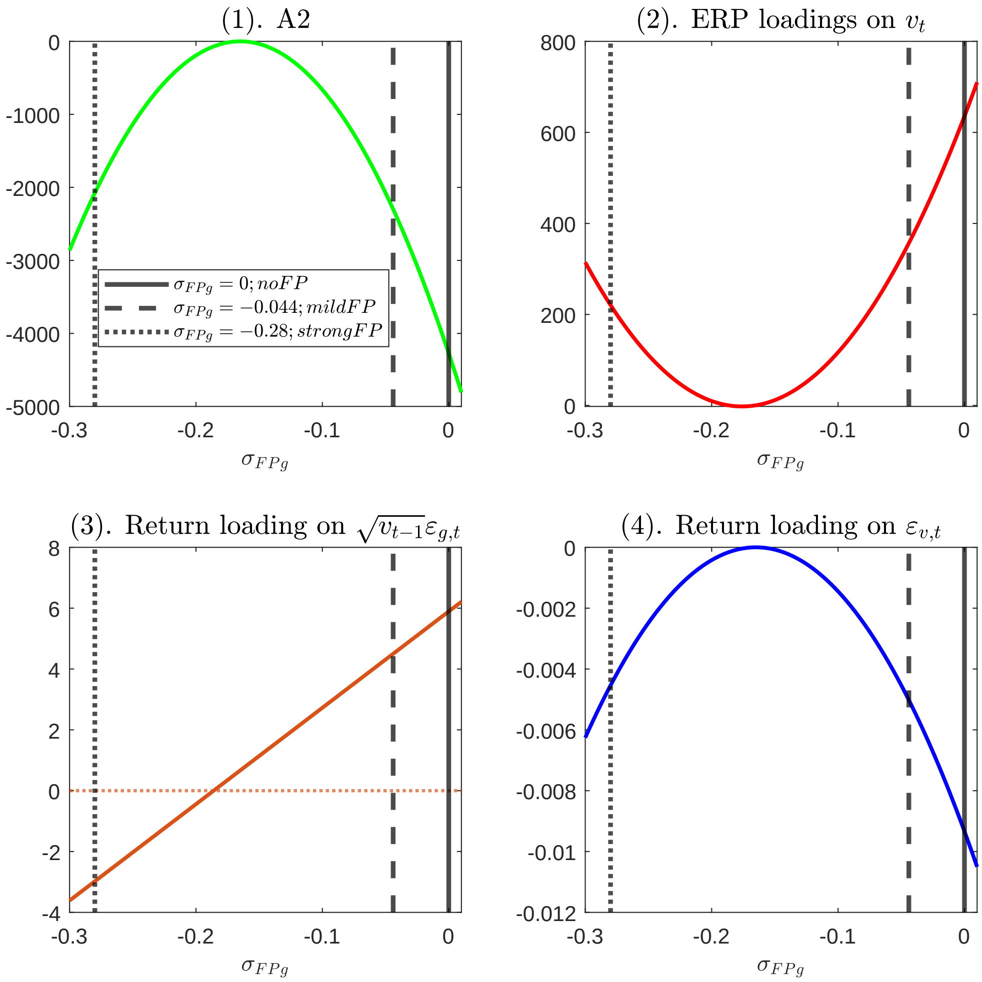
Next, let's focus on how the *fiscal policy* plays a role in the equilibrium log market return. In a world without the fiscal rule, when a bad output news $\varepsilon_{g,t}$ arrives (which is probably also accompanied with positive $\varepsilon_{v,t}$), increasing risk premium and lower expected future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

- ***First, expected cash flow channel.*** "①" in Equation (20) demonstrates that, fiscal policy could counteract the conventional positive relationship between expected growth (x_t) and price-dividend ratio (z_t), as $\sigma_{xFP}\sigma_{FPg} < 0$ and $\sigma_{xg} > 0$. As a result, fiscal policy could alter the sign of return loadings on growth news, potentially resulting in "bad is good" scenario as we observe in the empirical evidence of the present research. The effect should increase monotonically with the magnitude of σ_{FPg}.
- ***Second, risk premium channel.*** "②" in Equation (20) demonstrates changes in market prices coming from risk premium, and as closed-form solution above shows that A_2 is a non-linear function of σ_{FPg}. From Equation (19), fiscal policy could have a non-linear effect on the market compensation for stochastic volatility risk, via the long-run risk channel. To understand this risk premium channel better, we simulate the relation between $B_{erp}(\sigma_{FPg})$ and σ_{FPg} using Bansal and Yaron (2004) parameter choices; we discuss more in Section 5.5 below. Overall, the market compensation for volatility risk is always positive, given realistic parameter choices. The relation initially decreases when there is a

mild fiscal rule (when σ_{FPg} moving from 0 to a small negative number), precisely due to the counteracting effect in the expected growth channel; however, it eventually increases when there is a very strong fiscal rule (when σ_{FPg} becomes very negative), as the fiscal policy introduces large increases in expected growth and agents demand compensations for volatility risk.

- ***Third, discretionary fiscal shock.*** "③" in Equation (20) shows a discretionary fiscal policy shock that is orthogonal to the fiscal rule in response to the changing macro condition. Given the parameter signs, an unexpected government spending shock drives up stock prices given the higher expected cash flows.

5.5. Calibration



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

Plot (1) above shows that price decreases with volatility, as A_2 is always negative given a wide spectrum of σ_{FPg}. Starting from $\sigma_{FPg} = 0$ to its left, the fiscal rule starts to counteract with the volatility risk in the expected growth channel, leading to a smaller A_2 (in magnitude), a lower equity risk premium loading on v_t (as in Plot (2)), and a smaller return loading on volatility shock (as in Plot (4)). As the fiscal rule becomes more aggressive, the "strong FP" case arises, which is likely to closely represent what happened in handling the Covid-19 crisis – a bad macro news may trigger fiscal policy to respond so that the expected growth increases. The magnitudes of A_2, equity risk premium loading on volatility and return loading on volatility shock rebounce, through the higher risk compensation demanded given the high fluctuation fiscal policy may introduce to the economy. This rationalizes the **risk premium** channel, or referred to as the second channel Section 5.4. The covid implication is that the market compensation for stochastic volatility risk increases when a bad macro shock arrives, hence driving down the asset prices.

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

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

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

5.6. Cross-sectional implications

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

$$x^i_{t+1} = \rho^i_x x_t + \sigma^i_{xg}\sqrt{\upsilon_t}\varepsilon_{g,t+1} + \sigma^i_{xFP} FP_{t+1} + \sigma^i_x \varepsilon^i_{x,t+1}, \tag{21}$$

$$\Delta d^i_{t+1} = \mu^i_d + \rho^i_{dx} x^i_t + \sigma^i_{dg}\sqrt{\upsilon_t}\varepsilon_{g,t+1} + \sigma^i_d \varepsilon^i_{d,t+1}, \tag{22}$$

For our paper, we focus on one particular heterogeneity source: there may be firm-level σ^i_{xFP}, capturing potentially different firm-level pass-through of the fiscal rule. Following the intuition in Equation (20), one can prove that firms with higher sensitivity to the country fiscal rule should exhibit a higher chance to offset the standard dividend growth and long-run risk effects of macro news on their stock prices, hence resulting in a less positive or more negative coefficient in response to macro news.

6. External Validation: Monthly Macro Announcement Surprises

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

Table 13 shows the correlation coefficients between seven mainstream monthly macro surprises (constructed from their respective announcement days) and daily, open-to-close S&P500 returns,[31] 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 arrives (i.e., higher-than-expected unemployment rate and/or lower-than-

[31] Given that different macro variables may be released at different times of 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.)

expected changes in non-farm payrolls), daily stock return response is significantly less negative and more positive during the Covid period than it normally is. 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. In the other hand, its normal-period counterpart is typically found to be statistically insignificant around zero, partially due to the rounded 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 cause lower stock returns, but during Covid could cause higher stock returns. From Panel B, bad news about manufacturing, consumption or consumer confidence indicators normally would normally decrease stock returns significantly 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 – where macro announcements possibly 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 variables such as CPI changes and industrial production growth. Both should be quite informative about conventional monetary policy. Although the correlation coefficients are all statistically insignificant and economically less clear, these two variables seem to draw an opposite effect: bad news about the economy could decrease stock returns, yielding a positive coefficient.

7. 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. The phenomenon (a) appears only when bad news arrives, (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", which could be difficult for existing theories to reconcile and hence calls for a new explanation. 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 financial data, survey data, textual analysis, and cross-sectional evidence. 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 the cross-section, during periods with high fiscal policy expectation, firms/industries that are expected to receive more fiscal support show *higher* individual stock returns when bad IJC surprises arrive. We test it during the

Covid period and sort firms based on several fundamental firm Covid-impact measures (e.g., labor, revenue). Our external validations examine stock return responses to seven mainstream monthly macro announcement surprises, and find that those macro variables that likely paint a health report on Main Street households – employment, manufacturing and retail sales news – show such a phenomenon.

Moving forward, in a post-Covid era, interest rates will likely be constrained and stay at 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 incorporating fiscal policy expectation into pricing, even before Covid. The Covid crisis triggered an unprecedented adverse shock to the labor market, which helps unveil this new mechanism in a more salient fashion, as investors put an unprecedented weight on government responses. Future research should further examine the role of fiscal policy expectation in the financial market, which may be a novel form of the Federal Government intervening in the market.

Finally, we want to raise our concern that fiscal policy in this economy with constrained interest rates may exacerbate the "big disconnect" between the real economy and the financial market — ultimately, Wealth Inequality. Indeed, fiscal spending can be effective in helping get workers employed. However, the unexpected side effect is worth noting. Fiscal spending can also benefit those who are wealthy through the stock prices if investors believe government will stimulate the economy, particularly when the labor forces suffer – which is what we document in this paper. In dollar terms, from February 2020 to March 2021 (end of our sample), the average daily capital gain in the S&P500 market is 72.6 million dollars on bad IJC days, 17.5 million dollars on good IJC days and 44.2 million dollars on non-IJC days. In comparison, the average daily market capital gain from 2000 to 2019 is 2.1, 7.9 and 1.5 million dollars on bad, good, and non-IJC days, respectively (Appendix Table A13). Optimal fiscal policy and its communication should be more discussed in future studies.

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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 IJC_t indicates the actual initial claims from last week (ending Saturday) released by Employment and Training Administration (ETA) on Thursday of current week t, and $E_{t-\Delta}(IJC_t)$ indicates the median survey forecast submitted until shortly before the announcement at time $t - \Delta$. Both actual and expected claims are obtained from Bloomberg. Summary statistics using $IJC_t - E_{t-\Delta}(IJC_t)$ are reported in Appendix 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. We exclude identified IJC outlier days (3/19/2020, 3/26/2020, and 4/2/2020).

	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 and risk variables respond to macro shocks?

This table reports the responses of various asset prices and risk variables to IJC shocks on the announcement day during 5 non-overlapping periods. 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 (2021a). Row "IJC shock" shows the coefficients, with robust standard error, t-statistics and R-squared displayed in following rows; "SD chngs per 1SD shock" shows the standard deviation (SD) changes in the LHS variable given 1 SD IJC shock. 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: Pricing channels.

This table decomposes the unexpected part of log market returns (or market news) into changes in expectations of future cash flow growth ("NCF", or cash flow news) and changes in expectations of future discount rate ("NDR", or discount rate news). Our detailed construction method is written in Appendix B; in short, we estimate monthly parameter estimates of the Campbell and Vuolteenaho (2004) framework using monthly data from the past 30 years (1982-2021), and then we impute daily measures using daily data and these parameters. By design, NCF minus NDR yield the total unexpected return. 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 and asymmetry of this "Main Street pain, Wall Street gain" phenomenon. 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 (30=industrial; 20=transportation; 15=utility) 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 provides intradaily return responses of E-mini S&P 500 futures on IJC shocks. Intradaily returns (in basis points) are calculated using the same start time of 8AM Eastern Time and an end time of interest (from left to right): pre-announcement, 8:25AM ET; shortly after the announcement, 8:35AM ET; noon, 12:30PM ET; shortly before the close, 3:30PM ET. The left four columns display results using Period 3, which is a generally normal period with the majority of the time at the zero lower bound; the right four columns use Period 5, "Covid" period; period dates are detailed in Table 1. Row "Closeness (Covid-normal)?" provides t-statistics of whether the "Covid" coefficient is higher than the "normal" coefficient, with bold indicating significant t-statistics. High-frequency futures data are from TickData. See other 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 provides intradaily return responses of E-mini Dow futures on IJC shocks. See other tables notes in Table 5.

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 do people talk about on IJC announcement days?

This table complements Figure 5 and provides exact relative topic mentioning values in six non-overlapping subsamples from 2013-2021 (given the availability of manually-collected CNBC news articles on IJC announcement days). Each subsample has (around) 60 weeks each; block "All days" uses all 60 weeks to compute topic mentioning, and block "Bad days" ("Good days") uses bad (good) IJC days within the same 60-week subsample. **Panel A** reports text mentioning relative to the first subsample in 2013-2014. Five topics are considered; standard errors are reported in parentheses, and the closeness test examines whether this value equals 1 (***, p-value <1%; **, <5%; *, <10%). Figure 5 provides a continuous version of bad and good relative mentioning. **Panel B** provides the t statistics of whether the relative mentioning of the same topic during bad days is the same as that during good days (i.e., the higher the *t*, the higher relative mentioning in bad bays; 2.28** in row "Fiscal policy" means that 2.013*** from bad IJC days is significantly higher than 1.242 from good IJC days). **Textual data:** The original news articles are manually obtained from www.cnbc.com/jobless-claims/; see details of textual analysis in Section 3 and Appendix C.

