Online Appendices for "Main Street's Pain, Wall Street's Gain"

OA. Additional Tables and Figures

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

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

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

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

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

Table OA2: Univariate Results for Table 3.

This table reports the results of the following regression:

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

where t and τ denote daily and quarterly frequency, respectively, y stock returns (in basis points), and Z a standardized quarterly state variable of interest. See other details in Table 3. ***, p-value <1%; **, <5%; *, <10%.

	Panel A. Bad IJC days				Panel B. Good IJC days			
▶ **Quarterly state variable (standardized):**	**FP**	**MP**	**UNC**	**$\Delta Tbill3m$**	**FP**	**MP**	**UNC**	**$\Delta Tbill3m$**
▶ *Source:*	*CNBC textual analysis*			*SPF survey*	*CNBC textual analysis*			*SPF survey*
LHS: S&P500 daily returns (basis points)								
Constant	5.023	-1.183	4.033	1.798	-2.087	1.567	-6.520	-0.320
(SE)	(8.050)	(8.053)	(8.662)	(8.081)	(10.768)	(10.795)	(11.363)	(11.286)
IJC shock	-73.671	171.476	-5.018	51.286	60.255	148.762	66.756	120.205
(SE)	(134.664)	(127.867)	(154.077)	(123.900)	(204.547)	(204.936)	(208.513)	(214.196)
State variable	**-18.800****	-4.958	-13.463	4.303	19.062	0.036	**29.943****	9.965
(SE)	**(7.550)**	(6.810)	(8.357)	(7.181)	(13.043)	(9.769)	**(15.140)**	(12.533)
Interaction	**278.912*****	-33.432	**283.166****	**-213.665***	320.570	128.517	**502.839***	204.988
(SE)	**(90.228)**	(111.688)	**(134.457)**	**(118.131)**	(241.187)	(167.621)	**(264.661)**	(245.882)
R^2%	5.6%	2.0%	3.3%	2.4%	1.9%	0.8%	2.1%	0.5%
N	184	184	184	184	189	189	189	189
LHS: Dow Jones daily returns (basis points)								
Constant	8.201	2.728	7.511	4.962	-3.366	-1.000	-8.902	-3.318
(SE)	(7.909)	(8.012)	(8.533)	(8.039)	(11.018)	(10.741)	(11.398)	(11.215)
IJC shock	-69.929	151.308	-9.378	51.352	27.530	91.862	6.194	56.945
(SE)	(122.451)	(126.805)	(145.338)	(123.369)	(208.545)	(194.289)	(202.107)	(203.073)
State variable	**-18.693****	-6.057	**-14.832***	6.541	12.324	7.111	**29.719***	17.505
(SE)	**(7.443)**	(6.969)	**(8.552)**	(7.318)	(12.710)	(9.692)	**(15.293)**	(12.191)
Interaction	**262.472*****	43.146	**270.665****	-196.914	198.696	257.476	**492.411***	**409.691***
(SE)	**(94.620)**	(114.455)	**(137.879)**	(127.185)	(226.523)	(161.266)	**(268.294)**	**(233.899)**
R^2%	5.1%	1.5%	3.2%	1.9%	0.7%	1.1%	1.8%	1.3%
N	184	184	184	184	189	189	189	189

Table OA3: Summary Statistics of Raw Covid-Impact Measure in the S&P 500 universe.

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

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

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

This table calculates the simple cumulative and average daily capital gains of S&P 500 stocks on bad, good, and non-IJC days during the Covid period and during a general non-Covid period. Average daily capital gains are cumulative capital gains divided by the number of days, capturing what the average daily capital gains are during these three non-overlapping groups of days. In particular, for the first two columns, this table considers IJC surprise days that are economically sizable when calculating the average for clearer identification during each period (i.e., actual-expectation $> 10K$ or $\leq -10K$, which according to Table OA1 corresponds to around $> 75th$ or $\leq 25th$).

