Financial Sanction Spillovers and Firm Interdependence

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States frequently outsource coercion to the market, using sanctions to deter private actors from dealing with blacklisted entities. Yet research is ambiguous as to the effect and boundaries of such actions on market participants. To better understand the consequences of targeted sanctions, we analyze the impact of the Trump administration's actions against Chinese tech giants Tencent and ByteDance. Leveraging an event-study, we find that not only do sanctions negatively impact targets, but they also spread to co-nationals. We test two additional economic channels related to firm interdependencies. Tencent acts both as an investor in other companies and provides a technological platform for businesses unaffiliated with the firm. Both sets of firms, which include American tech companies, are negatively affected. The paper highlights the need for scholarship to incorporate firm-heterogeneity into theories of economic statecraft, and indicates how equity markets are an emerging arena of contention in the US-China rivalry.

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Over the summer of 2018, European leaders scrambled to lobby US officials over a sanctions campaign against Russian oligarch and Putin confidant Oleg Deripaska. Rather than seeking to ratchet up pressure, however, Europeans pleaded to ease up.[1] The reason, an investment by Deripaska in an obscure alumina factory in Limerick Ireland. A disruption at the plant would be dire for a continental auto industry that had become dependent on its products for its supply chain.[2] What at first seemed to the US Treasury as a clear way to strike back against Russian interference in the 2016 election quickly escalated into a potential global economic calamity. By January 2019, the Treasury had walked back the sanctions program.

Economic statecraft has been increasingly outsourced to the market, as great powers rely on the fear of legal action and reputational risk to deter private actors from working with firms or countries deemed as a risk (Morse 2019; Early and Preble 2020). And no state has made greater use of such tools than the United States: by 2021, there were 9,421 active designations constituting a 933% increase compared to the start of millennium (US Treasury 2021). Covering a range of topics from human rights violations to conventional war, most of these financial sanctions target individual entities. While the direct consequences of these targeted tools have been lauded by policymakers and academics as economically efficient and politically expedient, there is still only a rough understanding of how these tools ripple through markets.[3] Qualitative studies and news reports routinely cite firms "over-complying" or "derisking" given the ambiguity of the sanctions put in place (Verdier 2022). Quantitative studies further support such inferences. Whether by intention or accident, research indicates that firms in similar sectors and those that rely on a target

[1] https://www.irishtimes.com/business/manufacturing/european-ambassadors-urge-us-to-support-lifting-of-sanctions-on-aughinish-owner-1.3756231
[2] https://www.bloomberg.com/news/articles/2018-04-19/german-industry-sounds-alarm-that-rusal-sanctions-pain-is-coming?embedded-checkout=true
[3] For notable exceptions, see Katzenstein 2015; Early and Preble 2020

for revenue may be hindered as well (Ahn and Ludema 2020; Stone 2016). Derisking behavior appears to even spread to third-countries with similar geopolitical preferences (Newman and Zhang 2024). As the Limerick incident suggests, however, market complexities risk producing unanticipated consequences or even miscalculations.

How then do market actors price risk in the face of economic coercion? In this *Short Article*, we attempt to tease apart several discrete channels and test them empirically. In particular, we analyze (1) the direct sanction channel (whether sanctions negatively impact targeted firms) (2) the categorical channel (whether firms from the same country as the target suffer) (3) the product channel (whether firms that rely on products made by the targeted firm suffer) (4) the investment channel (whether firms that rely on investments from the targeted firm suffer). To examine these different pathways, we leverage a market event study of the US decision to ban the Chinese apps WeChat and Tik Tok in 2020.

The ban offers several important methodological advantages as compared to existing sanctions research. First, it provides a methodological toolkit to open up the black box on 'derisking', as the event study can identify different investor clusters and examine their behavior in the face of coercion. Second, the WeChat case, in particular, offers a comparatively clean market signal to test the product and investment channels. In late July 2020, while rumors swirled that Trump would be targeting TikTok after the app was increasingly used to build political momentum against his re-election campaign, targeting WeChat and its parent company Tencent, by contrast, was unexpected and signaled a step change. In the week leading up to the announcement, potential sanctions on TikTok got three times more news coverage than anything concerning WeChat,[4] but after an expansive executive order a notable political risk consultant said "I think it's going to be

[4] Author calculations based on Factiva news searches.

a challenge for any Chinese technology company operating in the US market."(Xu Klein, Feng, and Qu 2020). Findings of any categorical effect, given the already established geopolitical conflict in 2020, would inevitably be a hard test for one of the IPE of Finance's core findings on national spillovers (Brooks, Cunha, and Mosley 2015). We move forward established theories by leveraging the varied nature of Tencent's revenue generating activities. The company's main asset – WeChat – is a platform where a plethora of commerce is conducted. The product is essential to the business practices of many Chinese firms in our sample, so we can assess whether such instances of infrastructural power, which is becoming common in a range of industries across countries, can be turned into a tool of statecraft to channel the effects of economic coercion. Similarly, the firm epitomizes another growing trend in capitalist countries – Tencent has investments in a host of additional firms, including publicly traded American firms. While cross-ownership is considered central to coordinated forms of capitalism, and diversified family firms are the norm in emerging markets, such patterns of joint-ownership and cross-holdings have even become the baseline of American capitalism as a function of behemoth asset managers. When a major shareholder firm is sanctioned, affiliated firms could lose financing revenue or see the company forced to divest.

Our findings suggest that targeted sanctions can have much broader market consequences than simply shaping the economic prospect of the target firm. Moreover, the paper demonstrates empirically how this spillover occurs through a number of discreate channels. Despite the heightened geopolitical environment, Chinese firms as a whole performed substantially and statistically significantly worse following the sanction. We further document that WeChat's central role in the Chinese economic ecosystem conditions the spread of the targeted sanction – companies more reliant on the Tencent owned product suffer negative returns. But targeted sanctions are not restricted to those firms that work in tech or rely on direct-to-consumer channels that WeChat enables – direct financial ties matter as well. American and foreign firms with significant Tencent ownership are immediately and negatively impacted. Our findings have important theoretical and policy implications. First, they reorient analysis concerned with the political risks of sanctions to the firm level, highlighting how product and investment channels may generate important spillovers. Moreover, our research draws attention to equity markets as an important source of economic statecraft. The US's control of the reserve currency is rightfully regarded as the bedrock of its coercive capabilities. But in recent years we've seen growing prospects of conflict in equity markets; an additional vector of economic interdependence. Here, our paper has direct policy implications – not only are these financial sanctions having a more expansive effect, but the market reaction appears to boomerang back on some American companies given the interlinked investments across the US and China.

I. Case Description: Sanctioning WeChat and TikTok

On August 6th 2020, the Trump Administration announced two executive orders targeting WeChat and TikTok. Citing national security concerns, the orders barred transactions by any person under US jurisdiction with the two social media giants after 45 days from the announcement.[5] The sanctions targeted the respective holding companies—Tencent and ByteDance—but potentially also involved US companies tied to Tencent, like Tesla, Snapchat, Activision Blizzard, and Epic Games. Observers saw this order as broadening US-China economic tensions, with the US trying to deter future engagement with key Chinese actors. The *New York Times* reported that, given the economic importance of the targeted firms and the vagueness of the executive orders, the sanctions could have broader implications for Chinese firms doing business abroad (Swanson 2020).

[5] "Executive Order on Addressing the Threat Posed by WeChat," *White House*, August 6, 2020

II. Data and Research Design

Most quantitative studies on the effect of sanctions study country-level flows, which can yield confounded estimates of political risk (Kerner 2014). We overcome this issue – and estimate firm-level sanction effects – with a stock market event-study. Any event increasing political risk to a firm – such as sanctions – should cause market participants to redirect investments towards less risky assets. Because investors price in risk, pre-event stock prices incorporate all available risk-relevant information in equilibrium, while post-event drops in *Returns* (i.e., percentage change in stock price at closing, between trading days) evidence increasing risk. We estimate political risk effects as the difference between observed *Returns*, after the event, and how we expect *Returns* would have moved, absent it (counterfactual *Returns*) – see Kucik and Pelc (2016).

To study the effects of the sanctions, we construct four groups of firms (we describe sample selection in the appendix). First, we study individually the effect on Tencent stock.[6] Our second sample is composed of 210 US-traded Chinese firms, with which we explore spillover effects by nationality. To explore the "product channel" of spillover effects, we consider US-traded firms that used Tencent's app WeChat as part of their core business for revenue generation. Finally, our fourth sample, which we use to study spillover effects by corporate ownership and investment, includes US-traded firms that Tencent owned any share of before the sanctions. Our samples partly overlap, but the latter two also include non-Chinese firms like Tesla, Spotify, Activision Blizzard, and Sea Limited. For each firm, we compute daily *Returns* from stock prices data. The success of our design depends on getting counterfactual *Returns* right. To do so, we estimate a "market model," i.e. a baseline quantifying the relationship between *Returns* of a single firm and those of

[6] As the parent company of TikTok, ByteDance, is not listed on a US exchange, we do not conduct a target analysis for the company.

the market. This is done by considering data in a time-window entirely preceding sanctions ("estimation window") where, we assume, no information about the event was yet available. Once estimated, we use this model to predict *Returns* to a firm. We stretch this prediction outside of the estimation window, in an "event window" that shortly follows and that includes the sanctions. Expected *Returns* thus represent counterfactual market expectations. We compute the difference between observed and counterfactual *Returns*, called *Abnormal Returns* (AR) and *Cumulative Abnormal Returns* (CAR, the cumulative sum of AR to a firm). We study if the event increased firms' political risk by estimating average AR and CAR, and 95% confidence intervals (CIs), in the event window.[7]

Typical applications fit each firm's market model on aggregated market-wide indexes, such as the Standard & Poor's 500 (S&P 500). However, this can yield correlated predicted counterfactuals and introduce bias (Wilf 2016). To overcome the issue, we fit market models using *Returns* to *each* S&P 500 individual constituent and select the relevant constituents for each firm using the LASSO (Wilf 2016). We consider an estimation window of [-30; -3] trading days before the sanctions and impose a 15-fold cross-validation. These hyperparameters yield the best model fit among alternatives (see appendix). We discard firms whose estimation window yielded market models with an R^2 below 0.10. In appendix, we show robustness to all these choices.

III. Results

[7] In appendix, we use alternative estimation strategies and tests for statistical significance, including regression, parametric, and non-parametric tests used in corporate finance.