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

Table 8: Relationship between return responses and topic mentions from rolling windows.

This table examines the relationship between return responses to IJC shocks and topic mentions using rolling windows of 40 bad IJC days in Panel A and 40 good IJC days in Panel B. Three return responses are considered – rolling S&P 500 return coefficient, rolling S&P 500 economic magnitude (SDs changes in return given 1 SD IJC shock), and rolling Dow Jones 65 return coefficient. Each variable of topic mentions (fiscal policy "FP", monetary policy "MP", uncertainty "UNC"; see Section 3.1 for topic mention calculation) is standardized in these regressions, for interpretation purpose; Newey-West standard error (Newey and West (1987)) and the number of SD changes in return responses given 1 SD topic mentions are reported as well. Appendix Table A7 provides more robustness tests. ***, p-value <1%; **, <5%; *, <10%.

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

Table 9: Mechanism and quarterly state variables.

This table reports the following regression results:

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

where t and τ denote weekly and quarterly frequency, respectively, y stock returns (in basis points) and Z a standardized state variable of interest. The first three state variables are textual mentions using articles within the same quarter (fiscal policy "FP", monetary policy "MP", uncertainty "UNC"); with the same textual analysis methodology as mentioned before, we use all bad (good) days within the quarter and obtain a quarterly bad (good) measure. Next, we consider the difference between one-quarter-ahead forecast and nowcast of the 3-month Treasury bill rate ("$\Delta Tbill3m$") and recession probability ("$\Delta Recess$"), where both forecast and nowcast are provided given last quarter information set (source: Survey of Professional Forecasters, or SPF). Time series of all quarterly state variables are shown in Figure 7; due to news file availability, sample runs from 2013Q1 to 2021Q1; correlation table is shown in Appendix Table A8. ***, p-value <1%; **, <5%; *, <10%.

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

Table 10: Mechanism comparisons.

This table builds on Table 9 and includes multiple quarterly state variables and their shock interactions in one framework. We drop quarters when textual UNC mentions are missing. The appendix provides two more robustness evidence: using pre-2020 data only (Table 11); more results using S&P500 (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: Mechanism comparisons: pre-2020 results

This table replicates Table 10 using the 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 12: Cross section evidence: Relationship between firm stock return responses to IJC shocks and firm Covid impact measures.

This table uses economic magnitude (SD changes in returns given 1 SD IJC shock) as our main return response DV so that it can be used to compare across firms; sample uses IJC announcement days from February 2020 to March 2021 (excluding outliers 03/19, 03/26, 04/02/2020, FOMC overlaps, and an unconventional policy day 04/09/2020); we are able to identify 491 out of S&P500 with our Covid impact measures. **Firm/industry-level Covid impact measures:** (1) changes in the number of all-internet job postings, e.g. -0.8 would mean that firm job postings decreased by 80% between 2019 and April/May of 2020; (2) employment changes from fiscal year (FY) 2019 to FY 2020; (3) revenue changes from 2019Q2 to 2020Q2; (4) Earnings per share (EPS) first differences between 2019Q2 and 2020Q2; (5) is (1) but firms are merged using 2-digit NAICS-level values; (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 (source: LinkUp), and the rest are from Compustat Annual and Compustat Quarter (source: WRDS). Overall, the lower the measure, the larger the initial impact a firm/industry experienced. **Panels:** Panel A considers ranks of changes for (2)-(4) given potential skewness for these change variables (see Appendix Table A10); in Panel B, 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 13: 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). **Macro announcements:** The table focuses on 7 mainstream macro announcements: Panel A, employment; Panel B, manufacturing, consumption, consumer confidence; Panel C, other general macroeconomy and monetary policy indicators. All actual and forecast median data are obtained from Bloomberg. Discussions are included in Section 6. Appendix D provides the corresponding figures. Note that we drop macro data corresponding to March 2020 (abnormal underestimation of the Covid impact) and May 2020 (abnormal underestimation of the rebounce) – both can be identified as outliers using box plot-IQR analysis. **Columns:** Column (1) shows the sign of 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	

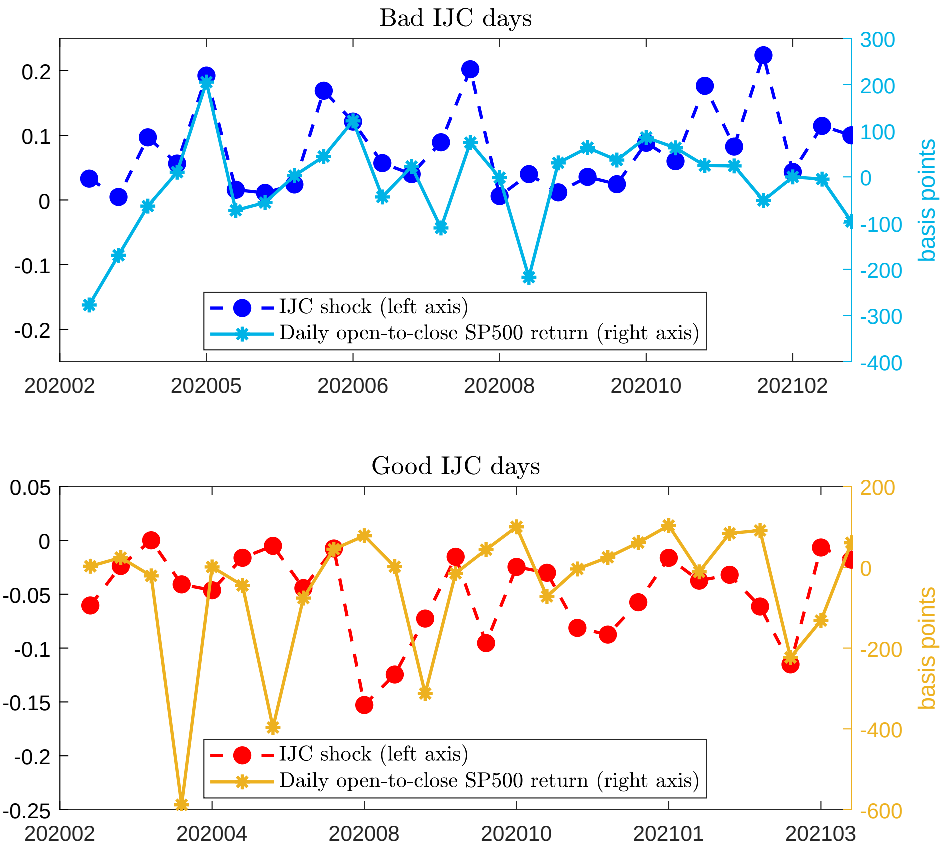


Figure 1: Relation between daily open-to-close S&P500 returns and IJC shocks during Covid (period 5). Excluding IJC shock outliers (2020/3/19, 3/26, 4/2), FOMC days, and other major Federal Reserve announcement (2020/4/9).

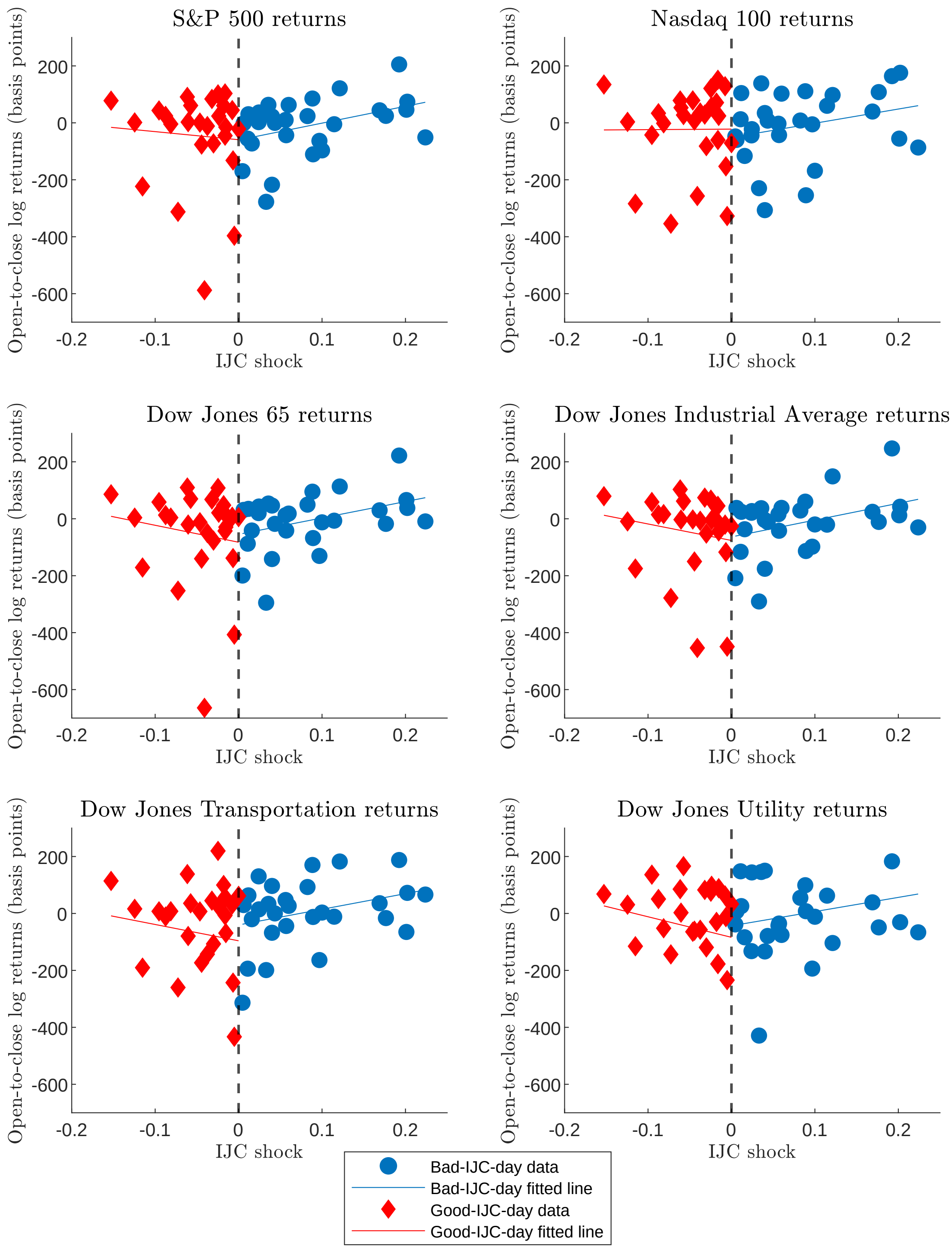


Figure 2: Relation between various daily open-to-close stock returns and IJC shocks during Covid (period 5). Excluding IJC shock outliers (2020/3/19, 3/26, 4/2), FOMC days, and other major Federal Reserve announcement (2020/4/9).

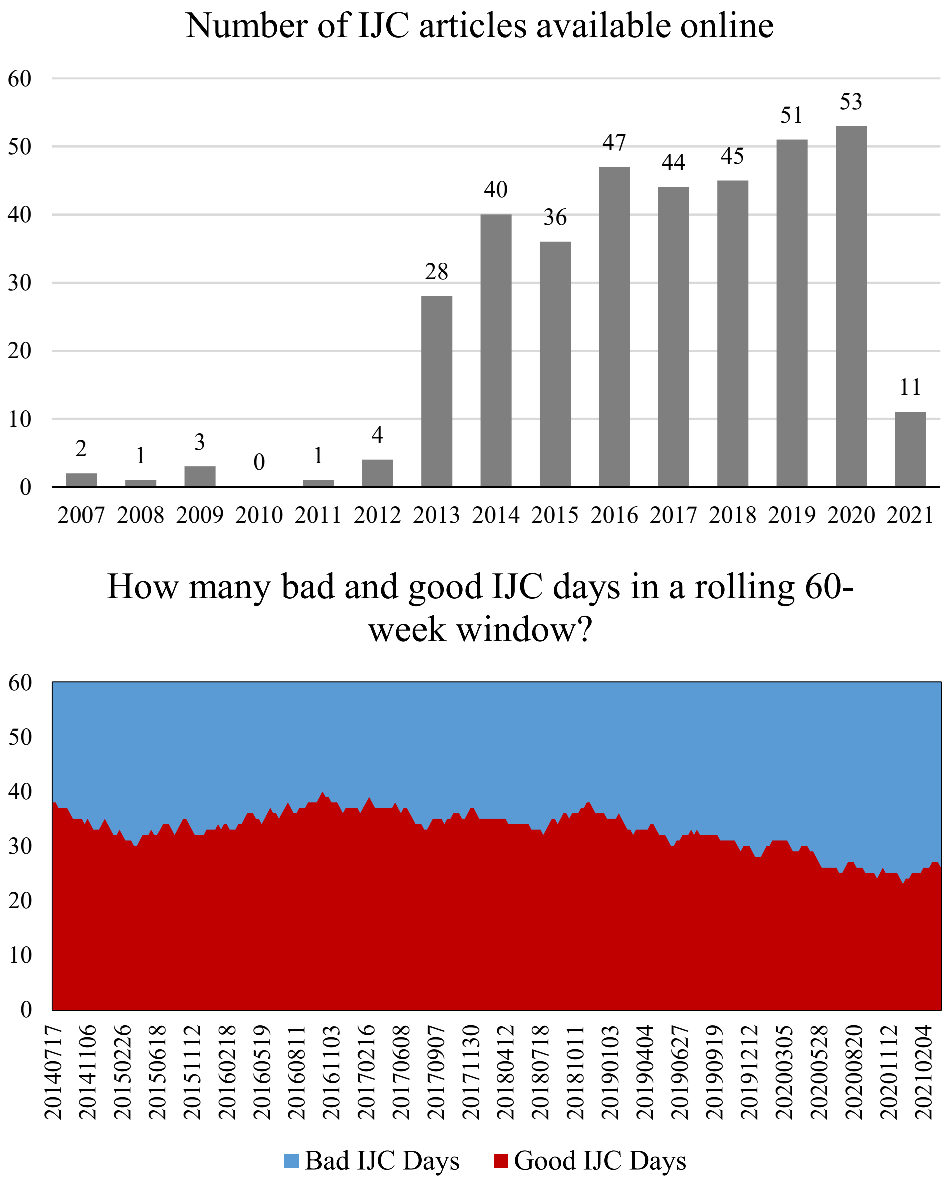


Figure 3: Summary of manually-collected CNBC jobless claim articles, until the IJC announcement date on 2021/3/18 (end of our sample); source: https://www.cnbc.com/jobless-claims/. Data collection process is described in Appendix C. Top plot: number of articles each year; bottom plot: take a rolling 60-week window (time stamp=last day of the rolling window) and calculate the number of articles with bad IJC surprises (blue) and good IJC surprises (red). The last 60-week rolling window is from 20200130 (exclude) to 20210318 (include).