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

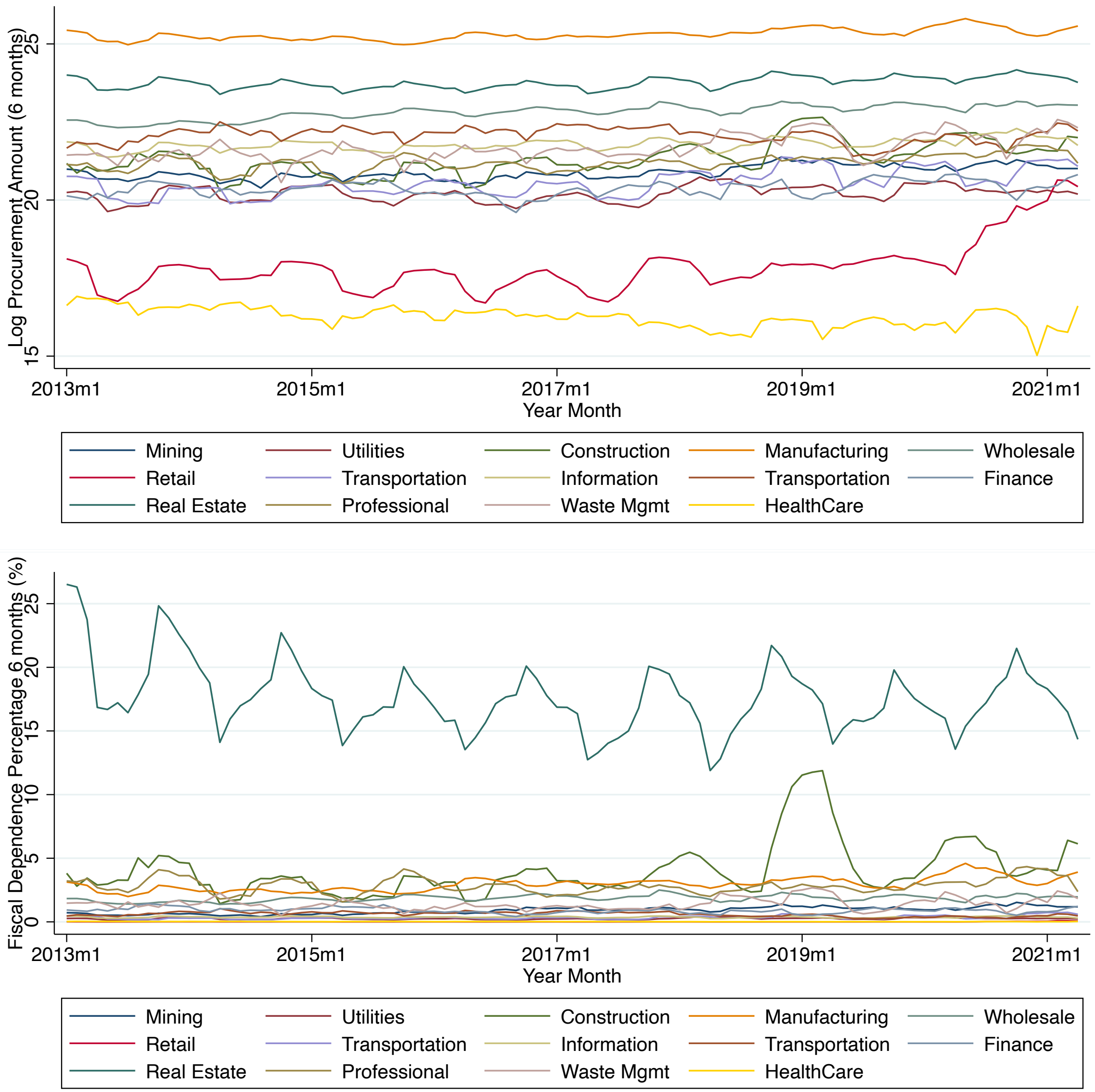


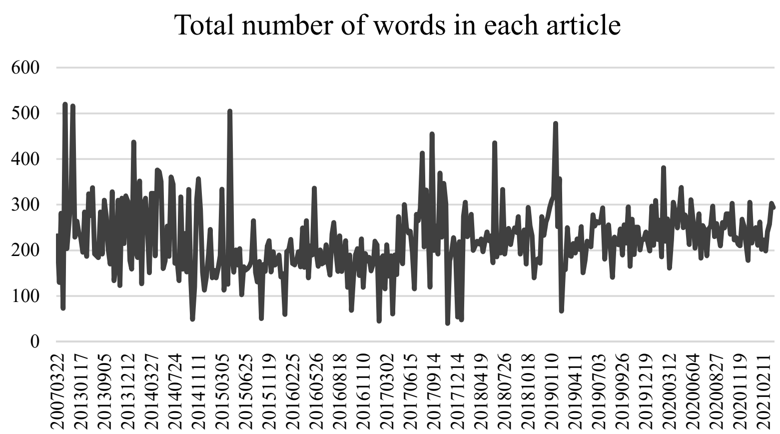
Figure OA1: Procurement allocations by industries. Panel A plots the log value of the total procurement amount in the past 6 months by two-digit NAICS code from January 2013 to April 2021. Panel B plots fiscal dependence, the share of total procurement amount in the past 6 months divided by half of the revenue in the past four quarters, by two-digit NAICS code. The manufacturing industry includes NAICS codes 31, 32, and 33, the retail industry includes NAICS codes 44 and 45; and the transportation industry includes 48 and 49. Other industries correspond to single two-digit NAICS codes.

OB. Details on Textual Analysis

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

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

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



OB.2. Texts by topic

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

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

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

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

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

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

Table OB1: Topic Keywords.