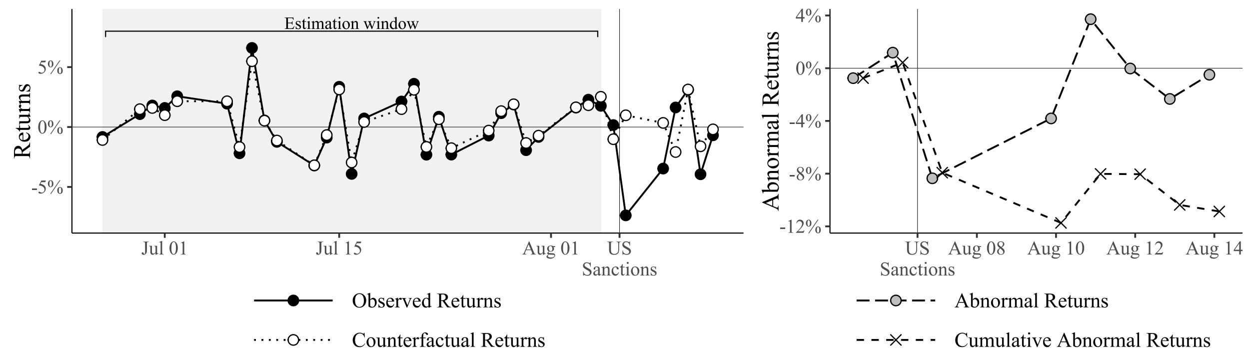

Figure 1: ***Stock Returns, Counterfactual Returns, AR, and CAR for Tencent before and after US sanctions***

When looking at the direct target, Tencent (Figure 1, left panel), we see observed and counterfactual *Returns* are remarkably similar before sanctions. On the sanction day, *AR* drop by about 8.35pp (right panel), statistically significant with p-value = 0.007 (computed via permutation inference, see appendix). This evidences that the targeted sanction was highly effective. However, effects were not limited to the direct targets. Figure 2 displays results for the three samples of US-

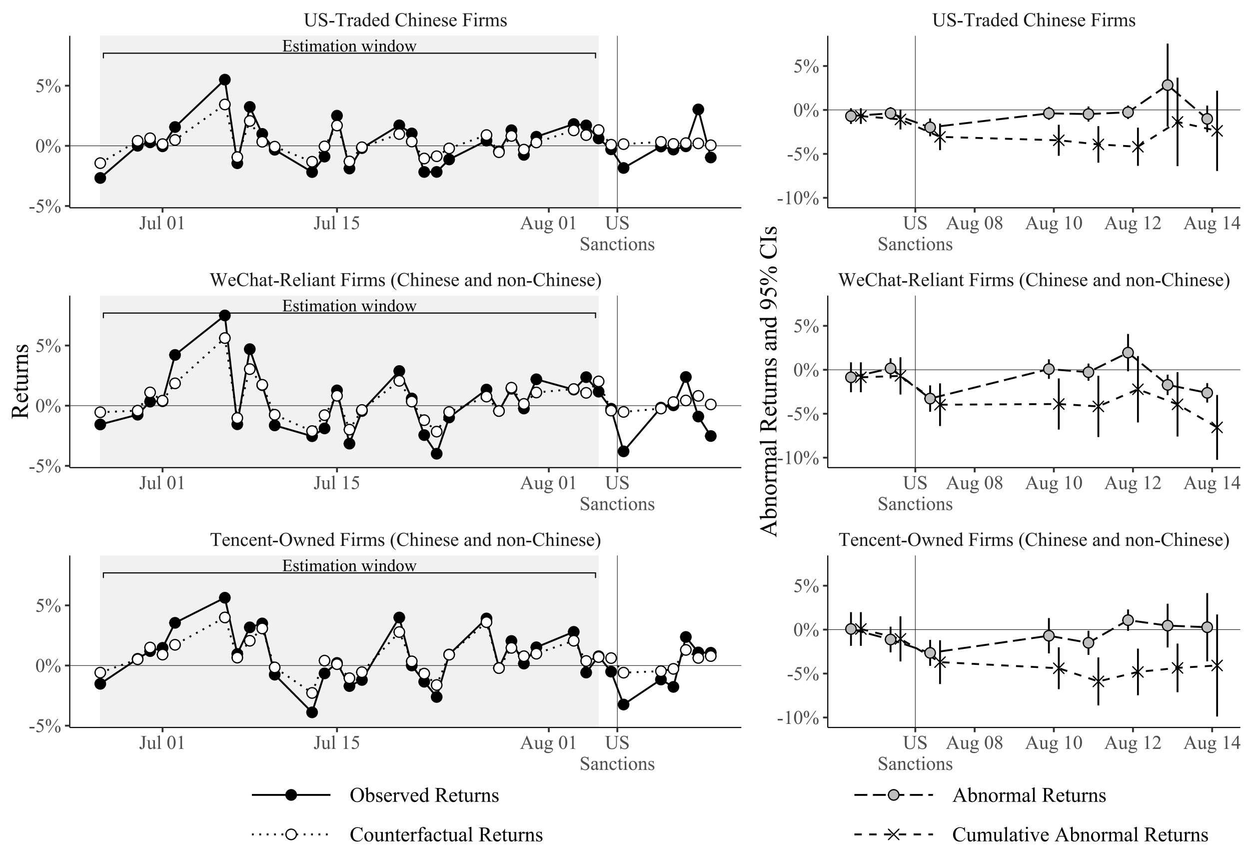

Figure 2: ***Stock Returns, Counterfactual Returns, AR, and CAR to firms traded in the US for Chinese firms (top), WeChat-reliant firms (middle), and Tencent-owned firms (bottom) before and after US sanctions targeting Tencent and ByteDance.***

traded firms (top panel: Chinese firms; middle panel: WeChat-reliant; bottom panel: Tencent-owned). We observe a very close fit between observed and counterfactual average *Returns* before the event (left panels) while Observed *Returns* drop well below counterfactuals following sanctions, in all samples. This indicates preliminary evidence in favor of our argument: Trump's sanctions on Tencent and ByteDance are associated with various spillover effects. The day after sanctions, firms with ties to the Chinese economy or to one of the direct sanction targets, Tencent, recorded significant losses on US markets. When looking at average *AR* and *CAR* (Figure 2, right panels), we see that Chinese firms' *Returns* underperformed US markets' expectations by 1.98pp [-3.00; -0.97]. The finding of a categorical effect is particularly striking given both the general media attention to US-China tensions and the case of TikTok, in particular. These factors should bias against finding a statistical result. The two other samples experienced even larger effects. WeChat-reliant firms recorded *AR* of -3.28pp [-4.78; -1.78]. Tencent-owned firms experienced *AR* of -2.65pp [-4.13; -1.17]. Spillovers were not limited to the immediate day following US executive orders. We observe significant and negative *CAR* losses even in the trading week after sanctions. Tencent-owned and WeChat-reliant firms experienced the strongest cumulative losses among our three samples, cumulatively underperforming US market expectations by 4.35pp [-7.12; -1.59] and 6.56pp [-10.2; -2.87], respectively, still on August 13 and 14.

IV. Conclusions

As governments turn to economic statecraft as a tool to shape interstate dynamics, a key question remains as to the extent to which investors interpret these signals and price emerging forms of political risk. At a minimum, sanctions shape market behavior towards explicitly targeted firms. But we further find evidence for a maximalist effect – all Chinese firms were negatively impacted. This counters some of the major economic and political justifications for a targeted approach, but does cement the beliefs and preferences of some factions of the US government. These effects do not appear to be limited to firms that are similar to the target via the sector: companies that rely on Tencent's key product, WeChat, are most adversely affected. Moreover, we do find evidence of an interdependence effect. While Chinese firms owned by Tencent are no worse off than other co-nationals, we see that non-Chinese firms owned by Tencent are significantly and negatively impacted as well. Financial interdependencies have received relatively limited academic and policy attention especially in contrast to concerns over reserve currencies, technology, or supply chain disputes. In particular, studying how different firm strategies and structures shape the costs of coercion is an essential next step in the research agenda on economic coercion and grand strategy. The market has the potential to both catalyze and amplify geopolitics.

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Appendix
Financial Sanction Spillovers and Firm Interdependence

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A Sample selection and data sources

Here, we describe how we built our three samples of US-traded firms on which we study sanctions' spillover effects. We also list the data sources we used to retrieve daily stock prices at closing for all firms' titles used in the analysis.

A.1 Sample 1: US-traded Chinese firms

First, we built a sample identifying Chinese firms trading on US exchanges. This is not as straightforward a task as it initially sounds as the majority of de facto Chinese entities list on American equity markets through offshore holding companies. For example, two of the most well-known Chinese tech firms, Alibaba and JD.com, are formally registered on the New York Stock Exchange and the NASDAQ as companies with headquarters in the Cayman Islands.

In order to build a sample of US-traded Chinese firms, we started from the so-called "China Concepts Stock" companies. These are firms whose assets or earnings have significant activities in mainland China. This list includes 555 firms that are listed on US stock exchanges, either trading common stocks or American Depositary Receipts (ADR). Not all these firms, however, are Chinese. In order to identify Chinese-headquartered firms we drew, from Compustat, the list of all firms trading on any US exchange ahead of the US sanctions. We searched this list for every firm registered in China and in Bermuda, Bahamas, Cayman Islands, British Virgin Islands, Hong Kong, and Singapore, the popular tax havens and foreign jurisdictions where Chinese firms are registered.

Next, we merged these two lists (the "China Concepts Stock" list and the Compustat list of firms headquartered in China or in popular foreign jurisdictions). Matches are US-traded firms which are, potentially, Chinese actors too. We manually coded as Chinese each of the matching firms if they met at least one of the following three conditions:

1. The firm is headquartered in mainland China
2. The firm's primary assets are located in mainland China, or its revenue comes primarily from its business in mainland China
3. The firm's controlling shareholder is a Chinese firm

Availability of stock prices data further restricted the number of firms in this sample. As a result of these steps, sample 1 comprises 210 firms.

A.2 Sample 2: Tencent-owned US-traded firms

Next, we needed a sample of US-traded firms which Tencent had stakes in, Chinese or not. We started from a database on Tencent ownership provided by Itjuzi, a data service provider of venture capital in China.[1] From this database, we built a list of all of Tencent's investments announced before the US sanctions. We supplemented this list by coding Tencent's Scheduled 13-D filings to the SEC, which obligate firms to disclose information when they own more than 5% of a company and when those holdings change by 1%. Adding these firms gives us an additional 17 companies over sample 1 (these are non-Chinese, US-traded firms that Tencent has some stake in). We further supplemented this sample by looking at news articles mentioning "stake," "equity," or "ownership" and "Tencent" in the major financial presses available through Factiva for the three months prior to our event. That generated one additional company—Australian company Afterpay (NASDAQ:APT). Availability of stock prices data further restricted the number of firms in this sample. As a result of these steps, sample 2 comprises 29 firms.

A.3 Sample 3: WeChat-reliant US-traded firms

Finally, we coded whether each firm in sample 1 or 2 is reliant on the main app provided by Tencent and targeted by the US executive orders, WeChat, as part of its core business for revenue generation. This step was initially coded manually by researching the business models of each of the 210 firms in our sample. Any firm that we found to be consumer—rather than business—facing was then coded as reliant on the app. We further verified the list by asking ChatGPT to come up with a list of WeChat reliant Chinese firms and our initially manual list was fully covered with some extraneous firms included by the AI algorithm. As a result of these steps, sample 3 comprises 38 firms.

A.4 Sample baseline: S&P 500 constituents

We also derive information on Standard & Poor's 500 constituents in order to support our estimation strategy. For this step, we use the Refinitiv API to download information on constituents. This yields 454 firms for which we can access stock prices data. Importantly, none of these firms feature in any of our three samples of interest.

[1] See: https://aboutus.itjuzi.com.

A.5 Stock data sources

We rely on data sources listed in Table A.1 to obtain daily stock prices data for the firms in our samples.

Table A.1: Stock data sources for firms by sample.