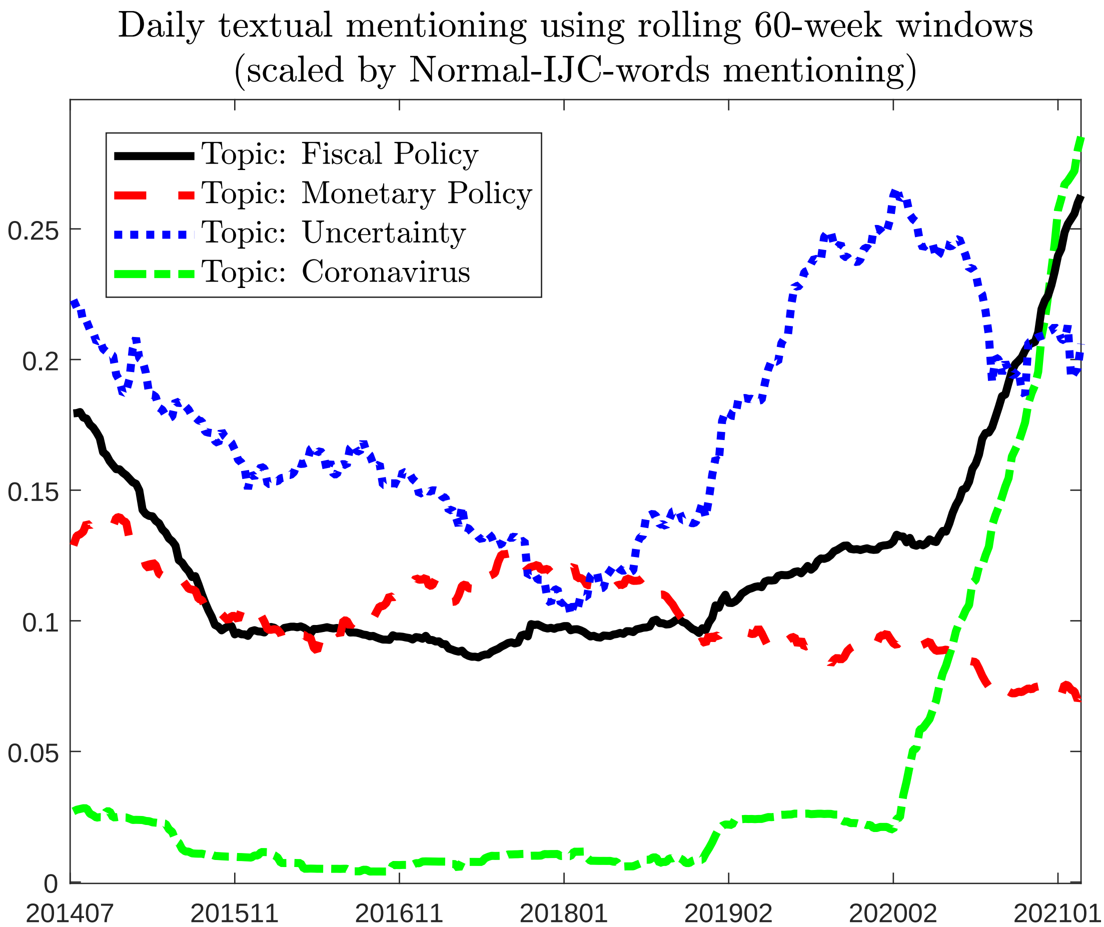


Figure 4: What do people talk about on IJC announcement days? This figure shows the topic mentions obtained from rolling 60-week windows, where the four topic mentions are scaled by the mentions of normal IJC words (see Appendix C for more details). The "0.2" in the y-axis can be interpreted as this topic is likely mentioned about 20 times per 100 times normal IJC words are mentioned. The datestamp always refers to the last day of the rolling window.

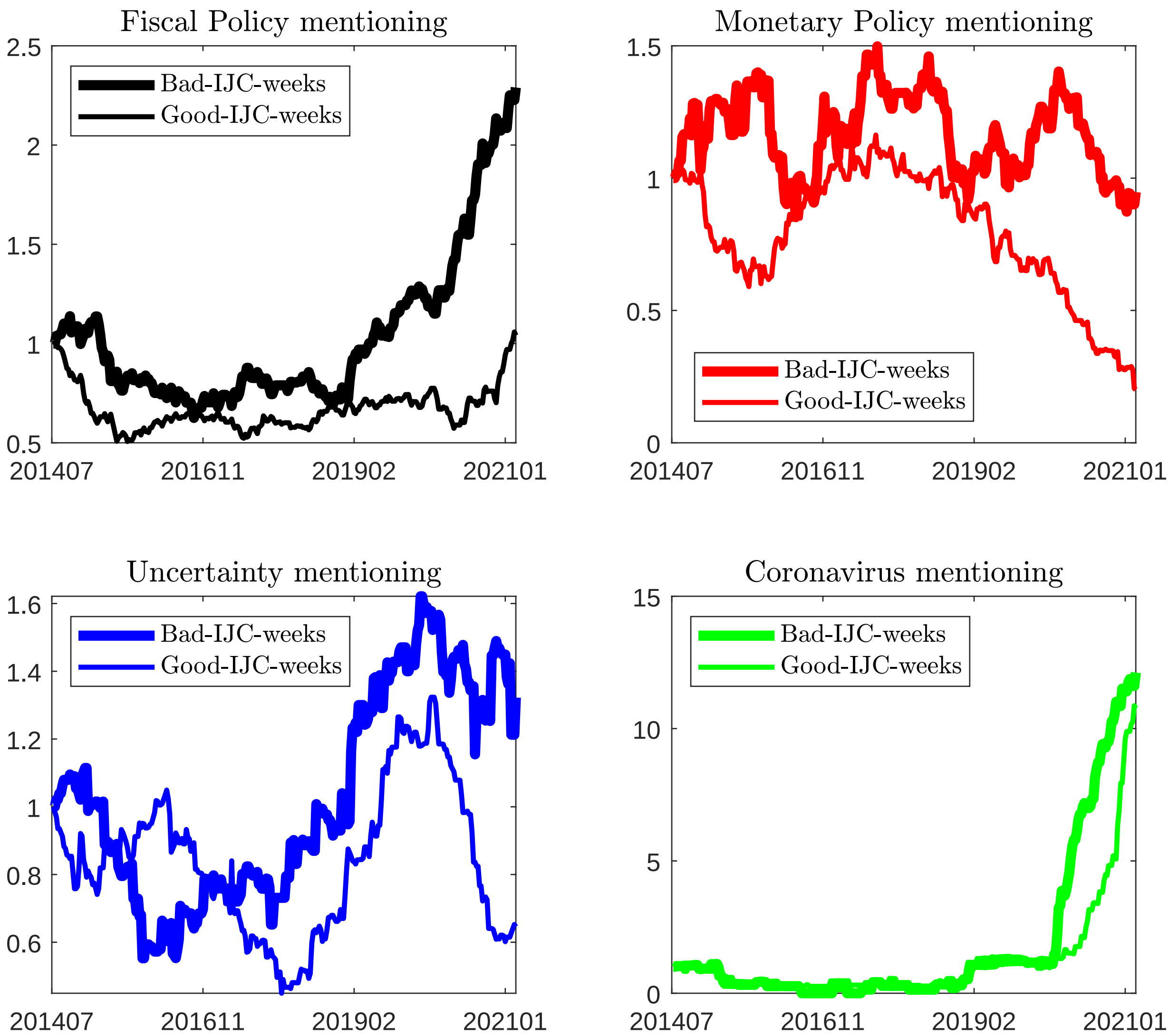


Figure 5: What do people talk about on "bad" and "good" IJC announcement days? This table complements Figure 4 and shows the relative topic mentions on bad (thick lines) and good (thin lines) IJC days within the same 60-week rolling window. Here, for interpretation purpose, each line is scaled with the first value in its series, as in Table 7. The "1.5" means that the mentions of this topic during (e.g.) bad days are 50% higher than at the beginning of the sample. The datestamp always refers to the last day of the rolling window.

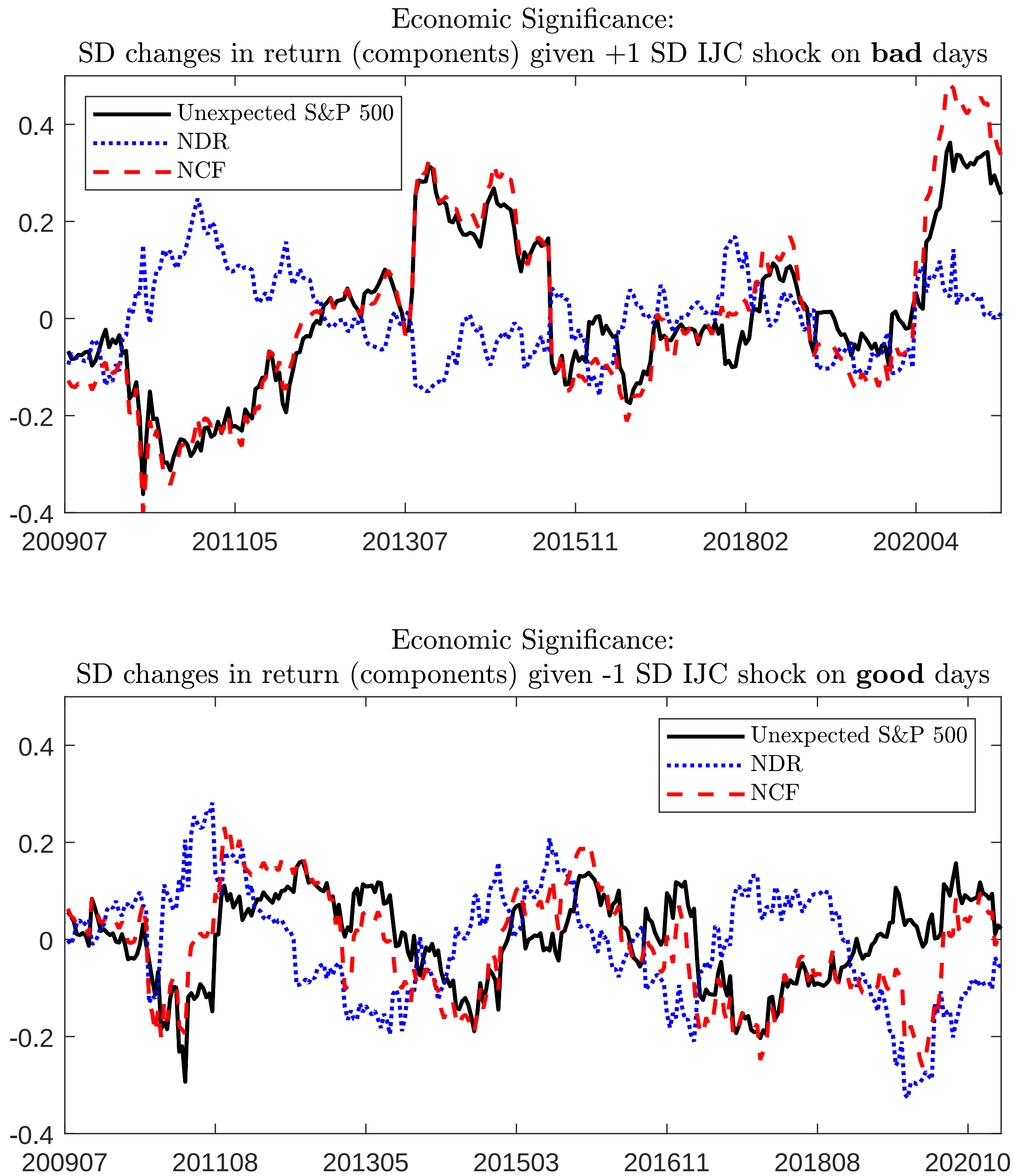


Figure 6: Depicting the economic significance of the rolling return (component) coefficients on IJC shocks, on bad and good days, respectively. Rolling window is always 40 consecutive bad or good IJC weeks, to be consistent with Table 8. The datestamp always refers to the last day of the rolling window. Top plot: if "bad is bad", risky asset returns should *drop* given +1SD IJC shock (jobless claims are higher/worse than expected); bottom plot: if "good is good", risky asset returns should *increase* given -1SD IJC shock (jobless claims are lower/better than expected). [61]