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

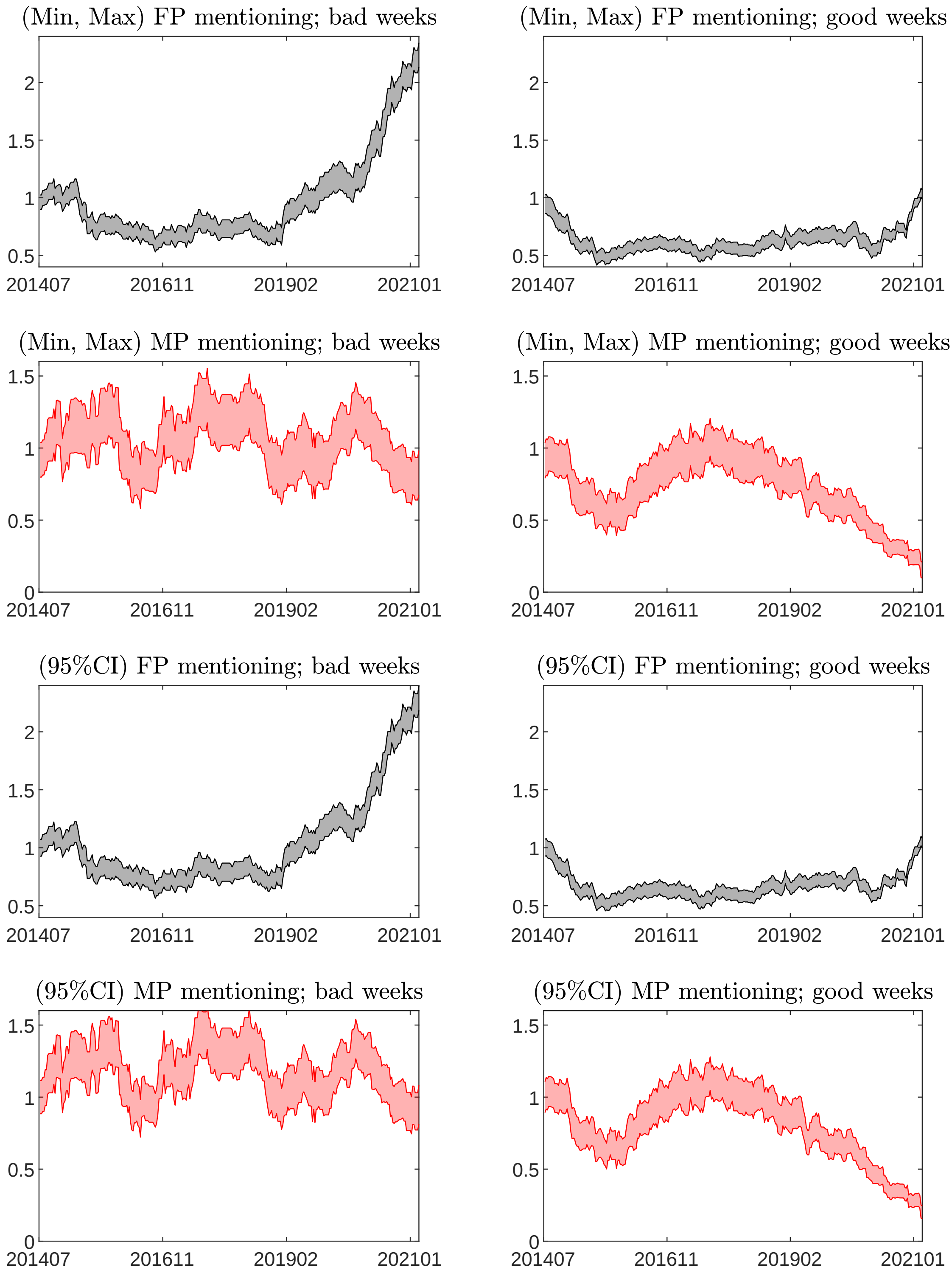


Figure OB1: Jackknife exercise of the scaled rolling topic mention values. This table complements Figure 3 in the main text and provides measurement uncertainty. In this plot, we drop one keyword at a time and recalculate the bad and good rolling topic mentions scores using all bad and good IJC announcement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

OC. Covid-Related Government Spending Data for Compustat Companies

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

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

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