Stock Source	No. of firms	Perc. of firms
Sample 1: US-traded Chinese firms		
Compustat	147	70.00%
CRSP	62	29.52%
Yahoo! Finance	1	0.48%
Total:	**210**	**100.00%**
Sample 2: US-traded Tencent-owned firms		
Compustat	24	82.76%
CRSP	3	10.34%
Yahoo! Finance	2	6.90%
Total:	**29**	**100.00%**
Sample 3: US-traded WeChat-reliant firms		
Compustat	34	89.47%
CRSP	4	10.53%
Total:	**38**	**100.00%**
Tencent (ADR)		
Yahoo! Finance	1	100.00%
Total:	**1**	**100.00%**
S&P 500 constituents		
Refinitiv API	454	100.00%
Total:	**454**	**100.00%**

Stock data in our three samples of interest come from Compustat if firms trade common stocks on US stock exchanges (respectively, 70.00%, 82.76%, and 89.47% for the three samples). Firms that trade ADR do not have stock prices reported on Compustat. We draw this information primarily from the Center for Research in Security Prices (CRSP) via Wharton Research Data Services. A minority is, still, not present in CRSP. We therefore get these stock prices data from a Yahoo! Finance API. Stock prices data for Tencent itself, which trades ADR in the US, are drawn from Yahoo! Finance. Finally, we derive all stock prices for the 454 S&P 500 constituents from the Refinitiv python API. We then compute, for every firm (or S&P 500 constituent), stock *Returns* defined as daily percentage change in closing stock prices between two trading days.

B Estimation window

B.1 Design description

Our design builds on the standard two-window event-study pioneered by corporate finance. The goal of the design is to estimate, for each firm, counterfactual *Returns* before and after the event (US sanctions). We compare observed and counterfactual *Returns* to estimate whether (and in which direction) the event affected risk, as market participants price it.

The design estimates counterfactual *Returns*, for each firm, as an expectation based on overall market trends. To do so, we divide the *Returns* to every firm in two windows: an "estimation window" which entirely precedes the event and an "event window" that shortly follows and that includes the event (the US sanctions). Figure B.1 represents the two windows. The estimation window spans over $[t_0, t_1)$. The event window covers $[t_1, t_2]$ and includes the US sanctions day t_e (August 07, 2020). In our implementation, we test different lengths of estimation windows and event windows. We also consider event windows that are symmetrical around the event or asymmetrical (Section D).

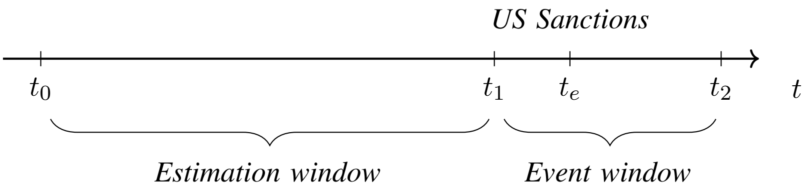

FIGURE B.1: Research design: Estimation and event window

We use estimation window data to estimate one model of daily *Returns* for each firm ("market model"), explained as a function of a matrix of predictors ($\boldsymbol{X}$). Equation 1 represents this step. Because we estimate one model per firm, all estimand parameters are specific to a given firm *i* (hence the subscripts).

$$Returns_{it} = \alpha_i + \boldsymbol{X}'_{it}\boldsymbol{w}_i\boldsymbol{\beta}_i + \varepsilon_{it} \mid t_0 \leq t < t_1 \tag{1}$$

Traditional applications of this design would build matrix $\boldsymbol{X}$ using *Returns* to aggregated market indexes, such as the S&P 500, the NYSE, or the FTSE (Aklin, 2018; Kucik and Pelc, 2016; Voeten, 2024). However, such procedure can yield correlated expected *Returns*, introducing bias when inferences are drawn in the event window. We therefore proceed differently. Inspired by Meredith Wilf's (2016) solution of using unaffected individual firms' *Returns* as predictors, we include in matrix $\boldsymbol{X}$ the individual constituents of the S&P 500 aggregate index.

A naive linear regression of firm *i*'s *Returns* including all S&P 500 constituents on the right-hand side would be, of course, unidentifiable. Because the longest estimation windows we consider span over 180 trading days (six months) and the number of S&P 500 constituents is 454, such a model would have more predictors than observations. To obviate the problem we use the least absolute shrinkage and selection operator (LASSO) (Tibshirani, 1996) to select, for each firm *i*, the set of S&P 500 constituents whose *Returns* are the most predictive. This is represented in Equation 1 by the set of non-negative weights $\boldsymbol{w}$ that accompanies each $\boldsymbol{\beta}$. The LASSO selects the single set of weights that maximizes fit through cross-validation (CV).[2] The optimal set of weights assigns to non-predictive S&P 500 constituents a 0-weight, effectively excluding them from the market model of that firm. That is, in our application we explain each firms' *Returns* using solely the individual S&P 500 constituents that yield the best fit in the estimation-window.

Once a single market model per firm is estimated via the LASSO, we use it to predict *Returns* to that firm. Such expectation represents a counterfactual measure of *Returns*, given that it is derived from market models that entirely pre-date US sanctions and given that, we assume, information relative to this event was not anticipated by markets. Equation 2 represents this step, where parameters $\hat{\alpha}_i$ and $\hat{\boldsymbol{\beta}}_i$ and optimal sets of weight ($\tilde{\boldsymbol{w}}_i$) are those that have been estimated through the LASSO. We obtain expected (or counterfactual) *Returns* over both estimation and event windows. When derived over the estimation window, such expectation is useful to gauge the aggregate quality of the fit obtained from the LASSO (Equation 1). When expectations are extended "out of sample" and into the event window, instead, they are useful for our inferential analysis, where we finally estimate the event effect.

$$E[Returns_{it}|\boldsymbol{X_{it}}] = \hat{\alpha}_i + \boldsymbol{X'_{it}}\tilde{\boldsymbol{w}}_i\hat{\boldsymbol{\beta}}_i \mid t_0 \leq t \leq t_2 \tag{2}$$

We then focus on event window data exclusively ($t_1 \leq t \leq t_2$) and obtain two measures of interest for each firm: *Abnormal Returns* (AR) and *Cumulative Abnormal Returns* (CAR) as represented in Equation 3. AR are measured as daily differences between observed and expected *Returns*, in essence representing the daily gap between observations and counterfactuals. CAR are defined as the running daily sum of AR for a given firm over the entire event window. They are useful to evaluate if a negative (positive) event effect cumulated to a substantive loss (gain).

[2] With CV, we produce 95 lambdas and select the single lambda yielding the minimum mean cross-validated error.

$$
\begin{aligned}
AR_{it} &= Returns_{it} - E[Returns_{it}|\boldsymbol{X_{it}}] \mid t_1 \leq t \leq t_2 \\
CAR_{it} &= \sum_{\tau=t_1}^{t} AR_{i\tau} \mid t_1 \leq t \leq t_2
\end{aligned}
\tag{3}
$$

The final step consists in studying the evolution of average AR and CAR before and after the event. In our main analysis, reported in Figure 2 of the main text, we do so by computing daily averages and 95% confidence intervals (CIs) using standard errors of the mean (based on the 1.96 critical value of a standard normal distribution). We simply assess whether the daily estimated average AR and CAR is distinguishable from zero at an alpha of 0.05 (or, which is the same, whether the 95% CIs overlap with 0). In additional robustness tests, we model AR and CAR in fixed effect regression models and in parametric and non-parametric event tests (Section D). Across all our tests, we adopt a conventional significance level (alpha) of 0.05.

B.2 Model specification: estimation choices, model fit, and hyper parameters

Here, we detail the procedure we followed when selecting the hyperparameters for fitting a market model on estimation window data.

In order to fit our market models, we need to make some modelling choices and fine-tune hyper parameters. A first choice pertains to the usage of the LASSO itself (and individual S&P 500 constituents) for estimating market models, as opposed to the canonical ordinary least squares (OLS) market models estimated using aggregated market-wide indexes. A second choice, specific to the usage of the LASSO, is the number of cross-validation (CV) folds imposed to define the optimal set of weights that selects predictors in or out of the market model. A third choice, common to both OLS and LASSO, is the length of the estimation window.

Here, we present the average model fit of all combinations of market models we estimated when varying modelling choices along these three dimensions. We select the single modelling choice that yields the best average model fit: market models estimated using the LASSO (and individual S&P 500 constituents), with 15-folds CV and estimation windows of 30 days. Results presented in the main text are based on these hyper parameters. We show robustness to other modelling choices in Section D.3.

We evaluated 15 sets of individual firm-specific market models. For modelling choice, we estimated both LASSO (with individual S&P 500 constituents) and OLS (with aggregate S&P 500 index) market models. For LASSO models, we imposed CV with 3, 5, 10, and 15 folds. For estimation window lengths (both LASSO and OLS), we evaluated windows starting 180, 90, and 30 trading days before the event (6, 3, and 1 month respectively). All estimation windows end 3 trading days before the event (that is, on August 4, 2020). There are 15 possible combinations of these model choices (OLS with 3 possible estimation windows; LASSO with 3 possible estimation windows × 4 possible CV choices). We therefore estimate one market model per each firm in our sample in these 15 different combinations.

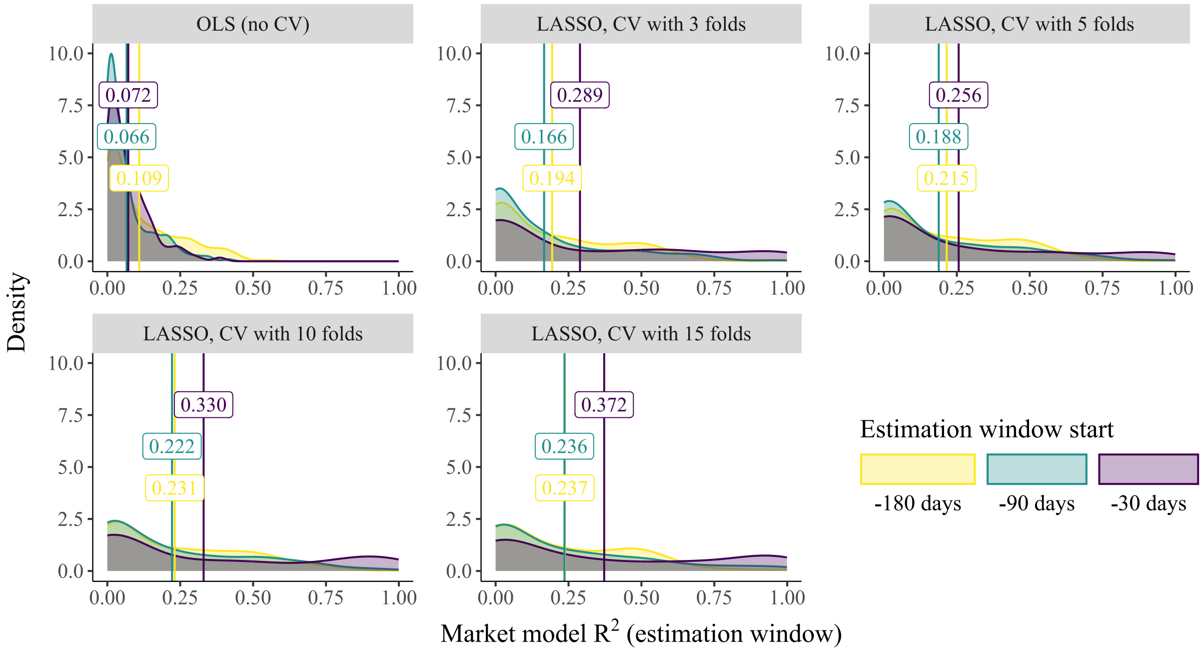

FIGURE B.2: Distribution of R^2 of market models estimated when varying modelling choices. Average R^2 reported as vertical lines

Figure B.2 presents the distribution of the R^2 of the firm-specific market models estimated for each of these modelling choices. We also report average R^2 across market models for each modelling choice as vertical lines. As the figure shows, LASSO models employing individual S&P 500 constituents perform significantly better than OLS with an aggregate S&P 500 index. For any given estimation window length, moving from an OLS model to a LASSO model with 3-folds CV always yields average R^2 that are at least 1.7× (180 days) and at most 4× (30 days) larger. Increasing the number of folds for the LASSO, moreover, further improves model fit. In terms of estimation window lengths, instead, we find that the shortest windows always perform better, on average, for the LASSO. This is not true for OLS, for which the longest window (180 trading days) performs significantly better.