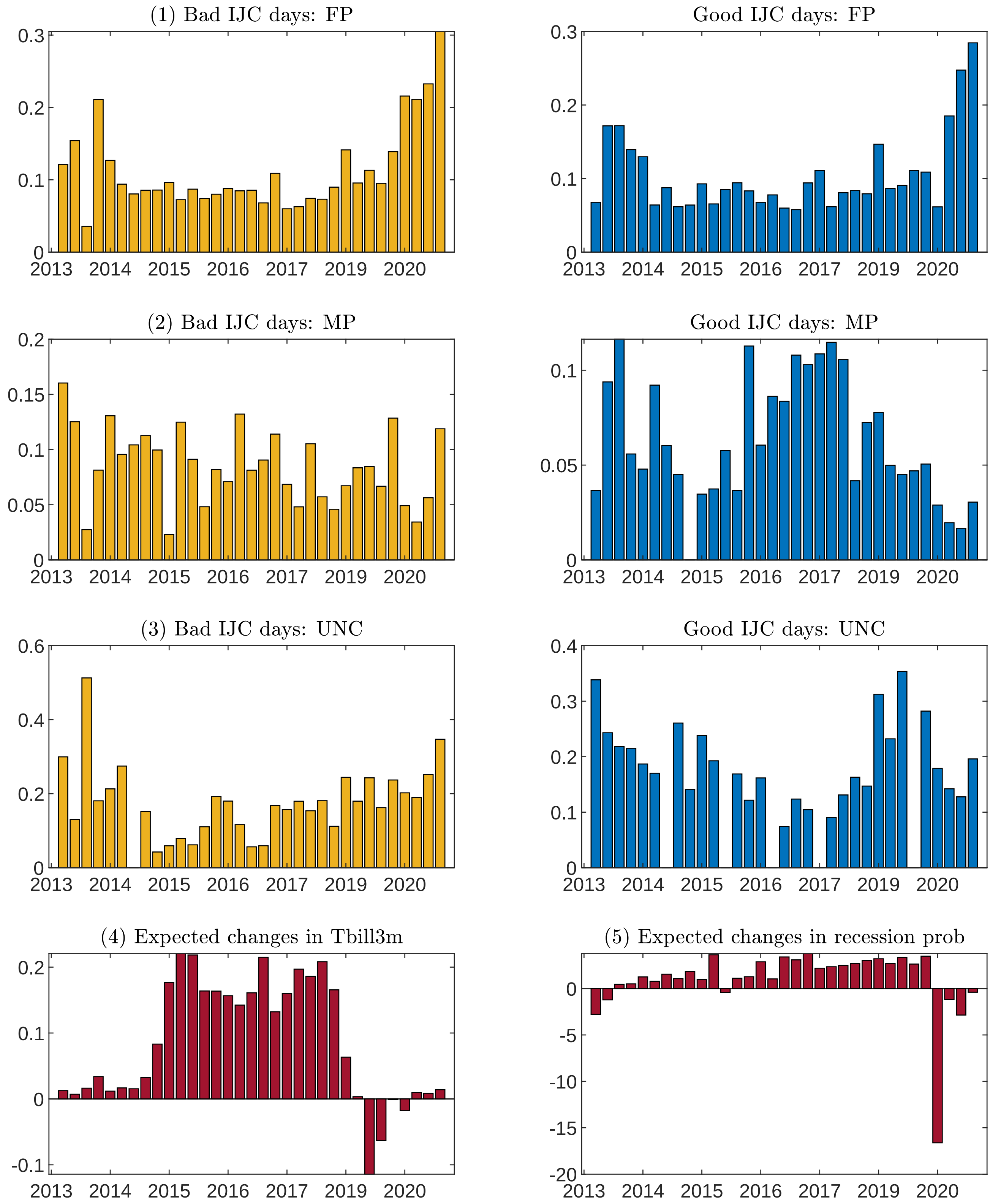
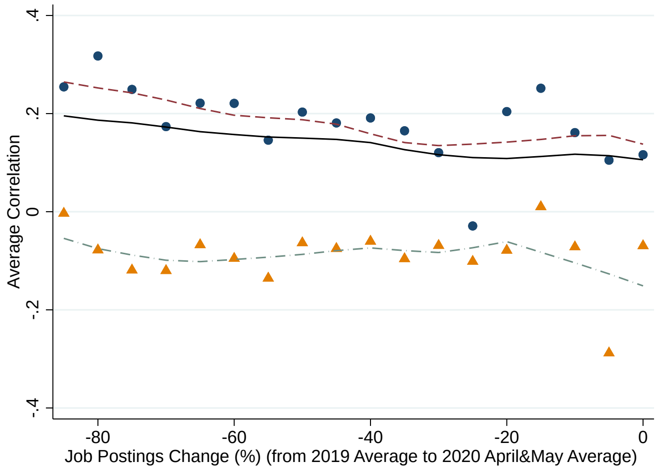
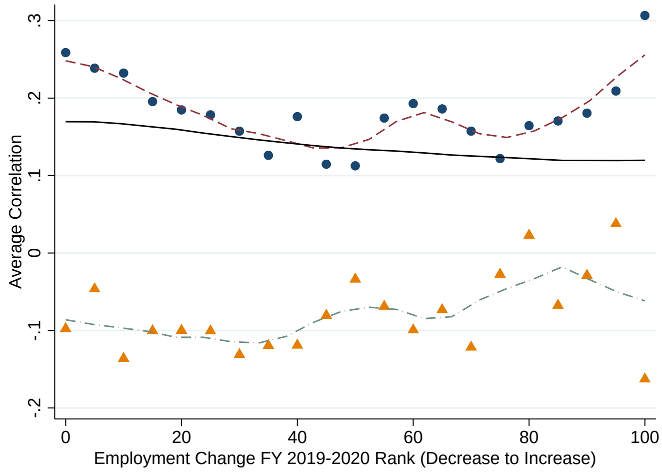


Figure 7: Quarterly state variables.

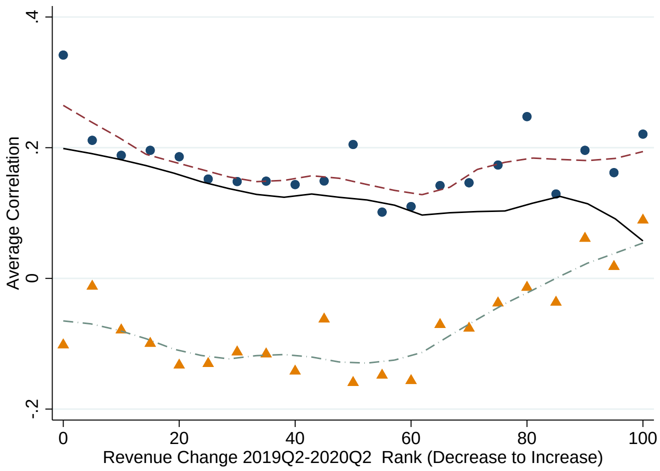
This figure depicts our non-overlapping quarterly topic mention state variables, scaled by the score of normal IJC words, in (1)-(3), and expected changes in T-bill rates and recession probability, in (4)-(5). Sources are CNBC and author calculation for the top six plots (first three rows), and the Survey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



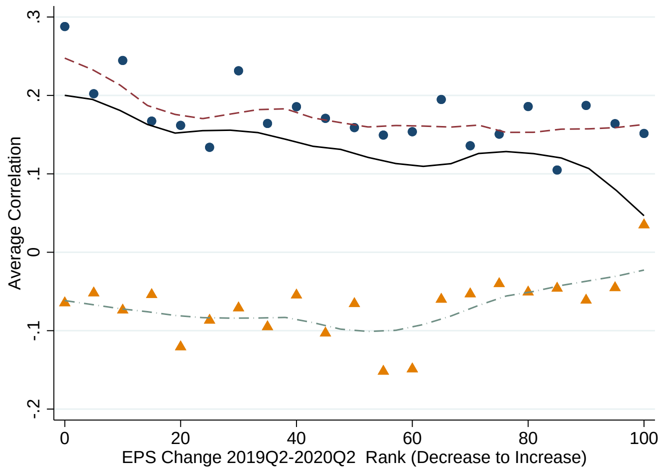
(a)



(b)



(c)



(d)

Figure 8: Cross-section evidence: Bad (circles) vs Good (triangles) IJC days

This figure shows the relationship between four "firm Covid impact" measures (x-axis) and firm return reactions to IJC shocks (y-axis) calculated using all (kernel lines shown in solid line), bad (blue circles), and good (orange triangles) IJC days. We group all firms (491 out of 500 S&P 500 firms) into 20 bins (5% each). Firms that suffer more (i.e., moving more towards left of the x-axis) show stronger "Main Street pain, Wall Street gain" phenomenon (captured by higher SD changes in individual stock returns given 1 SD IJC shock). The x variable in Figure (a) is the changes in the number of all-internet job postings, where "-80" indicates that for job postings decreased by 80% between 2019 and April/May of 2020. The x variables in Figures (b)-(d) are ranks of employment change, revenue change, and Earnings per share (EPS) change, respectively; employment change compares 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, and results using actual changes are robust and are shown in Table 12.

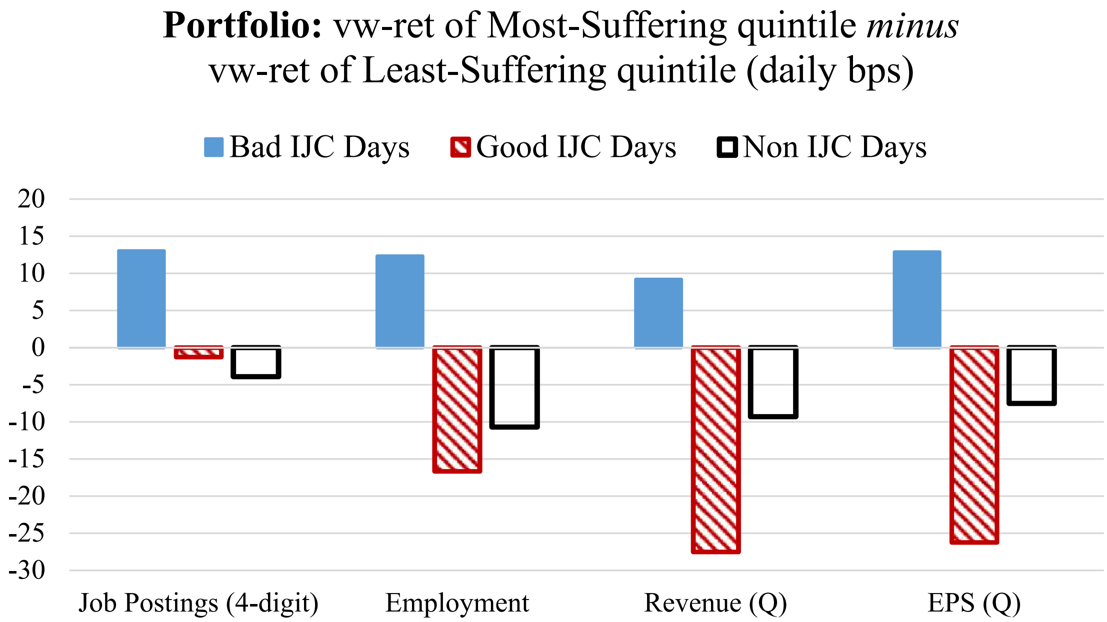


Figure 9: Investment strategy

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 12: (1) changes in the number of all-internet job postings (LinkUp; authors' calculation), (2) employment changes from FY 2019 to FY 2020 (Compustat), (3) revenue changes from 2019Q2 to 2020Q2 (Compustat), (4) EPS changes from 2019Q2 to 2020Q2 (Compustat). Step 2: We call the 1st (5th) 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 the actual IJC number is higher/worse than expected), good IJC days (when the actual IJC number is lower/better than expected), and non-IJC days. Returns refer to daily open-to-close stock returns in basis points; sample period runs from February 2020 to March 2021 (end of the sample) excluding 03/19, 03/26, 04/02, 04/09 of 2020 and FOMC overlaps. Robustness using equal weights, using alternative Covid-impact proxies, and including these four dates are shown in Figure A5 in the appendix.