We further manually validate our mapping file based on company names and recipient addresses in government records; namely, we use Google Maps to locate the establishment and check whether this establishment belongs to the Compustat company. After manual verification, we identify 11,018 records for 1670 Compustat companies matched with recipient (parent) names in Covid spending records at the time of writing in FY 2020. Table OC1 presents the summary statistics.

Table OC1: Summary of Covid-Related Spending in 2020 (in Millions of Dollars)

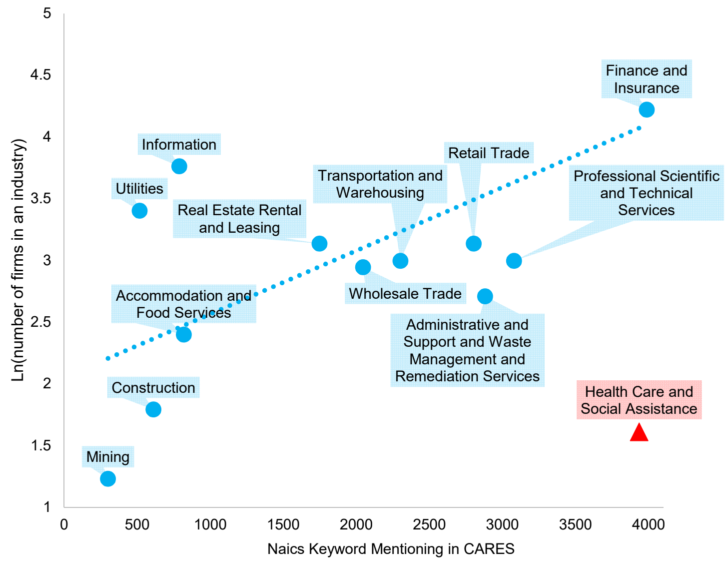
	Mean	STDEV	Min	Max	Median	10th Pct	90th Pct
Gross Outlay Amount	74753.69	1177.15	-0.02	32.1	0.01	0	0.93
Obligated Amount	46459.43	934.66	-34116.31	21.71	0.01	-0.05	1.52

OD. Who Gets What?