Based on these results, we select the LASSO with 15-fold CV and estimation window starting 30 days before the US sanctions as our preferred estimation choice. We stress that this model choice yields significantly better model performance than traditional OLS market models with aggregate market indexes. The average R^2 of our best-performing LASSO market model choice is 0.372, more than $3\times$ higher than the average R^2 of the best-performing OLS choice (OLS with estimation window starting 180 trading days before the sanctions), which is just 0.109.

We test robustness by considering alternatives to these modelling choices in Section D.3, which we pick up choosing the best fitting options. We vary estimation window lengths by considering expected *Returns* from windows starting 180 and 90 days before the US sanctions, with the same LASSO modelling choice and 15-fold CV. We vary CV choices by selecting estimates resulting from LASSO models with 3, 5, and 10 folds (and estimation windows starting 30 days before the event). For varying modelling strategy, we consider estimates resulting from OLS models with estimation windows starting 180 days before the event (the better performing OLS choice). Finally, we also show that our results do not hinge on ending the estimation window 3 trading days before the US sanctions (on Tuesday August 4, 2020). We replicate our analysis by drawing estimates from a window ending 5 trading days before the event (Friday, July 31, 2020)—with other choices unchanged: estimation window starting 30 days before US sanctions and market models estimated using the LASSO with 15-fold CV.

Figure B.3 plots the LASSO-weighted coefficients (the $\tilde{\boldsymbol{w}}_i\hat{\boldsymbol{\beta}}_i$ from Equation 2) that we obtain from our preferred specification (LASSO with 15 CV folds, estimation windows starting and ending 30 and 3 trading days before sanctions). We exclude firms whose market model results in R^2 lower than 0.10, as they do not enter our analyses (except for a robustness check in Table D.10). The y-axis reports the S&P 500 constituent firms in alphabetical order (corresponding names are omitted for visualization purposes). The x-axis reports the list of US-traded firms in our samples in alphabetical order (we only report Tencent's name for illustration). We report the estimated LASSO-weighted $\hat{\beta}$ as dots, colored according to the estimated weighted coefficients and with growing size in their absolute value. LASSO-estimated coefficients for a given firm are arranged on the same vertical line.

To illustrate, consider Tencent's model (which we highlight as a dashed vertical line). The LASSO model indicates that Tencent's *Returns* are well explained by the *Returns* to just 19 out of the total 454 S&P 500 constituents. Only these 19 firms contribute to Tencent's counterfactual *Returns*. Furthermore, they are assigned varying coefficients based on their association with Tencent's market trends. As one can gauge from the fit between observed and counterfactual *Returns* in Figure 1 of the main text, this market model creates extremely accurate expectations, indeed resulting in an R^2 of 0.96.

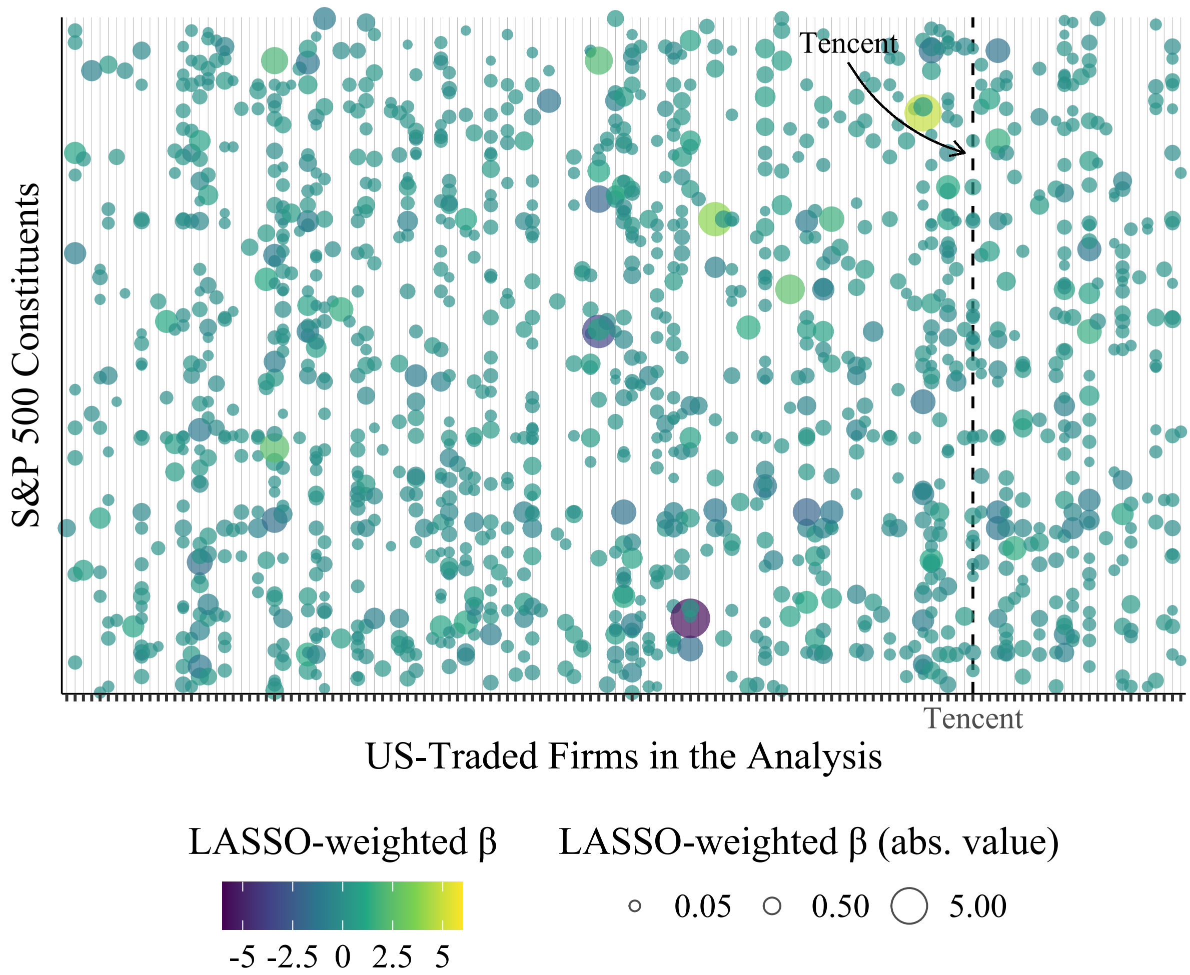

FIGURE B.3: LASSO-estimated coefficients from firm-specific market models estimated with 15-fold CV and estimation windows starting 30 trading days before US sanctions. Excludes firms whose market models results in R^2 lower than 0.10

We draw one further consideration from Figure B.3: dots do not cluster on any horizontal line. Instead, they seem rather equally distributed across the plotting area. This is reassuring evidence that counterfactuals for our firms' *Returns* are not predicted by a given small group of S&P 500 constituents. Such a pattern could raise some legitimate suspicion, as it would imply that a relatively small group of S&P 500 constituents is explaining *Returns* to several of the firms in our analysis. Reassuringly, we do not observe anything like that in the plot.

C Event window

C.1 Estimating direct sanction effect on Tencent with permutation inference

Figure 1 in the main text shows that, over the estimation window, Tencent's LASSO market model produces an extremely close fit between observed and counterfactual *Returns* (R^2 for this model is 0.96). Observed *Returns*, then, drop by 8.35 percentage points below market expectations immediately following the event. Although AR bounce back relatively quickly, CAR remain significantly negative.

Is the effect suffered by Tencent statistically distinguishable from zero? Because the estimate is relative to a single firm, we cannot compute p-values or confidence intervals by means of standard errors and conventional hypothesis-testing. We thus proceed differently. Inspired by how the problem of having only one treated unit is solved in the context of synthetic control designs (Abadie, Diamond, and Hainmueller, 2015), we resort to a placebo test of permutation inference.

Our intuition, here, is that firms with no nationality, ownership, or technology linkage to Tencent should not have been hit by the sanctions (at least not as severely as the direct target itself). We can thus compare Tencent's stock reaction to the event with the reactions of a generic sample of firms unimpacted by the sanctions, to gauge the probability of observing a shock as large as that experienced by Tencent under a null-hypothesis of no effect—that is, we can compute a p-value for Tencent. Exactly as it is done in a synthetic control design, we do so by repeating our estimation procedure on each one of the "donors" in the pool of firms that generate Tencent's counterfactual returns. That is, we repeat our procedure for each of the S&P 500 individual constituents, whose LASSO market models we fit by using the remaining constituents.

Figure C.1 compares the AR we obtain for Tencent (solid black line) and for every S&P 500 firm. Descriptively, we observe that Tencent experienced a significant shock after August 7, that appears quite rare against what S&P 500 firms experienced. Can we quantify how likely to occur at random this sizeable effect was?

We assess the statistical significance of the effect of the US sanctions on Tencent's AR on August 07, 2020 by testing the null hypothesis that the true effect is, in fact, null. What is the probability of observing an effect as large as that experienced by Tencent, under the null hypothesis? In order to answer to this question, we need a test statistic for Tencent and for the other placebo firms. Our test statistic follows what was proposed by Abadie, Diamond, and Hainmueller (2015) in the context of a synthetic