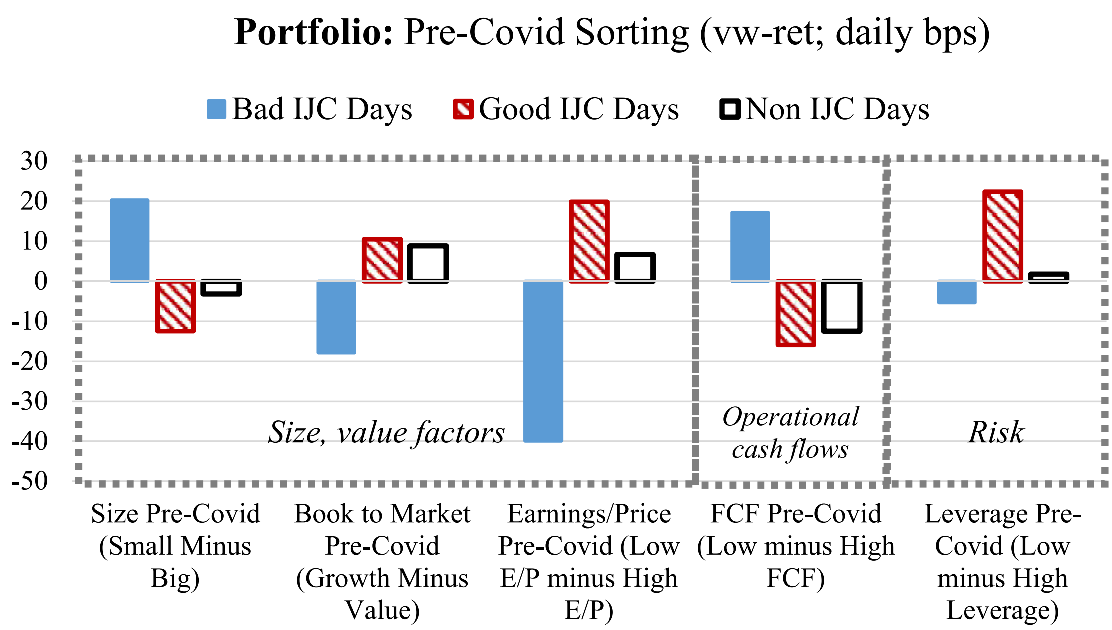


Figure 10: How do standard size, BM, EP portfolios perform?

We sort S&P500 firms into 5 bins based on firms' end-of-2019 characteristics: (1) standard size and value factor (B/M, E/P); (2) free cash flows (FCF=operating cash flow (OANCF)-gross capital expenditures (CAPX)); (3) risk (leverage=(long-term debt+short-term debt)/share holder equity). The portfolio takes the return difference between the lowest (lowest-size, lowest-BM, lowest-EP, lowest-FCF, lowest-leverage) and the highest quintile bins. Within each quintile, average returns can be calculated using bad IJC days (when the actual IJC number is higher/worse than expected), good IJC days (when the actual IJC number is lower/better than expected), and non-IJC days. Returns refer to daily open-to-close stock returns in basis points; sample period runs from February 2020 to March 2021 (end of the sample) excluding 03/19, 03/26, 04/02, 04/09 of 2020 and FOMC overlaps. Other robustnesses 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: 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). It is consistent with our story that results using Nasdaq futures are a bit weaker, as growth stocks are in general less exposed to cash flow risk. See other table details in Table 5. ***, 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 A3: High-frequency evidence using interest rate futures and VIX futures (risk proxies)

This table complements Tables 5 and 6 and tests whether the main "Bad IJC day" results in stock futures coincide with discount-rate-related asset prices (interest rate and VIX futures). Data sources at As in Table A2, 2020/4/9 (Thursday) is also dropped. Panel A uses log changes in the 10-year Treasury note futures prices (ticker symbol ZN); Panel B uses first differences in the 30-day Fed Fund futures (ticker symbol ZQ), as the index is directly related to (the inverse) Effective Fed Funds Rate; Panel C uses first differences in the VIX futures (ticker symbol VX); all are traded on the Chicago Mercantile Exchange (CME). See other table details in Table 6. ***, 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. 10-year Treasury Note Futures (LHS: returns in basis points); Bad IJC days								
IJC shock	9.928	58.874**	50.651	103.110	7.338	9.611	49.452	19.164
(SE)	(12.628)	(28.938)	(54.313)	(68.489)	(11.704)	(12.704)	(33.426)	(35.277)
[t]	[0.786]	[2.034]	[0.933]	[1.506]	[0.627]	[0.757]	[1.479]	[0.543]
SD chngs per 1SD shock	0.049	0.147	0.065	0.102	0.123	0.139	0.226	0.082
Closeness (Covid-normal)?					-0.15	-1.56	-0.02	-1.09
Panel B. 30-day Fed Fund Futures (LHS: first-differences$\times$100); Bad IJC days								
IJC shock	0.057	-0.251	0.255	0.206	0.011	0.011	-1.302	-2.808
(SE)	(0.259)	(0.196)	(0.410)	(0.479)	(0.451)	(0.451)	(2.189)	(3.326)
[t]	[0.219]	[-1.278]	[0.621]	[0.431]	[0.024]	[0.024]	[-0.595]	[-0.844]
SD chngs per 1SD shock	0.018	-0.068	0.045	0.032	0.005	0.005	-0.130	-0.187
Closeness (Covid-normal)?					-0.09	0.53	-0.70	-0.90
Panel C. VIX Futures (LHS: first-differences); Bad IJC days								
IJC shock coeff.	-0.130	0.071	1.174	1.022	0.414	1.152	-2.420	-5.820*
(SE)	(0.204)	(0.459)	(1.680)	(1.675)	(0.574)	(1.069)	(1.938)	(3.403)
[t]	[-0.636]	[0.155]	[0.699]	[0.610]	[0.721]	[1.078]	[-1.248]	[-1.710]
SD chngs per 1SD shock	-0.043	0.015	0.074	0.052	0.188	0.273	-0.207	-0.345
Closeness (Covid-normal)?					0.89	0.93	-1.40	-1.80

Table A4: 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 A5: Pricing channels.

This table complements Table 3 and considers the alternative IJC shock as well ($IJC_t - E_{t-\Delta}(IJC_t)$; see Table A1). The left panel uses Table 3's sample; the right panel uses the main IJC shock and a more restrictive sample without 2020/4/9 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 3. ***, p-value <1%; **, <5%; *, <10%.

		Unexpected return	**NCF**	**NDR**	**Unexpected return**	**NCF**	**NDR**
	Without:	*IJC 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 A6: "Bad is good": What assets, and When?

This table complements Table 4 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%.

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 A7: Relationship between return responses and topic mentions from rolling windows – More robustness results

This table complements Table 8 and shows 3 more robustness results, namely 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 mentions; using Dow Jones 65 open-to-close returns (rather than the S&P500 open-to-close returns).
- Robustness (4) here: using all IJC days.
- Robustness (5) here: dropping the 2020/4/9.
- Robustness (6) here: Using 30-IJC-day rolling windows to calculate both the rolling return responses to bad or good IJC shocks (LHS) and the rolling bad or good topic mentions (RHS). Table format follows Table 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 A8: Correlation among quarterly state variables in Tables 9 and 10. The "badX" means topic mentions of state variable X during bad IJC days only within the quarter (source: authors' construction). "$\Delta Tbill3m$" and "$\Delta Recess$" are the differences between one-quarter-ahead forecast and nowcast of the 3-month Treasury bill rate and recession probability, respectively, where both forecast and nowcast are provided given last quarter information set (source: Survey of Professional Forecasters, or SPF).

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 A9: 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 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 the 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

Table A13: Cumulative and average capital gain

This table calculates simple cumulative and average daily capital gains of S&P500 stocks on bad-, good- and non-IJC days during Covid period and a general non-Covid period. Average daily capital gain is cumulative/number of days. This table uses surprises that are economically sizable when calculating the average for better identification (i.e., actual-expectation $> 10K$ or $\leq -10K$, which according to Table A1 corresponds to around $> 75th$ or $\leq 25th$).

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

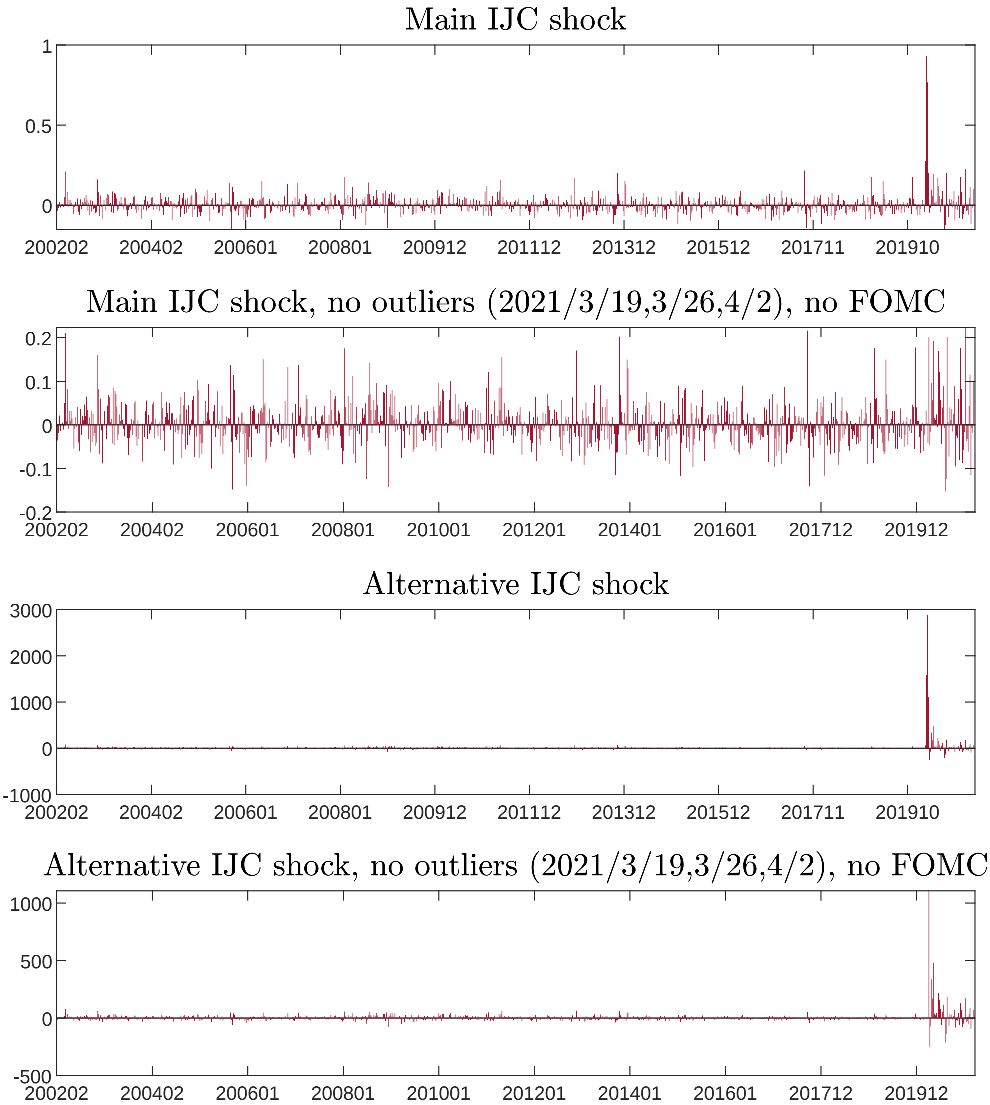


Figure A1: Time series of main IJC shocks ($\frac{IJC_t - E_{t-\Delta}(IJC_t)}{E_{t-\Delta}(IJC_t)}$) and alternative IJC shocks ($IJC_t - E_{t-\Delta}(IJC_t)$), with or without identified outliers and FOMC days.