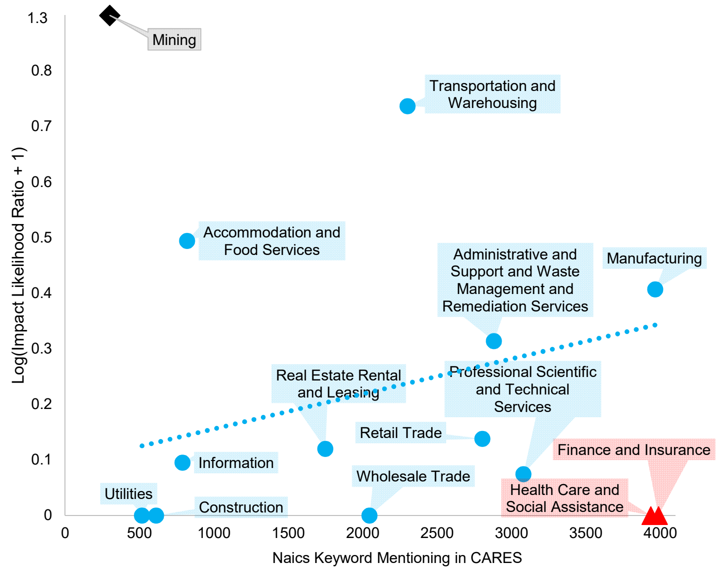
The three novel cross sections that we construct from various data sources (bill mentions, obligated and actual fiscal support, and expected Covid damage) give our research the unique opportunity to answer a key question: During the height of fiscal activity from 2020 to early 2021, who gets what? How related are these cross sections? Figure OD1 below addresses these questions at the industry level.

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

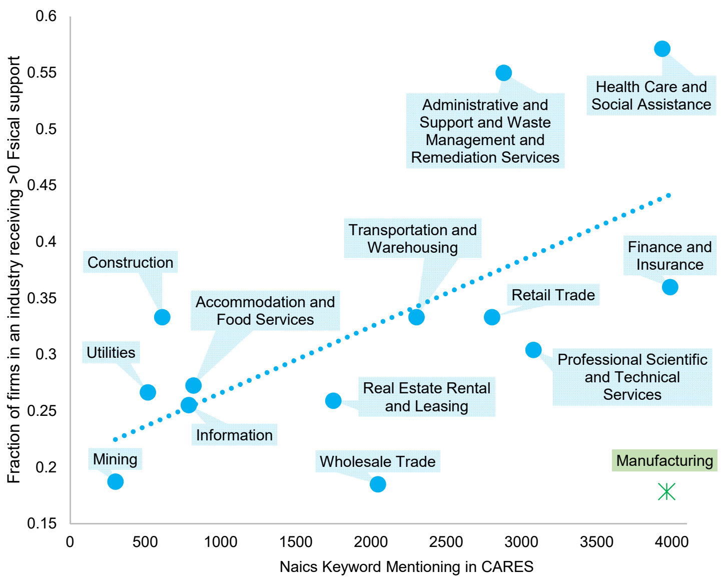
The next two plots compare bill mentions and fiscal support. Subfigure (C) proxies fiscal support by the fraction of firms in an industry that receive > $0 fiscal support (regardless of the type), and Subfigure (D) uses the log of promised PPP amounts. Both plots show statistically significant and strongly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