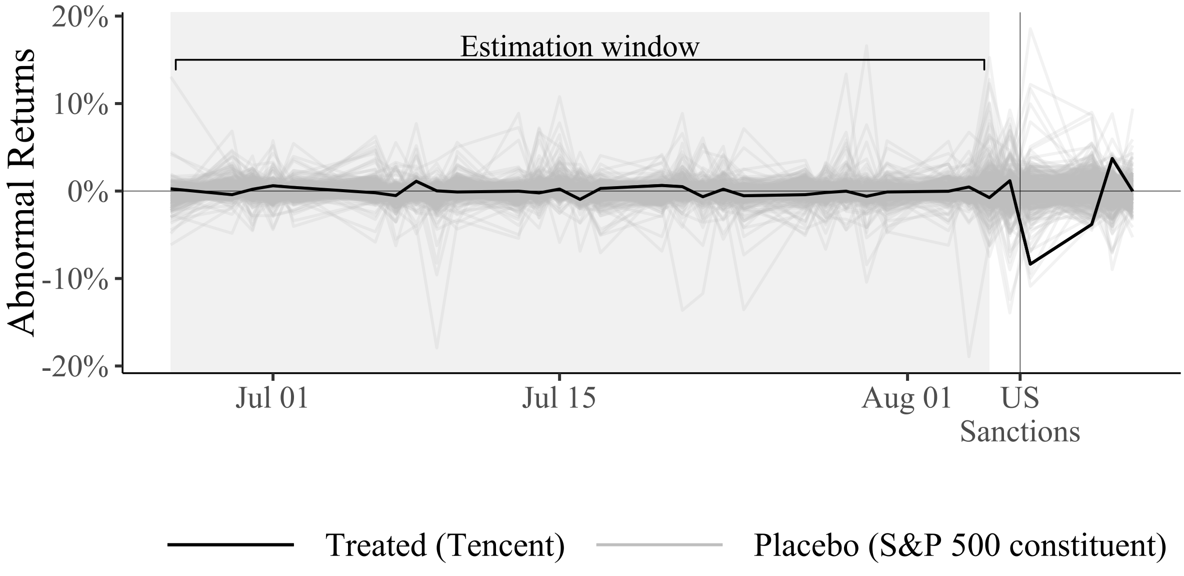

FIGURE C.1: The effect of US sanctions on *Abnormal Returns* to Tencent and to 454 placebo S&P 500 constituents

control design. First we compute, for each firm *i*, the root mean squared prediction error (RMSPE) before the event (RMSPE_{0i}) and on the day of the event (RMSPE_{1i}). Equation 4 presents our RMSPE calculation, where the time indicators t_0 and t_e refer, respectively, to the beginning of the estimation window and to the event day (see Figure B.1) and T indicates the number of days between t_0 and $t_e - 1$. Because we evaluate the post-event RMSPE only on the day of the event, the formula for RMSPE_{1i} simplifies to the absolute value of the difference between observed and counterfactual *Returns* on the event day (that is, absolute AR).

$$RMSPE_{0i} = \sqrt{\frac{\sum_{t=t_0}^{t_e-1}(Returns_{it} - E[Returns_{it}|\boldsymbol{X_{it}}])^2}{T}}, \forall i$$
$$RMSPE_{1i} = |Returns_{it_e} - E[Returns_{it_e}|\boldsymbol{X_{it_e}}]|, \forall i \tag{4}$$

The RMSPE increases as the difference between observed and expected *Returns* increases. Firms with a very poor pre-treatment fit will have a high RMSPE_{0i} and those experiencing extreme AR on the event day will have a high RMSPE_{1i}. For each firm, we define a *Test* statistic as the ratio between post-event and pre-event RMSPE, as presented in equation 5.

$$Test_i = \frac{RMSPE_{1i}}{RMSPE_{0i}}, \forall i \tag{5}$$

The intuition, here, is that a "large post intervention RMSPE is not indicative of a large effect of the intervention if the synthetic control does not closely reproduce the outcome of interest prior to the intervention." (Abadie, Diamond, and Hainmueller, 2015, 505). That is, you need RMSPE_{0i} to be small to conclude that a large RMSPE_{1i} indicates a sizeable event effect.

We present the distribution of each firm's *Test* statistics in Figure C.2. As the plot shows, Tencent's 8.35 percentage points loss in AR on August 07, 2020 results in the fourth most extreme test statistic when considering AR to the S&P 500. That is, there were only three firms out of 455 (454 S&P 500 constituents + Tencent) with a more extreme test statistic than Tencent on August 07, 2020. This means that, under the null hypothesis that the US sanctions had no direct effect (which is represented by the distribution of *Test* for placebo firms), the p-value of the Tencent effect is 3/455 = 0.007.

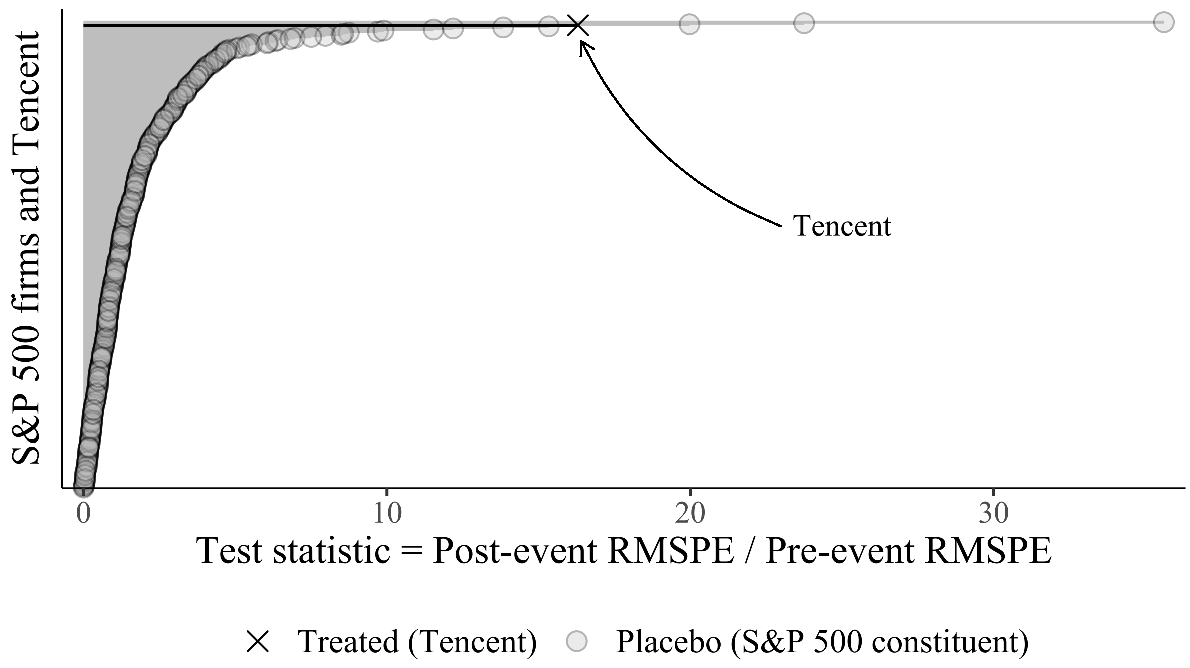

FIGURE C.2: Placebo test of significance for the effect of US sanctions on *Abnormal Returns* to Tencent on August 07, 2020

A closer investigation reveals that the high test statistics for the top three firms were, in fact, due to unrelated events occurring on August 07, 2020. All three single most extreme AR on this day—respectively for Tripadvisor, Inc (NASDAQ: TRIP), Illumina, Inc (NASDAQ: ILMN), and Teradata Corp (NYSE: TDC)—are likely driven by the fact that, on August 07 2020 or late August 06 2020, these firms announced their second-quarter revenues for the year. Tripadvisor, Inc and Illumina, Inc announced net losses due to the impact of the COVID-19 pandemic, whereas Teradata announced positive earnings.[3]

C.2 Spillover sanction effects on connected firms

We report results from the main text Figure 2—*i.e.*, the averages AR and CAR by sample, their standard errors, and corresponding statistical significance at a 0.05 alpha—in Table C.1.

Table C.1: The spillover effect of US sanctions against Tencent. Main results

	Chinese firms		Tencent-owned firms		WeChat-reliant firms	
	(1) AR	(2) CAR	(3) AR	(4) CAR	(5) AR	(6) CAR
Pre-sanctions:						
Wed, Aug 05 2020	-0.699	-0.699	0.073	0.073	-0.855	-0.855
	(0.457)	(0.457)	(0.977)	(0.977)	(0.869)	(0.869)
Thu, Aug 06 2020	-0.383	-1.082	-1.126	-1.053	0.159	-0.695
	(0.358)	(0.580)	(0.745)	(1.310)	(0.585)	(1.081)
Post-sanctions:						
Fri, Aug 07 2020	-1.984*	-3.066*	-2.648*	-3.701*	-3.279*	-3.974*
	(0.518)	(0.771)	(0.754)	(1.271)	(0.766)	(1.239)
Mon, Aug 10 2020	-0.387	-3.453*	-0.694	-4.394*	0.078	-3.895*
	(0.379)	(0.901)	(1.026)	(1.216)	(0.568)	(1.484)
Tue, Aug 11 2020	-0.469	-3.923*	-1.498*	-5.892*	-0.273	-4.168*
	(0.438)	(1.060)	(0.699)	(1.392)	(0.499)	(1.779)
Wed, Aug 12 2020	-0.266	-4.188*	1.078	-4.815*	1.952	-2.216
	(0.393)	(1.110)	(0.622)	(1.354)	(1.084)	(1.926)
Thu, Aug 13 2020	2.826	-1.362	0.459	-4.356*	-1.716*	-3.932*
	(2.411)	(2.568)	(1.267)	(1.411)	(0.592)	(1.869)
Fri, Aug 14 2020	-1.017	-2.379	0.274	-4.081	-2.625*	-6.557*
	(0.771)	(2.330)	(1.981)	(2.963)	(0.565)	(1.882)
N of firms	125	125	22	22	24	24

* $p < 0.05$
Average *Abnormal Returns* (AR) and *Cumulative Abnormal Returns* (CAR) to firms in each sample per day. Standard errors of the mean reported in parentheses. P-values computed from a two-tailed test of difference from zero for the average against a standard normal distribution. Estimation window starts 30 days and ends 3 days before US sanctions. Market models estimated using the LASSO and individual S&P 500 constituents as predictors, selected using 15-fold cross validation. Data exclude firms whose market models resulted in an R^2 smaller than 0.10

[3] See, respectively statements by Tripadvisor (https://ir.tripadvisor.com/static-files/2546aeba-e86e-4de1-983a-9671cb560aff), Illumina (https://sapac.illumina.com/company/news-center/press-releases/2020/eef21b8a-2ecd-4735-b6a8-6f02fb4798a6.html), and Teradata (https://s23.q4cdn.com/501457330/files/doc_financials/2020/q2/TDC-2Q20-Earnings-Release.pdf).

D Robustness tests

D.1 Alternative event tests

D.1.1 Regressions with firm-fixed effects

As an alternative to estimating spillover effects as sample averages of AR and CAR in the event window, here we fit linear regressions of AR and CAR. We fit models with firm fixed effects (FE) and cluster standard errors at the firm level. We explain AR using a binary variable that takes value of 1 only on the day of US sanctions (August 07, 2020). We explain CAR with a binary taking value of 1 on August 07, 2020 and on every following day until the end of the event window. We consider an event window that is symmetrical around the day of the sanctions, starting two days before and ending two days after. Results, in Table D.1, are broadly consistent with what we detect when studying sample averages.

Table D.1: The spillover effect of US sanctions against Tencent. Firm-FE models, windows of size [-2, +2]

	Chinese firms		Tencent-owned firms		WeChat-reliant firms	
	(1) AR	(2) CAR	(3) AR	(4) CAR	(5) AR	(6) CAR
Event day	-1.499*		-1.837		-3.056*	
	(0.558)		(0.919)		(0.899)	
Post-event		-2.590*		-4.173*		-3.237*
		(0.658)		(1.063)		(1.019)
Num.Obs.	625	625	110	110	120	120
R2	0.250	0.735	0.135	0.707	0.367	0.801
Std.Errors	by: firm	by: firm	by: firm	by: firm	by: firm	by: firm
FE: firm	X	X	X	X	X	X
Number of firms	125	125	22	22	24	24
Event window length	[-2, +2]	[-2, +2]	[-2, +2]	[-2, +2]	[-2, +2]	[-2, +2]

* $p < 0.05$
Linear regression models of *Abnormal Returns* (AR) and *Cumulative Abnormal Returns* (CAR) with firm fixed effects. Standard errors clustered by firm are reported in parentheses. "Event day" is a binary taking value 1 exclusively on August 07, 2020 whereas "Post-event" is a binary taking value 1 on August 07, 2020 and in the following days. Event windows start two trading days before the event and end two trading days after the event. Estimation window starts 30 days and ends 3 days before US sanctions. Market models estimated using the LASSO and individual S&P 500 constituents as predictors, selected using 15-fold cross validation. Data exclude firms whose market models resulted in an R^2 smaller than 0.10

Results are similar if we arbitrarily change the length of the event window. We replicate our firm-FE models with event windows starting four days before and ending four days after sanctions. Once again our results, reported in Table D.2, are consistent with earlier findings. Finally, we show that we can obtain similar results with non-symmetrical event windows, too. In Table D.3, we find similar results with an event window starting two days before and ending four days after the event.