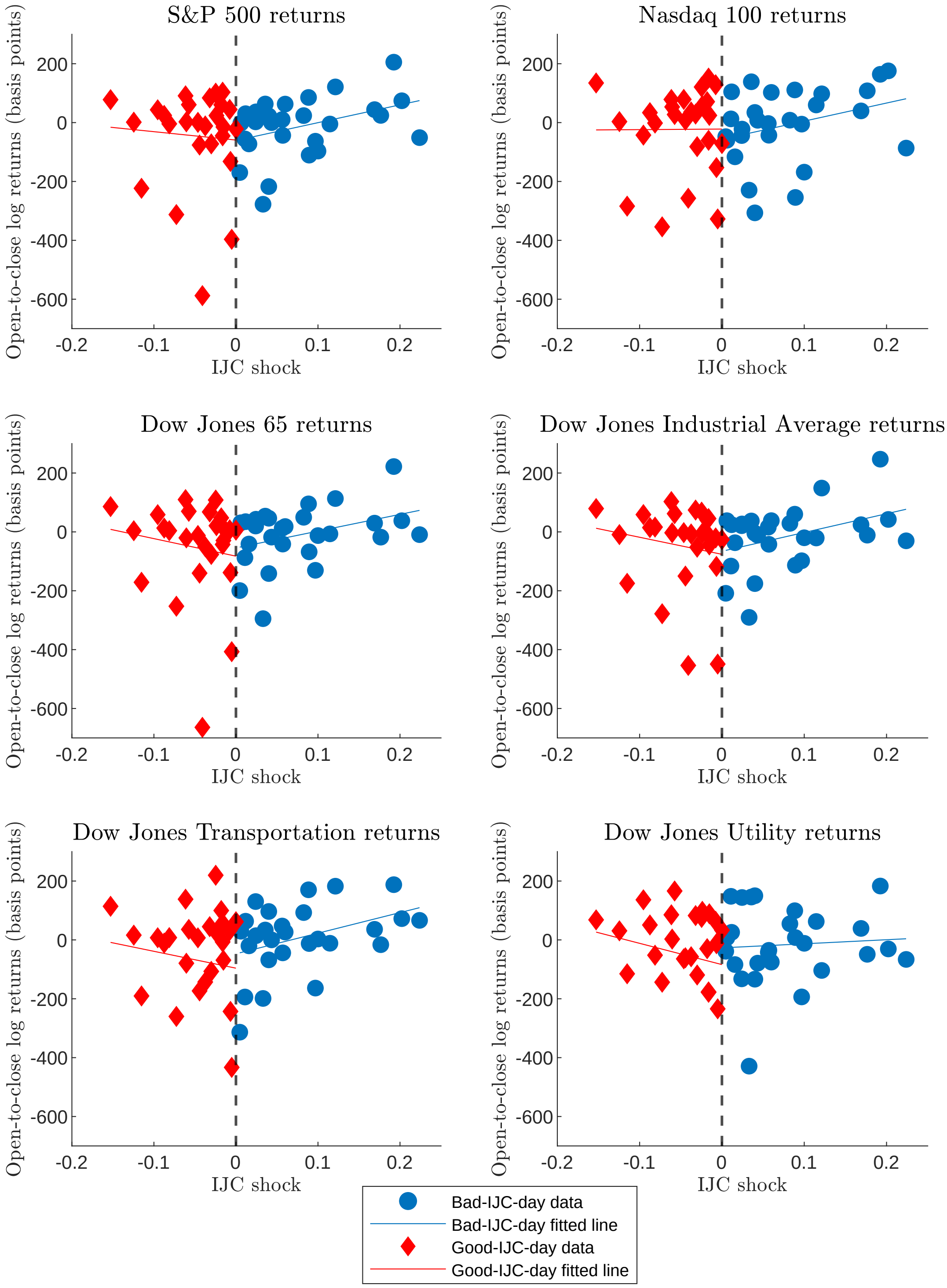
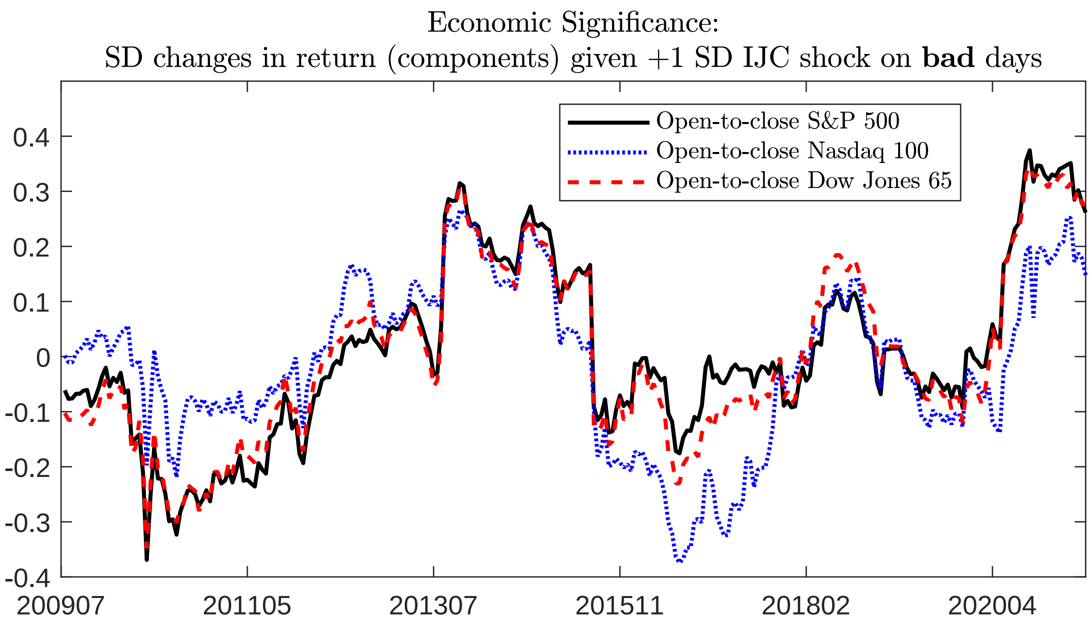


Figure A2: Robustness to Figure 2: Relation between stock returns and IJC shocks during Covid (period 5); without 2020/4/9.



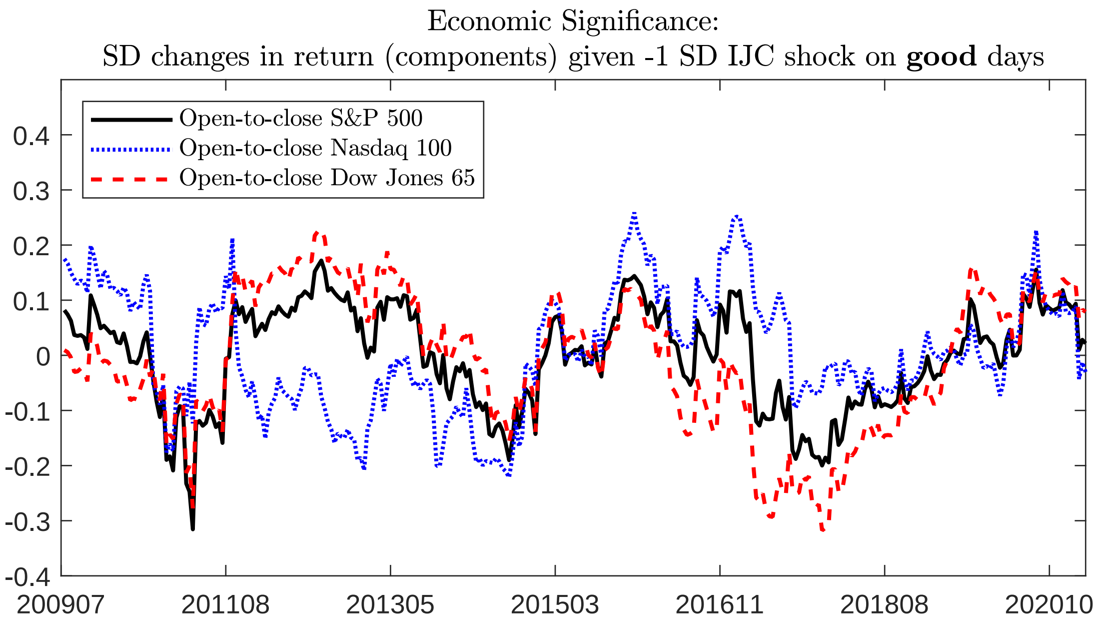


Figure A3: Depicting the economic significance of the rolling return coefficients on IJC shocks, on bad and good days, respectively. Top plot: if "bad is bad", risky asset prices should drop given +1SD IJC shock (jobless claims are higher than expected); bottom plot: if "good is good", risky asset prices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

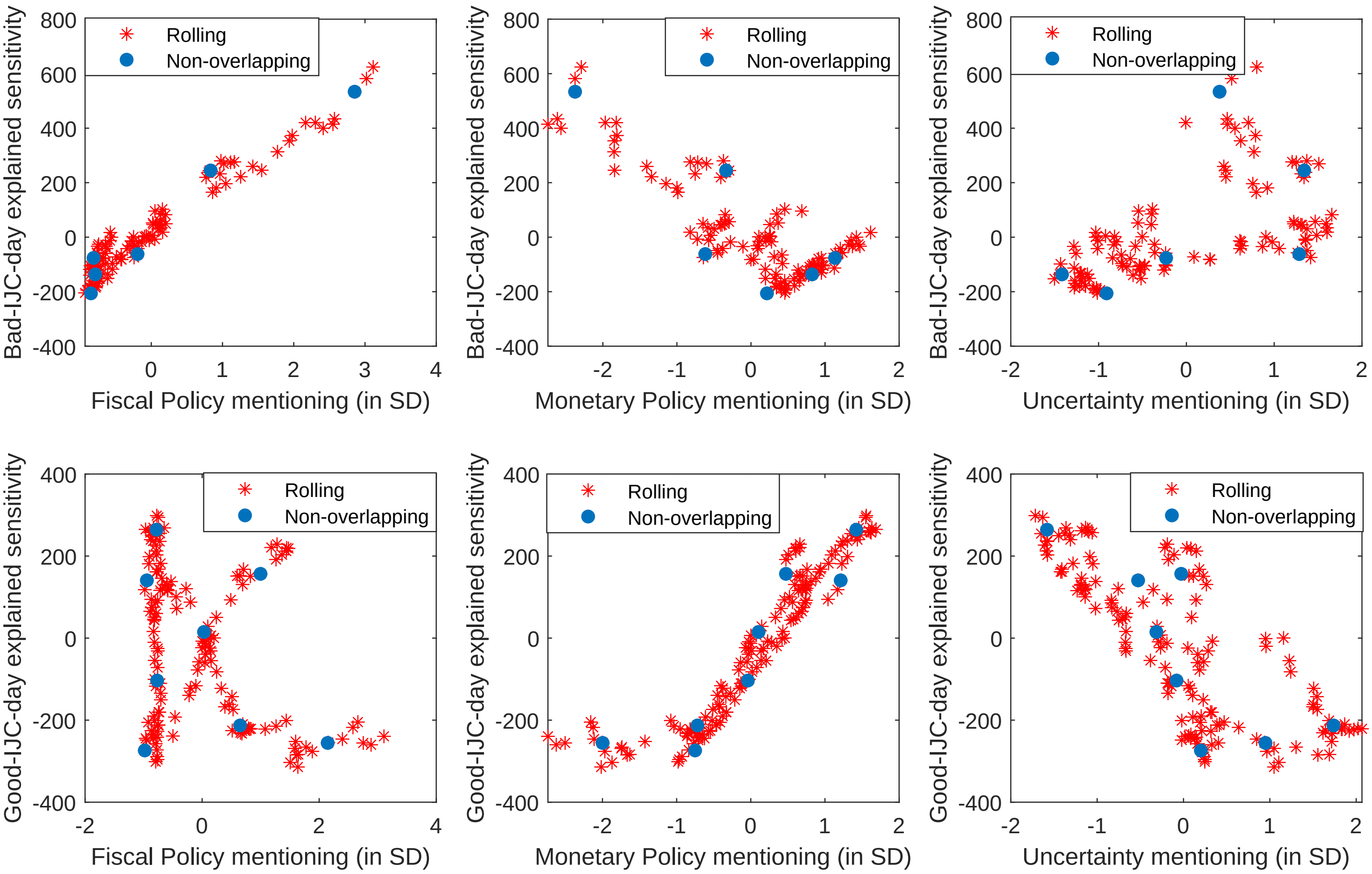
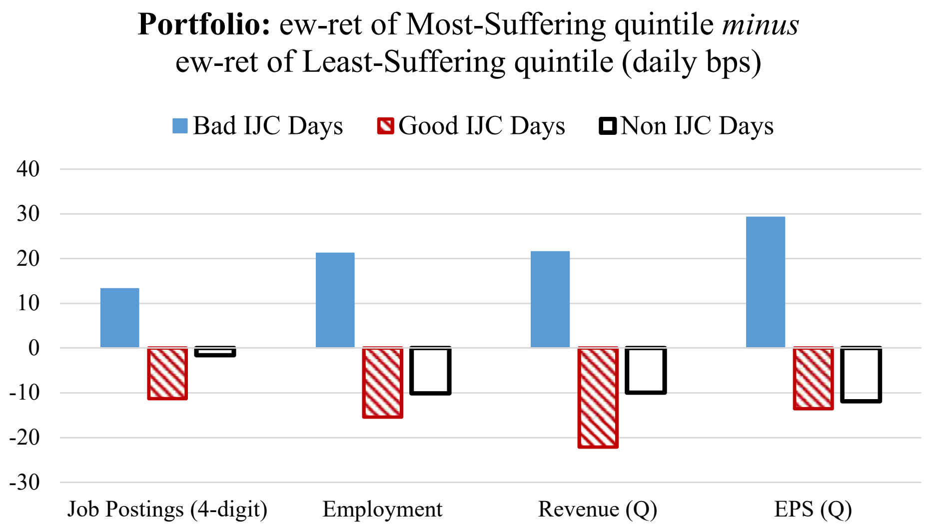
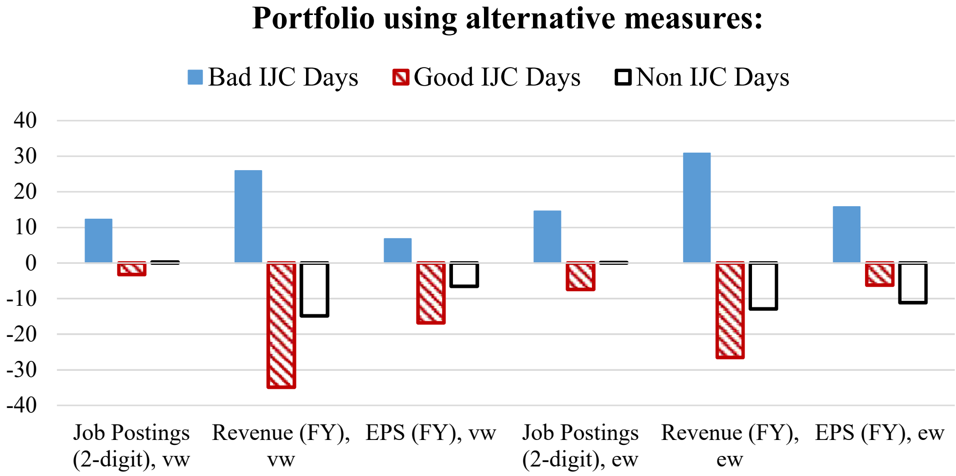


Figure A4: Rolling and non-overlapping sample S&P500 return coefficients (on IJC shocks), explained by rolling textual topic mentions (standardized within each topic). This is to mainly show that Table 8 is not driven by the rolling feature; non-overlapping data points (the first plot in the first row, and the second plot in the second row) tell consistent story already.