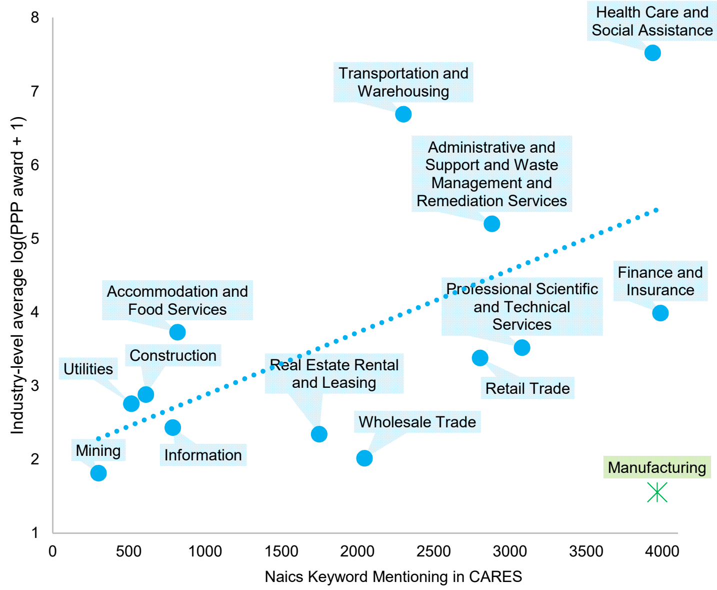
(A) y-axis: Industry presence in S&P 500



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



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



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

Figure OD1: Comparison across three cross-sectional dimensions at the industry level: Who gets what?

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

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

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

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

OE.1. Monthly unemployment macro variables

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

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

Table OE1: External Validation: Correlations Between Monthly Macro Announcement Surprises and Daily Open-to-Close S&P 500 Returns.

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

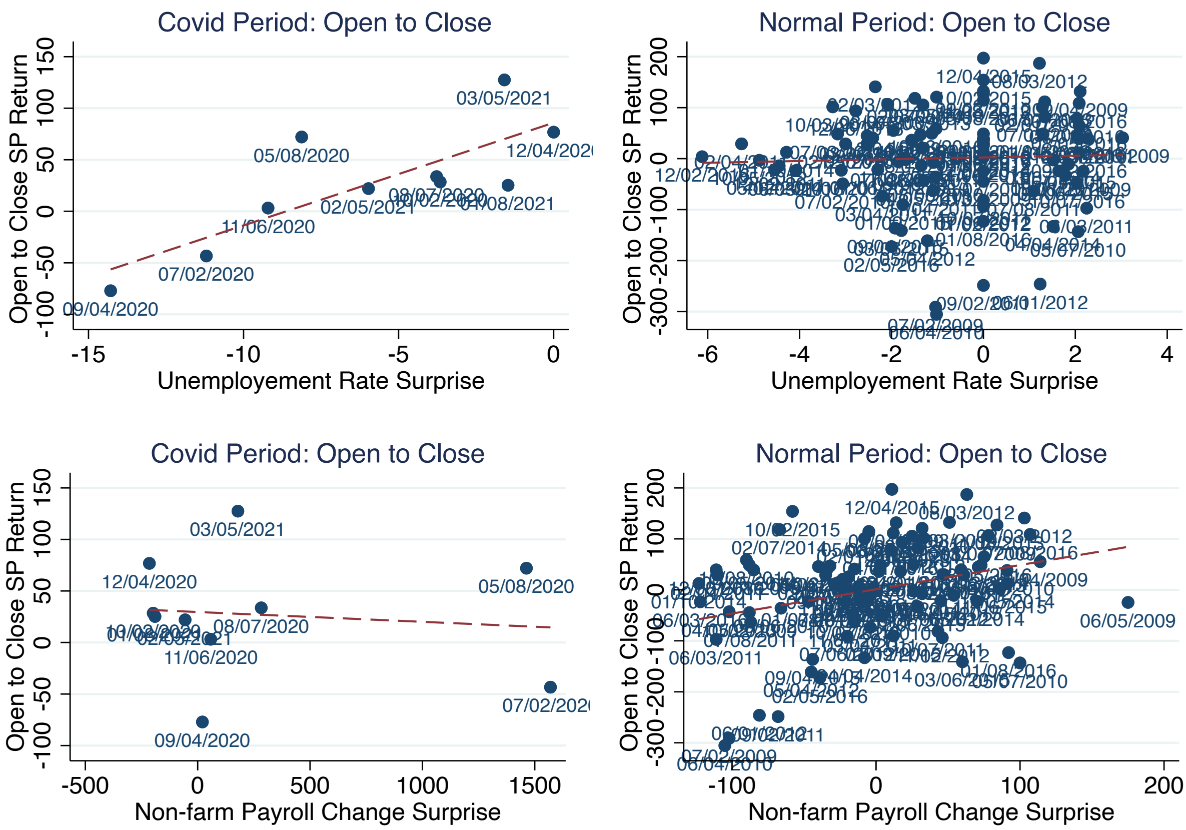


Figure OE1: Unemployment news and daily open-to-close returns.