Table D.2: The spillover effect of US sanctions against Tencent. Firm-FE models, windows of size [-4, +4]

	Chinese firms		Tencent-owned firms		WeChat-reliant firms	
	(1) AR	(2) CAR	(3) AR	(4) CAR	(5) AR	(6) CAR
Event day	-2.305*		-2.230*		-3.504*	
	(0.597)		(0.922)		(0.878)	
Post-event		-2.095*		-4.230*		-2.430*
		(0.836)		(1.180)		(0.971)
Num.Obs.	1125	875	198	154	216	168
R2	0.108	0.438	0.065	0.624	0.137	0.711
Std.Errors	by: firm	by: firm	by: firm	by: firm	by: firm	by: firm
FE: firm	X	X	X	X	X	X
Number of firms	125	125	22	22	24	24
Event window length	[-4, +4]	[-4, +4]	[-4, +4]	[-4, +4]	[-4, +4]	[-4, +4]

* $p < 0.05$
Linear regression models of *Abnormal Returns* (AR) and *Cumulative Abnormal Returns* (CAR) with firm fixed effects. Standard errors clustered by firm are reported in parentheses. “Event day” is a binary taking value 1 exclusively on August 07, 2020 whereas “Post-event” is a binary taking value 1 on August 07, 2020 and in the following days. Event windows start four trading days before the event and end four trading days after the event. Estimation window starts 30 days and ends 3 days before US sanctions. Market models estimated using the LASSO and individual S&P 500 constituents as predictors, selected using 15-fold cross validation. Data exclude firms whose market models resulted in an R^2 smaller than 0.10

Table D.3: The spillover effect of US sanctions against Tencent. Firm-FE models, windows of size [-2, +4]

	Chinese firms		Tencent-owned firms		WeChat-reliant firms	
	(1) AR	(2) CAR	(3) AR	(4) CAR	(5) AR	(6) CAR
Event day	-2.087*		-2.364*		-3.170*	
	(0.655)		(0.910)		(0.880)	
Post-event		-2.308*		-4.142*		-2.862*
		(0.855)		(1.120)		(1.127)
Num.Obs.	875	875	154	154	168	168
R2	0.139	0.439	0.084	0.648	0.195	0.769
Std.Errors	by: firm	by: firm	by: firm	by: firm	by: firm	by: firm
FE: firm	X	X	X	X	X	X
Number of firms	125	125	22	22	24	24
Event window length	[-2, +4]	[-2, +4]	[-2, +4]	[-2, +4]	[-2, +4]	[-2, +4]

* $p < 0.05$
Linear regression models of *Abnormal Returns* (AR) and *Cumulative Abnormal Returns* (CAR) with firm fixed effects. Standard errors clustered by firm are reported in parentheses. “Event day” is a binary taking value 1 exclusively on August 07, 2020 whereas “Post-event” is a binary taking value 1 on August 07, 2020 and in the following days. Event windows start two trading days before the event and end four trading days after the event. Estimation window starts 30 days and ends 3 days before US sanctions. Market models estimated using the LASSO and individual S&P 500 constituents as predictors, selected using 15-fold cross validation. Data exclude firms whose market models resulted in an R^2 smaller than 0.10

D.1.2 Parametric event tests

As alternative ways to estimate event effects, in Tables D.4, D.5, and D.6 we show results obtained when employing a range of parametric event-study tests of AR proposed in the corporate finance literature to account for such issues as event-induced variance in AR, serial correlation, and correlation in event effects. We consider tests by Brown and Warner (1980), Brown and Warner (1985), a standard t-test, tests by Patell (1976), Boehmer, Masumeci, and Poulsen (1991), and Lamb (1995).

Generally speaking, we find consistent evidence with that detected above. Our estimates generally pass these tests returning statistically significant results. Results are less strong for the test by Boehmer, Masumeci, and Poulsen (1991) in the case of Tencent-owned and WeChat-reliant firms where, however, limited sample size reduces the extent to which we can make substantive evaluations out of these tests (N = 22 and 24, respectively).

Table D.4: The spillover effect of US sanctions against Tencent. Parametric tests, US-traded Chinese firms

Date	Estimate	BW 1980	BW 1985	T-test	Patell (1976)	BMP 1991	Lamb (1995)
Pre-sanctions:							
Wed, Aug 05 2020	-1.298	-5.212*	-2.532*	-2.435*	-2.945*	-0.175	-2.486*
Thu, Aug 06 2020	-0.229	-0.919	-0.446	-0.569	-8.158*	-0.812	-0.438
Post-sanctions:							
Fri, Aug 07 2020	-2.045	-8.208*	-3.987*	-3.679*	-43.867*	-2.151*	-3.899*
Mon, Aug 10 2020	-0.610	-2.448*	-1.189	-1.353	-13.353*	-1.030	-1.166
Tue, Aug 11 2020	-0.255	-1.024	-0.498	-0.486	-24.727*	-1.019	-0.477

* $p < 0.05$
Parametric event test results respectively from Brown and Warner (1980, BW 1980), Brown and Warner (1985, BW 1985), regular t-test, Patell (1976), Boehmer, Masumeci, and Poulsen (1991, BMP 1991), and Lamb (1995). Estimation window starts 30 days and ends 3 days before US sanctions. Market models estimated using the LASSO and individual S&P 500 constituents as predictors, selected using 15-fold cross validation. Data exclude firms whose market models resulted in an R^2 smaller than 0.10

Table D.5: The spillover effect of US sanctions against Tencent. Parametric tests, US-traded Tencent-owned firms

Date	Estimate	BW 1980	BW 1985	T-test	Patell (1976)	BMP 1991	Lamb (1995)
Pre-sanctions:							
Wed, Aug 05 2020	-0.111	-0.240	-0.220	-0.106	2.465*	0.19	-0.216
Thu, Aug 06 2020	-1.159	-2.505*	-2.300*	-1.465	-0.001	0.00	-2.256*
Post-sanctions:							
Fri, Aug 07 2020	-1.979	-4.278*	-3.928*	-2.392*	-18.424*	-1.32	-3.833*
Mon, Aug 10 2020	-0.290	-0.627	-0.576	-0.289	-16.575*	-1.02	-0.565
Tue, Aug 11 2020	-1.392	-3.009*	-2.762*	-1.678	-1.408	-0.52	-2.711*

* $p < 0.05$
Parametric event test results respectively from Brown and Warner (1980, BW 1980), Brown and Warner (1985, BW 1985), regular t-test, Patell (1976), Boehmer, Masumeci, and Poulsen (1991, BMP 1991), and Lamb (1995). Estimation window starts 30 days and ends 3 days before US sanctions. Market models estimated using the LASSO and individual S&P 500 constituents as predictors, selected using 15-fold cross validation. Data exclude firms whose market models resulted in an R^2 smaller than 0.10

Table D.6: The spillover effect of US sanctions against Tencent. Parametric tests, US-traded WeChat-reliant firms

Date	Estimate	BW 1980	BW 1985	T-test	Patell (1976)	BMP 1991	Lamb (1995)
Pre-sanctions:							
Wed, Aug 05 2020	-1.509	-4.120*	-2.380*	-1.531	-7.759*	-1.53	-2.337*
Thu, Aug 06 2020	0.511	1.396	0.806	0.773	10.770*	1.91	0.792
Post-sanctions:							
Fri, Aug 07 2020	-2.919	-7.973*	-4.606*	-3.395*	-35.101*	-2.42	-4.449*
Mon, Aug 10 2020	0.228	0.622	0.359	0.349	-8.724*	-0.72	0.347
Tue, Aug 11 2020	-0.118	-0.321	-0.186	-0.186	0.786	0.16	-0.182

* $p < 0.05$
Parametric event test results respectively from Brown and Warner (1980, BW 1980), Brown and Warner (1985, BW 1985), regular t-test, Patell (1976), Boehmer, Masumeci, and Poulsen (1991, BMP 1991), and Lamb (1995). Estimation window starts 30 days and ends 3 days before US sanctions. Market models estimated using the LASSO and individual S&P 500 constituents as predictors, selected using 15-fold cross validation. Data exclude firms whose market models resulted in an R^2 smaller than 0.10

D.1.3 Non-parametric event tests

In Tables D.7, D.8, and D.9 we present results obtained using non-parametric event tests for US-traded Chinese, Tencent-owned, and WeChat-reliant firms, respectively. We consider a sign test (Boehmer, Masumeci, and Poulsen, 1991), a generalized sign test (McConnell and Muscarella, 1985), a Corrado sign test (Corrado and Zivney, 1992), a rank test (Cowan, 1992), a modified rank test (Corrado and Zivney, 1992), and a Wilcoxon test (Wilcoxon, 1992).

Similarly to what we presented before, we find significant event effects on the day of the US sanctions. Effects are weaker for our smallest sample, the one of US-traded Tencent-owned firms (Table D.8) where our statistical power is significantly limited.

Table D.7: The spillover effect of US sanctions against Tencent. Non-parametric tests, US-traded Chinese firms

Date	Sign test	Gen. sign test	Corrado sign test	Rank test	Mod. rank test	Wilcoxon test
Pre-sanctions:						
Wed, Aug 05 2020	-1.699	-1.650	-0.821	-0.861	-0.861	3204.000
Thu, Aug 06 2020	-0.447	-0.398	0.043	-0.102	-0.102	3740.000
Post-sanctions:						
Fri, Aug 07 2020	-4.204*	-4.154*	-2.118*	-2.449*	-2.449*	2084.000*
Mon, Aug 10 2020	0.089	0.139	0.216	0.050	0.050	3746.000
Tue, Aug 11 2020	1.878	1.928	1.081	0.684	0.684	4165.000

* $p < 0.05$
Non-parametric event test results respectively from a sign test (Boehmer, Masumeci, and Poulsen, 1991), a generalized sign test (McConnell and Muscarella, 1985), a Corrado sign test (Corrado and Zivney, 1992), a rank test (Cowan, 1992), a modified rank test (Corrado and Zivney, 1992), and a Wilcoxon test (Wilcoxon, 1992). Estimation window starts 30 days and ends 3 days before US sanctions. Market models estimated using the LASSO and individual S&P 500 constituents as predictors, selected using 15-fold cross validation. Data exclude firms whose market models resulted in an R^2 smaller than 0.10

Table D.8: The spillover effect of US sanctions against Tencent. Non-parametric tests, US-traded Tencent-owned firms