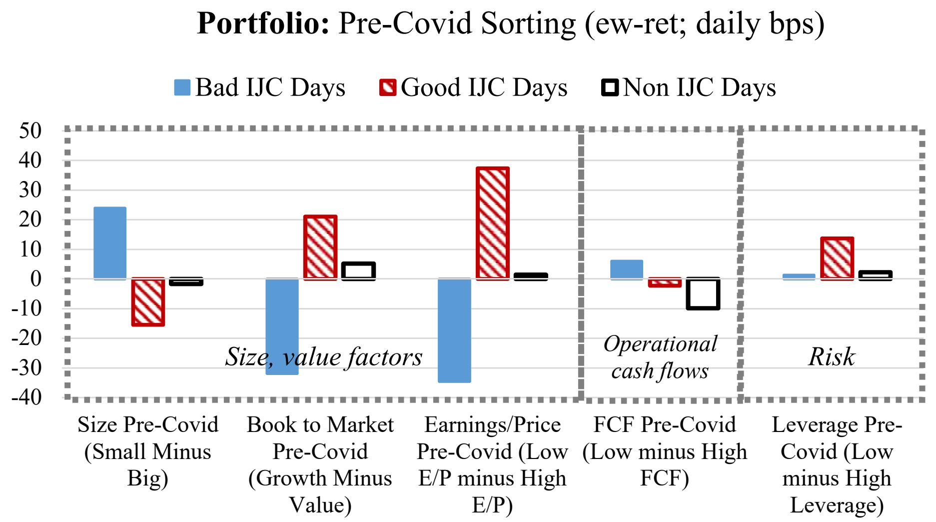


Figure A5: Robustness: Portfolio returns

This table complements Figure 9 and provides robustness results using equal weights (plot 1) and using alternative (less accurate) Covid-impact measure at the firm level (plot 2). Plot 3 complements Figure 10 using equal weights. See other details in Figures 9 and 10.

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

We first conduct four estimation exercises to (a) replicate the Campbell and Vuolteenaho (2004) results using their exact sample and data sources and (b) extend the framework to samples until 2021/04. We also consider using cumulative daily open-to-close returns within the same month as an alternative monthly return, given that some parts of our paper need to focus on intradaily returns. Samples are summarized in Table B1. Estimation results using monthly data are provided in Table B2. Figure B1 shows the dynamics of the cash flow and the minus discount rate news from Sample 4.

In the second step, we use the monthly parameters estimated from Sample 4, and then use the parameters to impute daily NCF and NDR results using 22 non-overlapping, quasi-monthly samples. For instance, subsample 1 uses daily data from Day 1, 23, 45 ...; subsample 2 uses daily data from Day 2, 24, 46 ...; and so on. We also considered re-estimating the monthly system within each subsample; results are very close and are not statistically differentiable. Here are data sources for daily data: excess market returns, CRSP for 1982-2020 and Datastream for 2021; yield spread between 10-year and 2-year government bond yields, FRED; the log ratio of the S&P500 price index to a ten-year moving average of SP500 earnings, or a smoothed PE, `http://www.econ.yale.edu/~shiller/data.htm`; small-stock value spread (VS), `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`. These sources are standard, following Campbell and Vuolteenaho (2004); smoothed PE and small-stock VS cannot be constructed at the daily frequency, and hence we use monthly values.

Moment properties of cash flow and discount rate news are reported in Table B3. In the original Campbell and Vuolteenaho (2004) sample (1928/12-2001/12), our replication shows that 92% (19%) of the total return variability is explained by the NDR (NCF), and NDR and NCF are weakly negatively correlated, which makes sense in a model where a good real economic shock can decrease discount rate (and risk variables) while increasing expected future cash flow growth. In our modern sample (1982/01-2021/04), we find that NDR (NCF) now explains 31% (34%) with a positive covariance between NDR and NCF now. Results are robust using only open-to-close stock market returns.

Table B1: Four monthly estimation samples.

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

Table B2: Estimation results, formatted as in Campbell and Vuolteenaho (2004)'s Table 2. Notations: log excess market return, r^e; log excess cumulative, open-to-close market return, $r^{e,oc}$; term yield spread, TY; price-earnings ratio, PE; small-stock value spread, VS. The first five columns report coefficients on the five explanatory variables, adn the remaining columns show R^2 and F statistics. Bootstrapped standard errors are in parentheses (2,500 simulated realizations).

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

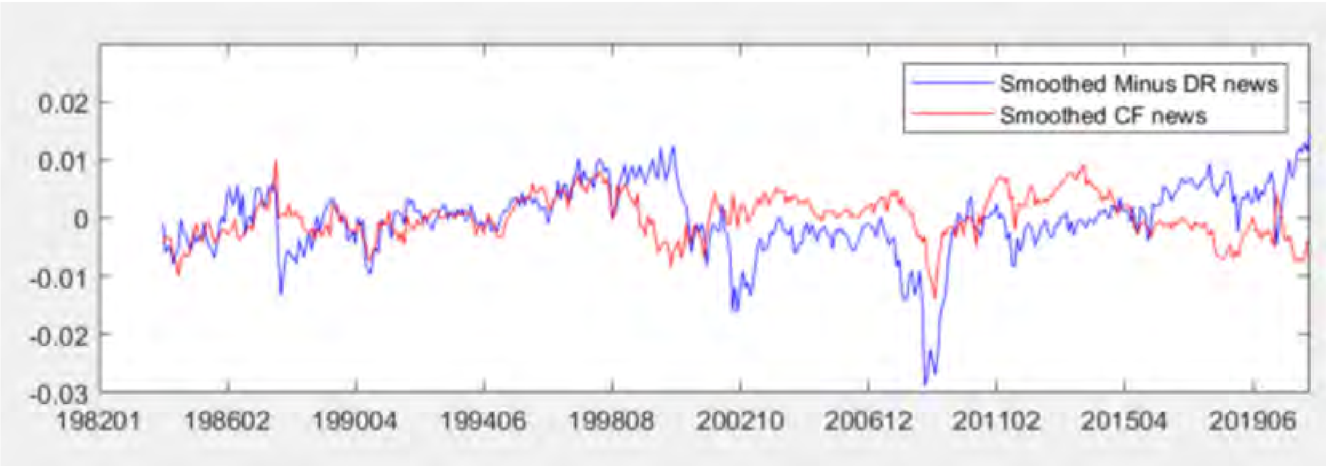


Figure B1: Replicate Figure 1 of Campbell and Vuolteenaho (2004) using our Sample 4: Cash flow and the minus discount rate news, smoothed with a trailing exponentially weighted moving average and estimated from Sample 4. The decay parameter is set at 0.08 per month. Estimation details are in Table B2.

Table B3: Cash flow and discount rate news moments, and stock return variance decomposition. The first four rows of each of the four blocks replicate Table 3 of Campbell and Vuolteenaho (2004). The three numbers in the fifth row adds up to 1: var(r) = var(NCF) + var(NDR)-2*cov(NCF, NDR). For instance, in Sample 1, var(NCF) explains 19.1% of total return variance, var(NDR) explains 92.0%, and -2*cov(NCF, NDR) explains -11.1%.

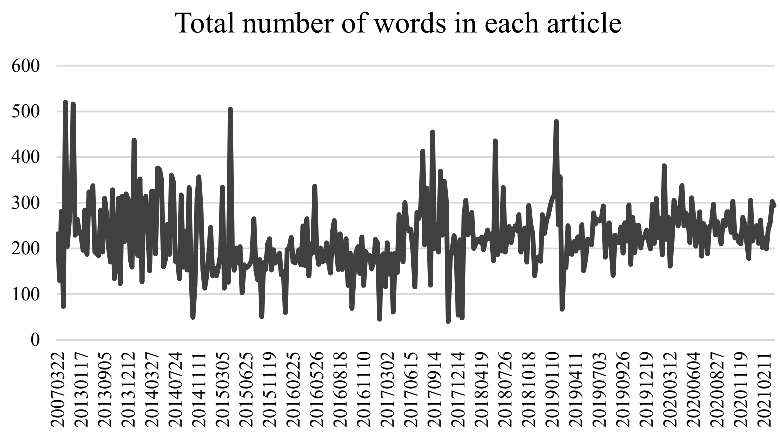
	Sample 1			Sample 2		
	NCF	NDR	NCF,NDR	NCF	NDR	NCF,NDR
Std/Corr	0.02412	0.05298	0.13237	0.02571	0.04340	-0.12449
	(0.00095)	(0.00244)	(0.06036)	(0.00101)	(0.00174)	(0.05281)
Var/Cov	0.00058	0.00281	0.00017	0.00066	0.00188	-0.00014
	(0.00005)	(0.00025)	(0.00008)	(0.00005)	(0.00015)	(0.00006)
r^e shock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

C. Details on textual analysis

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

In order to prepare a list of all articles on CNBC about weekly jobless claims, the first step is to download initial jobless claims announcement dates, and we obtain it from a tabulated version from Bloomberg which provides both actual and survey median. Once all those articles are tabbed in the excel file as per the dates, we go to cnbc.com and search for "Weekly Jobless Claims" with a specific date in the same search box, and then identify the articles. For recent articles, they can be easily found on this website by scrolling down, https://www.cnbc.com/jobless-claims/. Here we often come across with multiple articles which have the same keywords i.e. jobless claims articles for the same dates — some entirely related to the stock market, futures market, etc; but we make sure that we select the links to only those articles which are categorized in *US Economy* or *Economy* headers. The reason is that we need to read texts describing the economic environment, hence a state variable, rather than texts describing current or possible market reactions. The search was finalized manually, after using the google search package on Python; that package typically found not only CNBC articles, but other news articles too (that may be referring to CNBC), and therefore we need manual effort to finalize it.

Next, once we had the final list of dates and corresponding url links on CNB, the package used for scraping the articles is "BeautifulSoup" – wherein the links to be scraped are read from the excel sheet which was prepared from the search process. BeautifulSoup is a Python library for pulling data out of HTML and XML files.



C.2. Texts by topic

Table C1 summarizes the keywords for each of the five topics; their variants are also considered in the search (see details above). The time variation in the topic mentions (either using rolling rule or the non-overlapping quarterly rule) is insignificantly different after deleting one word at a time for Fiscal Policy, Monetary Policy, Coronavirus-related, and Normal-IJC topics. Figure C1 drops one keyword at a time from the FP and MP lists, and recalculates the 60-week rolling topic mentioning scores; as mentioned in the paper, for instance,"bad" uses all weeks within the same 60-week interval that corresponds to bad IJC announcements. As in Figure 5, we standardize the series with its first data value for interpretation purpose (that is, 1.5 means that the mentions are 50% higher than around its 2013-2014 value). Both the min-max bandwidths (see top four plots in Figure C1) and the 95% confidence intervals (see bottom four plots in Figure C1) are tight relative to the overall fluctuations.

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

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

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

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

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

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

Figure C2 uses simple word clouds to show that, from 2013-2019 (left) to 2020-2021 (right), the relative mentions of monetary policy (red) has dropped while that of fiscal policy has increased.

Table C1: Topic keywords.

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

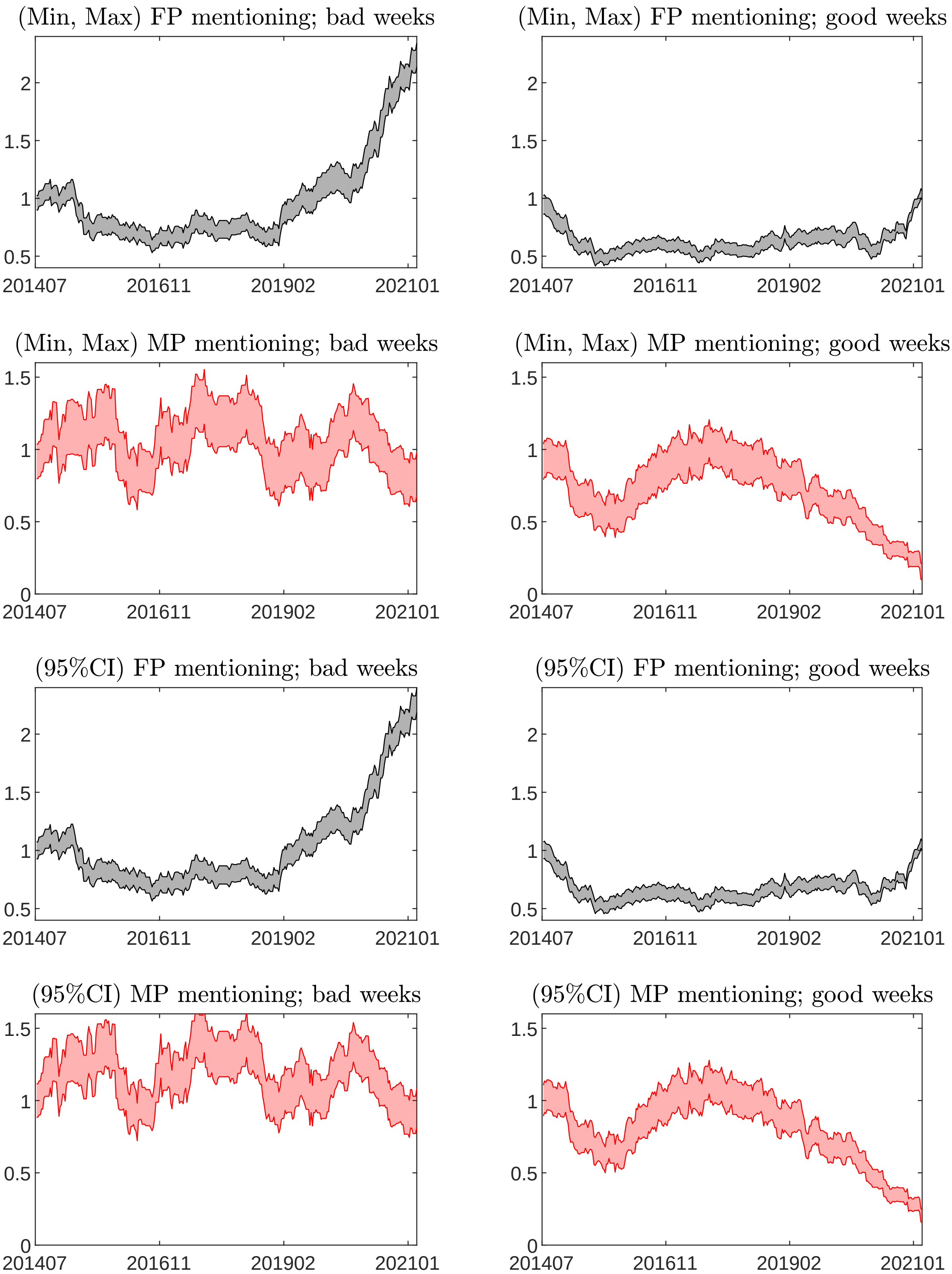


Figure C1: Jackknife exercise of the scaled rolling topic mention values. This table complements Figure 5 in the main text and provides measurement uncertainty. In this plot, we drop one keyword at a time and recalculate the bad and good rolling topic mentioning scores using all bad and good IJC announcement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