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

OE.2. The phenomenon across macro variables

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

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

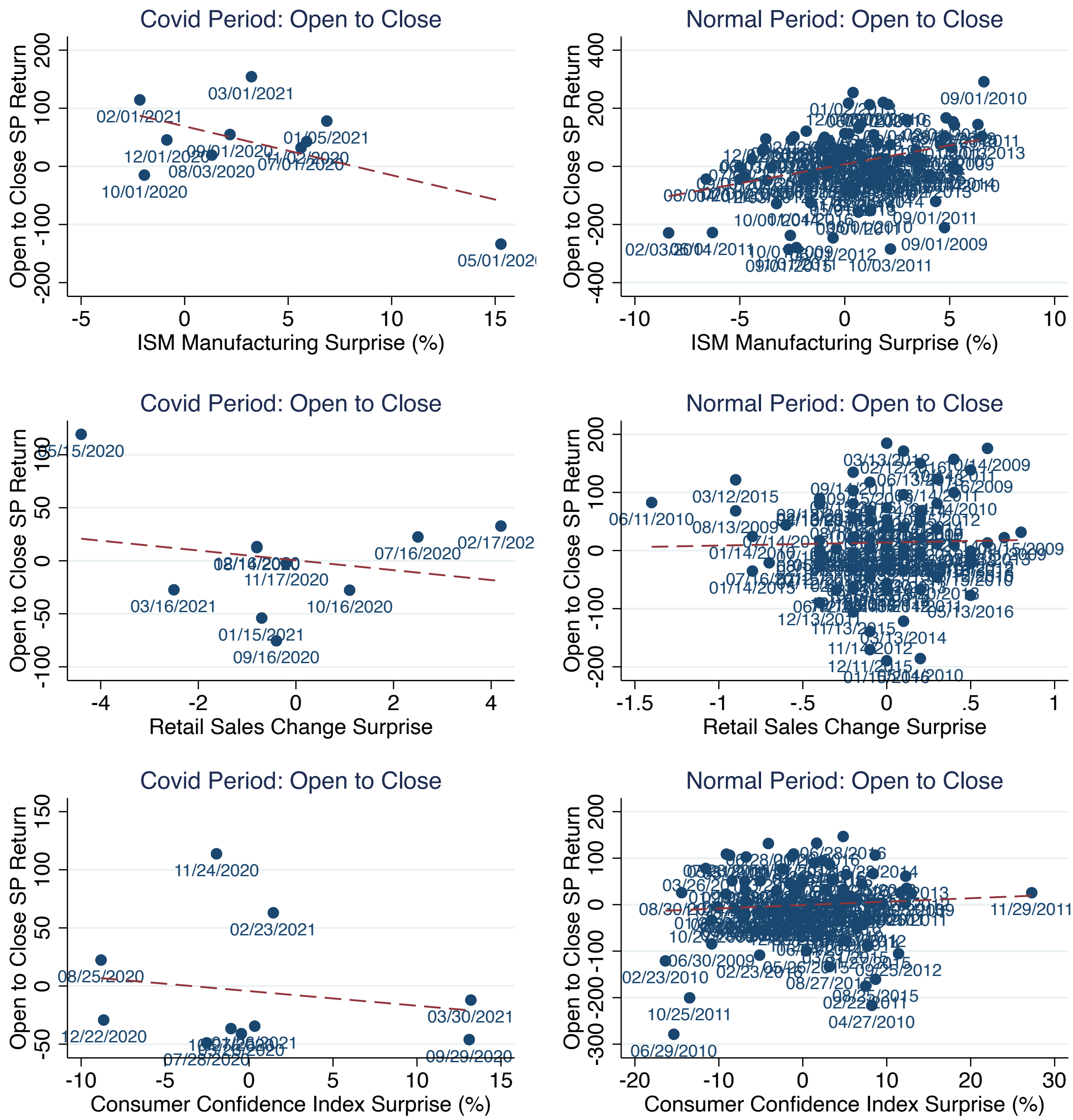


Figure OE2: Manufacturing and consumption/consumer news and daily open-to-close returns.

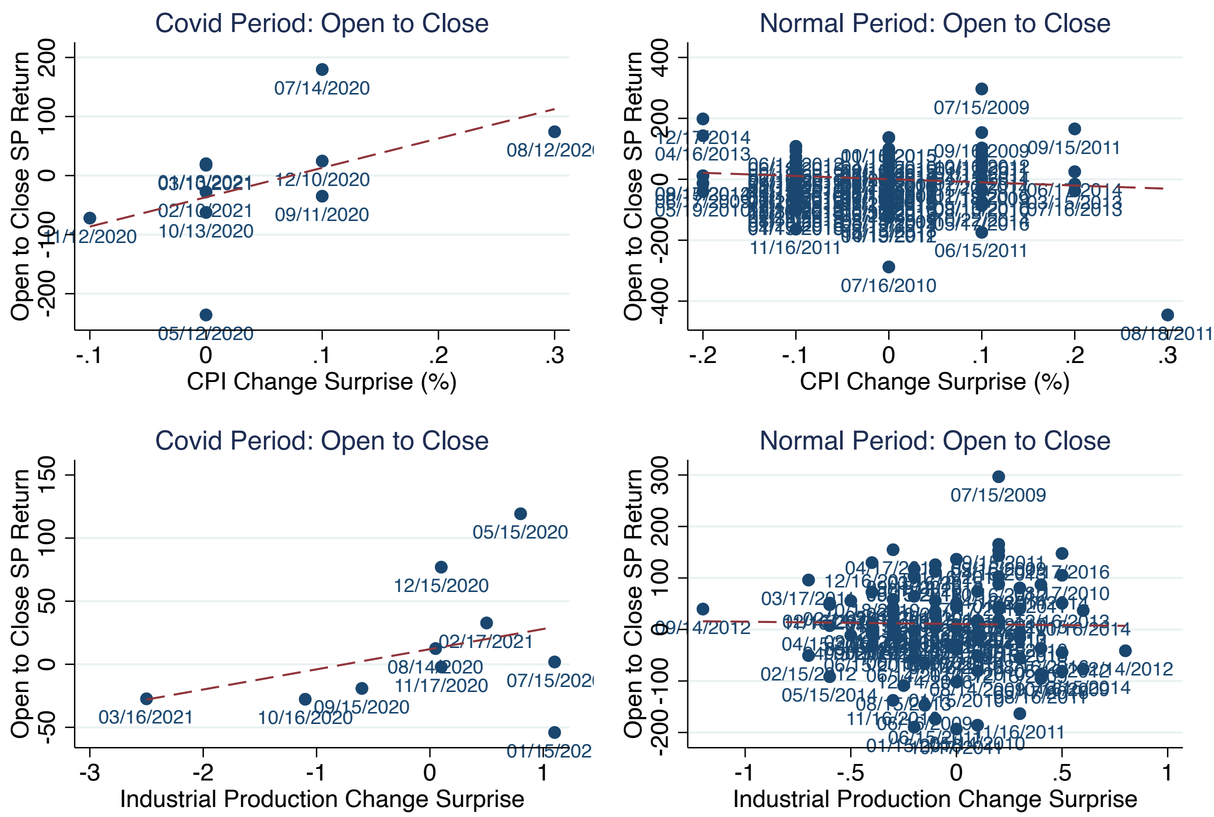


Figure OE3: Other economy news and daily open-to-close returns.