Date	Sign test	Gen. sign test	Corrado sign test	Rank test	Mod. rank test	Wilcoxon test
Pre-sanctions:						
Wed, Aug 05 2020	-0.426	-0.442	-0.332	0.274	0.274	132.000
Thu, Aug 06 2020	-1.279	-1.295	-0.995	-0.941	-0.941	80.000
Post-sanctions:						
Fri, Aug 07 2020	-1.706	-1.721	-1.326	-1.918	-1.918	62.000*
Mon, Aug 10 2020	-2.558*	-2.574*	-1.326	-1.206	-1.206	81.000
Tue, Aug 11 2020	-1.279	-1.295	-0.995	-1.279	-1.279	85.000

* $p < 0.05$
Non-parametric event test results respectively from a sign test (Boehmer, Masumeci, and Poulsen, 1991), a generalized sign test (McConnell and Muscarella, 1985), a Corrado sign test (Corrado and Zivney, 1992), a rank test (Cowan, 1992), a modified rank test (Corrado and Zivney, 1992), and a Wilcoxon test (Wilcoxon, 1992). Estimation window starts 30 days and ends 3 days before US sanctions. Market models estimated using the LASSO and individual S&P 500 constituents as predictors, selected using 15-fold cross validation. Data exclude firms whose market models resulted in an R^2 smaller than 0.10

Table D.9: The spillover effect of US sanctions against Tencent. Non-parametric tests, US-traded WeChat-reliant firms

Date	Sign test	Gen. sign test	Corrado sign test	Rank test	Mod. rank test	Wilcoxon test
Pre-sanctions:						
Wed, Aug 05 2020	-1.225	-0.999	-0.739	-0.925	-0.925	99.000
Thu, Aug 06 2020	0.816	1.044	0.739	0.578	0.578	188.000
Post-sanctions:						
Fri, Aug 07 2020	-2.449*	-2.225*	-1.477	-1.977*	-1.977*	49.000*
Mon, Aug 10 2020	-1.633	-1.408	-0.739	-0.405	-0.405	138.000
Tue, Aug 11 2020	0.000	0.227	0.000	-0.116	-0.116	146.000

* $p < 0.05$
Non-parametric event test results respectively from a sign test (Boehmer, Masumeci, and Poulsen, 1991), a generalized sign test (McConnell and Muscarella, 1985), a Corrado sign test (Corrado and Zivney, 1992), a rank test (Cowan, 1992), a modified rank test (Corrado and Zivney, 1992), and a Wilcoxon test (Wilcoxon, 1992). Estimation window starts 30 days and ends 3 days before US sanctions. Market models estimated using the LASSO and individual S&P 500 constituents as predictors, selected using 15-fold cross validation. Data exclude firms whose market models resulted in an R^2 smaller than 0.10

D.2 Inclusion and exclusion of firms from the samples

D.2.1 Inclusion of firms with poor model fit

Our main results are obtained when excluding firms whose market models resulted in an R^2 smaller than 0.10. In Table D.10 we relax this choice and consider all firms in the samples for which we have estimated a market model. Results are, again, broadly consistent with earlier findings. We note that, with this sample that comprises firms with poorly-estimated counterfactuals, negative CAR seem to be significantly large for a longer time and at least until August 14, 2020.

Table D.10: The spillover effect of US sanctions against Tencent. All firms included

	Chinese firms		Tencent-owned firms		WeChat-reliant firms	
	(1) AR	(2) CAR	(3) AR	(4) CAR	(5) AR	(6) CAR
Pre-sanctions:						
Wed, Aug 05 2020	-0.022	-0.022	-0.435	-0.435	0.250	0.250
	(0.435)	(0.435)	(0.864)	(0.864)	(1.309)	(1.309)
Thu, Aug 06 2020	-2.007	-2.029	-1.493*	-1.927	0.085	0.335
	(1.284)	(1.254)	(0.616)	(1.196)	(0.466)	(1.337)
Post-sanctions:						
Fri, Aug 07 2020	-3.644*	-5.835*	-2.644*	-4.571*	-3.021*	-2.686
	(1.285)	(2.457)	(0.746)	(1.282)	(0.933)	(1.999)
Mon, Aug 10 2020	-1.004	-6.839*	-1.019	-5.590*	-0.270	-2.957
	(0.901)	(3.063)	(0.967)	(1.684)	(0.806)	(2.646)
Tue, Aug 11 2020	-1.927*	-8.767*	-1.603*	-7.192*	-1.567	-4.524
	(0.907)	(3.734)	(0.738)	(1.786)	(0.976)	(2.389)
Wed, Aug 12 2020	-0.008	-8.775*	0.604	-6.589*	1.136	-3.388
	(0.333)	(3.640)	(0.546)	(1.968)	(0.778)	(2.703)
Thu, Aug 13 2020	1.996	-6.779	0.033	-6.556*	-0.695	-4.083
	(1.494)	(3.829)	(0.987)	(2.114)	(0.773)	(2.932)
Fri, Aug 14 2020	-0.717	-7.496*	-0.477	-7.033*	-3.126*	-7.209*
	(0.608)	(3.676)	(1.547)	(3.140)	(0.600)	(3.017)
N of firms	206	206	29	29	38	38

* $p < 0.05$
Average *Abnormal Returns* (AR) and *Cumulative Abnormal Returns* (CAR) to firms in each sample per day. Standard errors of the mean reported in parentheses. P-values computed from a two-tailed test of difference from zero for the average against a standard normal distribution. Estimation window starts 30 days and ends 3 days before US sanctions. Market models estimated using the LASSO and individual S&P 500 constituents as predictors, selected using 15-fold cross validation

D.2.2 Exclusion of firms experiencing unrelated events

In Table D.11, we repeat our analysis after discarding all firms that experienced any other price-relevant event, unrelated to the sanctions, in the event window. We identified these events through Factiva searches.

This test significantly reduces our sample size, shrinking the sample of US-traded Chinese firms from 125 to 98, the sample of US-traded firms owned by Tencent from 22 to 9 and the sample of WeChat-reliant US-traded firms from 24 to 15. That notwithstanding, we are able to detect a significant effect of the event on AR and CAR for *all* samples. We still detect significant negative CAR up until August 14, 2020 for the first and third sample, but not for the second one (for which we detect negative and statistically significant CAR until August 12, 2020).

Table D.11: The spillover effect of US sanctions against Tencent. Exclusion of firms with unrelated events

	Chinese firms		Tencent-owned firms		WeChat-reliant firms	
	(1) AR	(2) CAR	(3) AR	(4) CAR	(5) AR	(6) CAR
Pre-sanctions:						
Wed, Aug 05 2020	-0.669	-0.669	0.137	0.137	0.375	0.375
	(0.506)	(0.506)	(1.611)	(1.611)	(0.591)	(0.591)
Thu, Aug 06 2020	-0.365	-1.035	-2.247	-2.110	-0.169	0.205
	(0.392)	(0.599)	(1.406)	(2.090)	(0.780)	(0.801)
Post-sanctions:						
Fri, Aug 07 2020	-2.179*	-3.213*	-3.581*	-5.690*	-3.155*	-2.950*
	(0.451)	(0.854)	(1.253)	(2.418)	(0.927)	(1.380)
Mon, Aug 10 2020	-0.204	-3.417*	0.598	-5.092*	0.118	-2.831
	(0.428)	(1.006)	(2.087)	(2.293)	(0.736)	(1.790)
Tue, Aug 11 2020	-0.431	-3.848*	-2.418	-7.510*	0.133	-2.698
	(0.525)	(1.249)	(1.467)	(2.842)	(0.670)	(2.161)
Wed, Aug 12 2020	-0.655	-4.503*	0.878	-6.632*	1.351*	-1.347
	(0.360)	(1.283)	(0.989)	(2.890)	(0.643)	(1.924)
Thu, Aug 13 2020	0.709	-3.794*	2.580	-4.052	-1.456*	-2.802
	(0.491)	(1.367)	(2.858)	(3.054)	(0.499)	(1.882)
Fri, Aug 14 2020	-0.061	-3.855*	1.390	-2.663	-3.350*	-6.152*
	(0.767)	(1.702)	(4.768)	(6.963)	(0.814)	(2.065)
N of firms	98	98	9	9	15	15

* $p < 0.05$
Average *Abnormal Returns* (AR) and *Cumulative Abnormal Returns* (CAR) to firms in each sample per day. Standard errors of the mean reported in parentheses. P-values computed from a two-tailed test of difference from zero for the average against a standard normal distribution. Estimation window starts 30 days and ends 3 days before US sanctions. Market models estimated using the LASSO and individual S&P 500 constituents as predictors, selected using 15-fold cross validation. Data exclude firms whose market models resulted in an R^2 smaller than 0.10 and firms experiencing price-relevant events unrelated to the sanctions in the event window.

D.2.3 Exclusion of one firm at the time (jackknife test)

In the spirit of ensuring that our results are not driven by any single firm, we proceed at a jackknife test. We exclude one firm from each of the three samples at the time and re-estimate our main analysis iteratively. For ease of presentation, here we report average AR and 95% CIs on the day of the US sanctions (August 07, 2020) as coefficient plots. We report one point estimate and CI for each iteration of our procedure (every time discarding a different firm). For comparison, we also report the estimated average AR from the full sample (in red, same estimates as in Table C.1). Results are reported in Figure

D.1. We find a consistent and negative effect of US sanctions on the three samples across all iterations. That is, the detected negative effects do not depend on any single outlier.

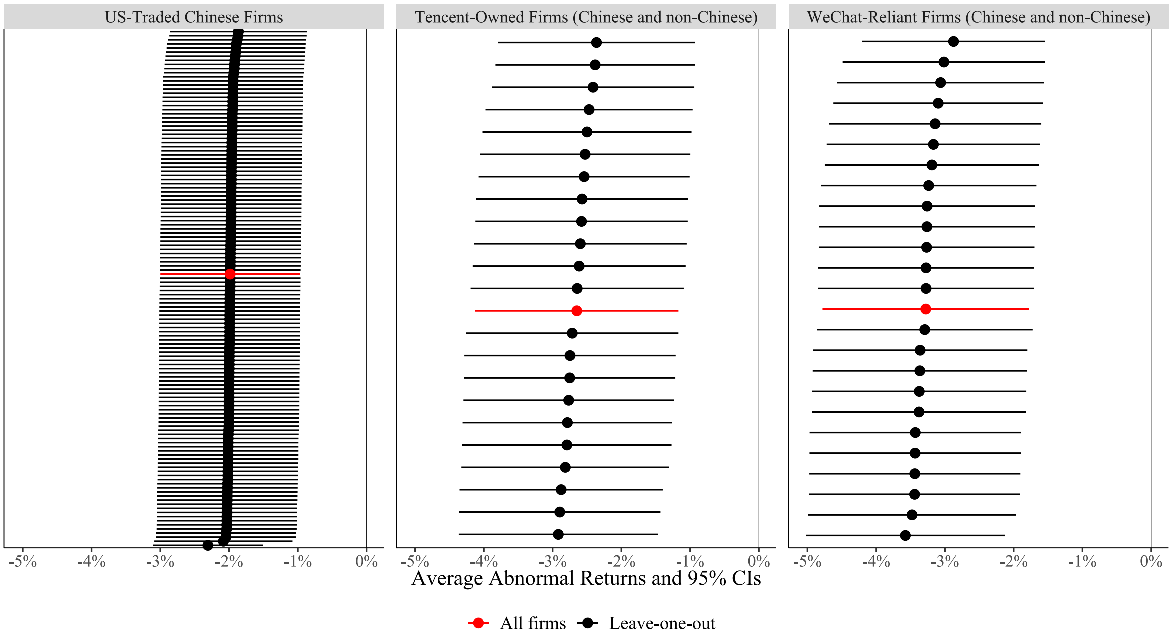

FIGURE D.1: Average AR from a jackknife test on August 07, 2020. Exclusion of one firm at the time from each sample

D.3 Alternative choices for estimating market models and counterfactual *Returns*

D.3.1 Estimation window lengths

We show results obtained when estimating *Returns* in market models that consider an estimation window starting 180 days before US sanctions. Just as in the main results, estimation windows end 3 days before US sanctions and market models are estimated using 15-fold LASSO CV. Results (Table D.12) are similar to those above, although CAR are significant only for the Tencent-owned sample. Next, we do the same but start our estimation windows 90 days before sanctions. Results (Table D.13) lead us to similar considerations.