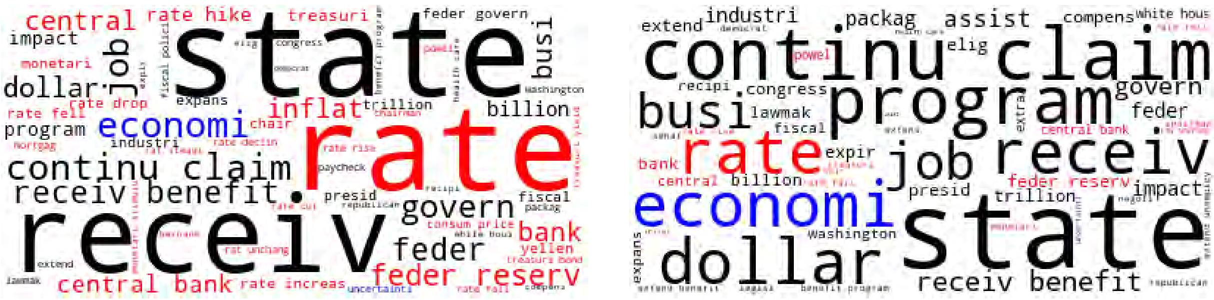


Figure C2: Left: Pre 2020; right: Post 2020 (black: FP; red: MP; blue: UNC)

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

This appendix section complements Table 13 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 13, we display return relationships with macro news about the labor market, manufacturing, consumption, and some other economic variables (which are likely priced through monetary policy and risk channels) in three subsequent figures below.

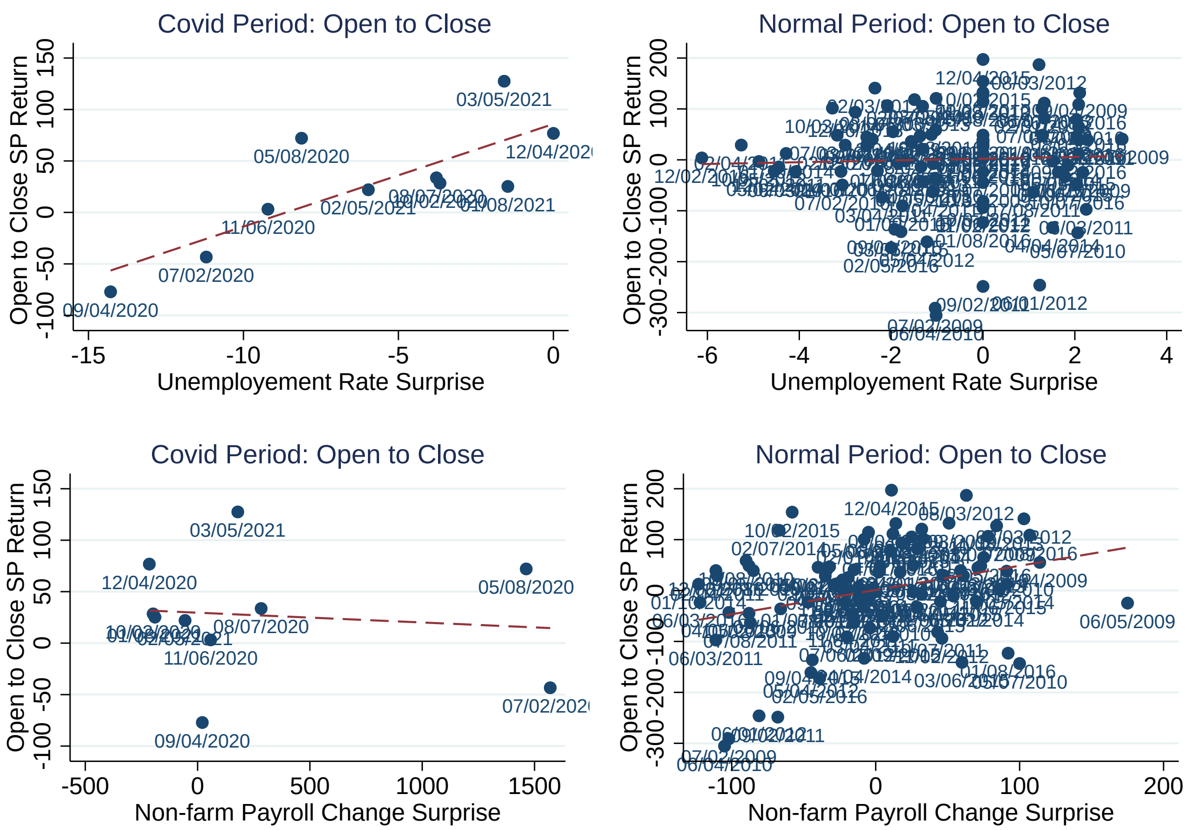


Figure D1: Employment news and daily open-to-close returns

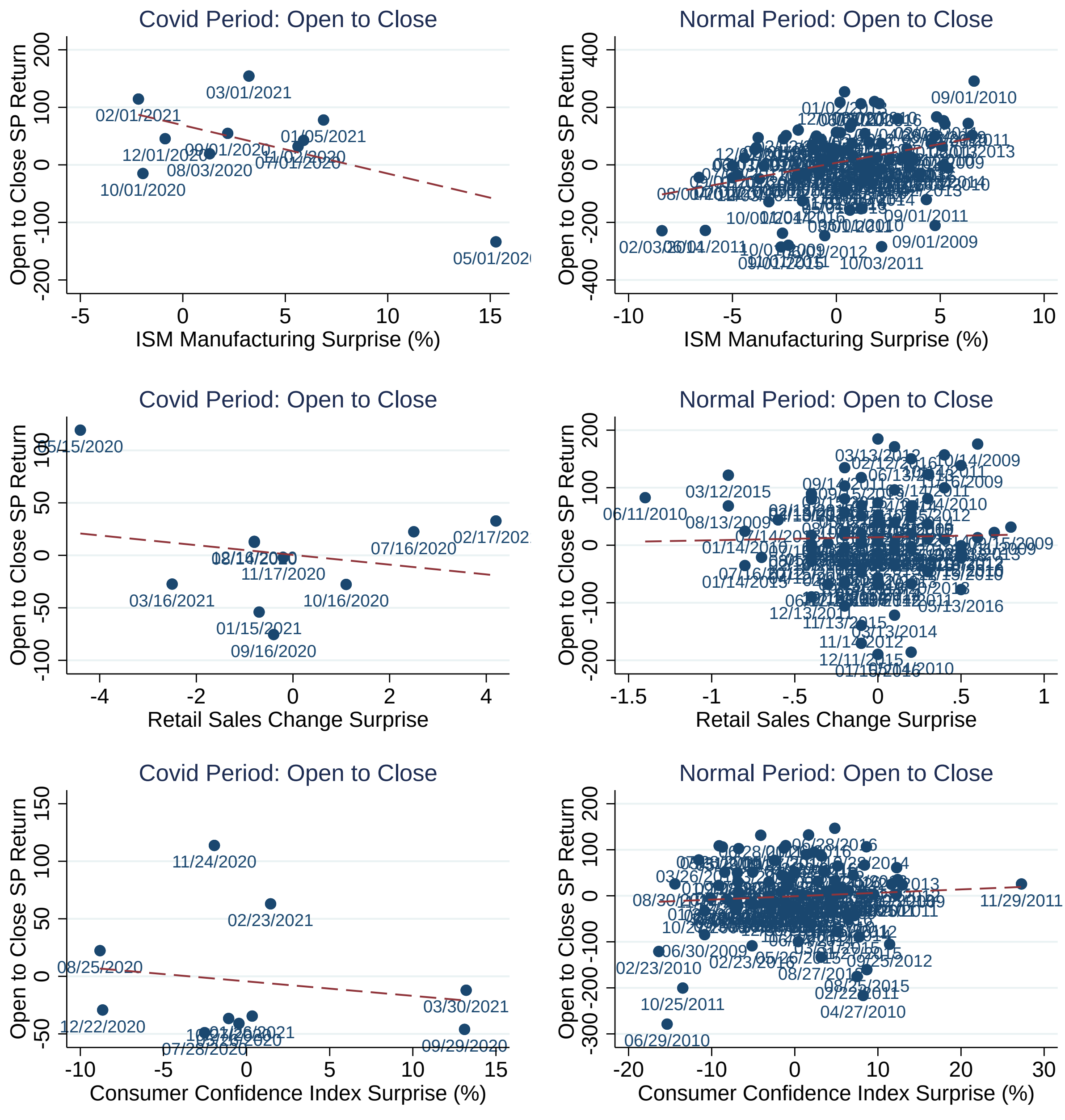


Figure D2: Manufacturing, consumption/consumer news and daily open-to-close returns

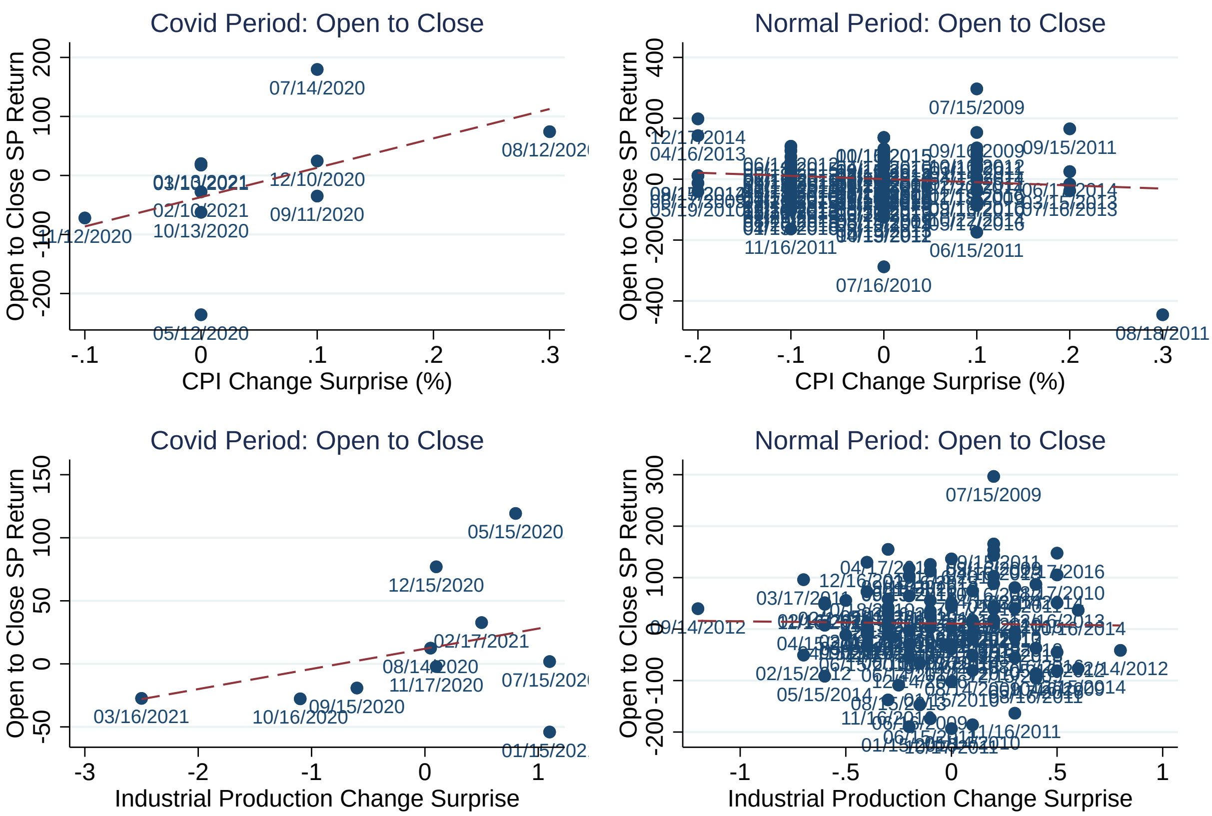


Figure D3: Other economy news and daily open-to-close returns