Table D.12: The spillover effect of US sanctions against Tencent. Estimation window starts 180 days before sanctions

	Chinese firms		Tencent-owned firms		WeChat-reliant firms	
	(1) AR	(2) CAR	(3) AR	(4) CAR	(5) AR	(6) CAR
Pre-sanctions:						
Wed, Aug 05 2020	0.919	0.919	0.335	0.335	2.168	2.168
	(0.627)	(0.627)	(0.826)	(0.826)	(1.379)	(1.379)
Thu, Aug 06 2020	0.430	1.349	-1.936	-1.602	-0.120	2.048
	(0.561)	(1.073)	(1.365)	(1.768)	(0.483)	(1.397)
Post-sanctions:						
Fri, Aug 07 2020	-1.607*	-0.257	-1.999*	-3.601*	-2.593*	-0.545
	(0.772)	(1.685)	(0.817)	(1.588)	(0.987)	(2.194)
Mon, Aug 10 2020	0.071	-0.187	-1.846*	-5.447*	-0.324	-0.869
	(0.587)	(2.185)	(0.695)	(1.837)	(0.736)	(2.816)
Tue, Aug 11 2020	0.453	0.267	-1.324*	-6.771*	-0.792	-1.661
	(0.603)	(2.610)	(0.633)	(2.194)	(0.898)	(2.111)
Wed, Aug 12 2020	0.806	1.073	0.516	-6.255*	1.443	-0.218
	(0.487)	(2.957)	(0.580)	(2.334)	(0.744)	(2.425)
Thu, Aug 13 2020	1.087	2.160	-0.347	-6.602*	-0.471	-0.688
	(0.593)	(3.444)	(0.456)	(2.186)	(0.350)	(2.592)
Fri, Aug 14 2020	-0.012	2.148	-0.900	-7.502*	-2.211*	-2.900
	(0.680)	(3.857)	(0.501)	(2.507)	(0.447)	(2.635)
N of firms	126	126	27	27	31	31

* $p < 0.05$
Average *Abnormal Returns* (AR) and *Cumulative Abnormal Returns* (CAR) to firms in each sample per day. Standard errors of the mean reported in parentheses. P-values computed from a two-tailed test of difference from zero for the average against a standard normal distribution. Estimation window starts 180 days and ends 3 days before US sanctions. Market models estimated using the LASSO and individual S&P 500 constituents as predictors, selected using 15-fold cross validation. Data exclude firms whose market models resulted in an R^2 smaller than 0.10

Table D.13: The spillover effect of US sanctions against Tencent. Estimation window starts 90 days before sanctions

	Chinese firms		Tencent-owned firms		WeChat-reliant firms	
	(1) AR	(2) CAR	(3) AR	(4) CAR	(5) AR	(6) CAR
Pre-sanctions:						
Wed, Aug 05 2020	1.652	1.652	-0.136	-0.136	1.227	1.227
	(1.132)	(1.132)	(1.070)	(1.070)	(1.603)	(1.603)
Thu, Aug 06 2020	-0.352	1.300	-1.032	-1.168	-0.313	0.915
	(1.465)	(1.520)	(0.831)	(1.313)	(0.517)	(1.603)
Post-sanctions:						
Fri, Aug 07 2020	-2.089	-0.788	-2.206*	-3.374*	-2.528*	-1.614
	(1.315)	(2.595)	(0.756)	(1.359)	(0.985)	(2.402)
Mon, Aug 10 2020	2.002	1.214	-1.325	-4.699*	0.196	-1.418
	(1.132)	(3.048)	(0.955)	(1.593)	(0.714)	(2.958)
Tue, Aug 11 2020	2.173	3.387	-0.769	-5.468*	-0.997	-2.414
	(1.164)	(3.816)	(0.597)	(1.763)	(0.937)	(2.246)
Wed, Aug 12 2020	1.433	4.820	0.350	-5.119*	1.278	-1.136
	(0.850)	(4.270)	(0.708)	(1.857)	(0.836)	(2.601)
Thu, Aug 13 2020	2.498*	7.319	-0.651	-5.770*	-0.618	-1.754
	(1.133)	(5.242)	(0.591)	(1.830)	(0.408)	(2.800)
Fri, Aug 14 2020	1.017	8.336	-1.056	-6.826*	-2.509*	-4.263
	(1.040)	(6.051)	(0.713)	(2.143)	(0.499)	(2.788)
N of firms	116	116	23	23	29	29

* $p < 0.05$
Average *Abnormal Returns* (AR) and *Cumulative Abnormal Returns* (CAR) to firms in each sample per day. Standard errors of the mean reported in parentheses. P-values computed from a two-tailed test of difference from zero for the average against a standard normal distribution. Estimation window starts 90 days and ends 3 days before US sanctions. Market models estimated using the LASSO and individual S&P 500 constituents as predictors, selected using 15-fold cross validation. Data exclude firms whose market models resulted in an R^2 smaller than 0.10

D.3.2 Estimation window ending

Here, we replicate our analysis employing our preferred estimation window starting 30 days before US sanctions, where market models are estimated with the LASSO and 15-fold CV. Unlike in our main analysis, however, we stop the estimation window 5 days before US sanctions (instead of 3). Results (Table D.14) are consistent with those detected in our main analysis.

Table D.14: The spillover effect of US sanctions against Tencent. Estimation window stops 5 days before sanctions

	Chinese firms		Tencent-owned firms		WeChat-reliant firms	
	(1) AR	(2) CAR	(3) AR	(4) CAR	(5) AR	(6) CAR
Pre-sanctions:						
Wed, Aug 05 2020	-0.963*	-0.963*	-1.088	-1.088	-0.695	-0.695
	(0.439)	(0.439)	(1.235)	(1.235)	(0.910)	(0.910)
Thu, Aug 06 2020	0.015	-0.947	-1.056	-2.145	0.884	0.189
	(0.416)	(0.639)	(0.690)	(1.528)	(0.729)	(1.104)
Post-sanctions:						
Fri, Aug 07 2020	-2.147*	-3.094*	-2.704*	-4.848*	-2.914*	-2.725*
	(0.520)	(0.793)	(0.765)	(1.618)	(0.737)	(1.266)
Mon, Aug 10 2020	-0.470	-3.564*	-1.365	-6.214*	-0.463	-3.188
	(0.421)	(0.973)	(1.290)	(2.119)	(0.867)	(2.015)
Tue, Aug 11 2020	-0.466	-4.030*	-1.255	-7.469*	0.198	-2.991
	(0.492)	(1.108)	(0.747)	(2.099)	(0.397)	(1.996)
Wed, Aug 12 2020	0.113	-3.917*	0.849	-6.619*	1.327*	-1.663
	(0.333)	(1.158)	(0.681)	(2.165)	(0.538)	(2.123)
Thu, Aug 13 2020	3.142	-0.775	0.397	-6.223*	-1.284*	-2.947
	(2.474)	(2.653)	(1.281)	(2.351)	(0.434)	(2.156)
Fri, Aug 14 2020	-1.056	-1.831	-0.282	-6.505	-2.620*	-5.567*
	(0.779)	(2.418)	(2.052)	(3.833)	(0.713)	(2.602)
N of firms	122	122	22	22	24	24

* $p < 0.05$
Average *Abnormal Returns* (AR) and *Cumulative Abnormal Returns* (CAR) to firms in each sample per day. Standard errors of the mean reported in parentheses. P-values computed from a two-tailed test of difference from zero for the average against a standard normal distribution. Estimation window starts 30 days and ends 5 days before US sanctions. Market models estimated using the LASSO and individual S&P 500 constituents as predictors, selected using 15-fold cross validation. Data exclude firms whose market models resulted in an R^2 smaller than 0.10

D.3.3 Number of LASSO cross-validation folds

Here, we replicate the analysis of our main text but change the number of folds for the CV procedure employed by the LASSO to consider 10 (Table D.15), 5 (Table D.16), and 3 (Table D.17) folds. All estimation windows have the same hyper-parameters selected in our main study: they start 30 days before and end 3 days before the US sanctions. Results are, once again, consistent with those presented in our main text.

Table D.15: The spillover effect of US sanctions against Tencent. 10-fold LASSO estimation window

	Chinese firms		Tencent-owned firms		WeChat-reliant firms	
	(1) AR	(2) CAR	(3) AR	(4) CAR	(5) AR	(6) CAR
Pre-sanctions:						
Wed, Aug 05 2020	-0.933	-0.933	0.052	0.052	-0.379	-0.379
	(0.499)	(0.499)	(0.889)	(0.889)	(0.857)	(0.857)
Thu, Aug 06 2020	-0.524	-1.457*	-1.269	-1.217	0.053	-0.326
	(0.387)	(0.609)	(0.669)	(1.180)	(0.584)	(1.006)
Post-sanctions:						
Fri, Aug 07 2020	-2.167*	-3.624*	-2.816*	-4.033*	-3.692*	-4.018*
	(0.560)	(0.768)	(0.778)	(1.233)	(0.778)	(1.287)
Mon, Aug 10 2020	-0.563	-4.187*	-0.859	-4.891*	-0.735	-4.753*
	(0.405)	(0.927)	(0.981)	(1.291)	(0.578)	(1.611)
Tue, Aug 11 2020	-0.769	-4.956*	-1.852*	-6.743*	-0.609	-5.362*
	(0.494)	(1.148)	(0.687)	(1.521)	(0.543)	(1.977)
Wed, Aug 12 2020	-0.438	-5.394*	0.952	-5.791*	1.087	-4.275*
	(0.337)	(1.155)	(0.572)	(1.510)	(0.610)	(2.159)
Thu, Aug 13 2020	3.313	-2.081	0.269	-5.522*	-1.107*	-5.383*
	(2.813)	(2.957)	(1.208)	(1.583)	(0.495)	(2.160)
Fri, Aug 14 2020	-1.168	-3.249	0.057	-5.465	-2.780*	-8.162*
	(0.880)	(2.643)	(1.822)	(2.928)	(0.612)	(2.178)
N of firms	107	107	24	24	22	22

* $p < 0.05$

Average *Abnormal Returns* (AR) and *Cumulative Abnormal Returns* (CAR) to firms in each sample per day. Standard errors of the mean reported in parentheses. P-values computed from a two-tailed test of difference from zero for the average against a standard normal distribution. Estimation window starts 30 days and ends 3 days before US sanctions. Market models estimated using the LASSO and individual S&P 500 constituents as predictors, selected using 10-fold cross validation. Data exclude firms whose market models resulted in an R^2 smaller than 0.10

Table D.16: The spillover effect of US sanctions against Tencent. 5-fold LASSO estimation window

	Chinese firms		Tencent-owned firms		WeChat-reliant firms	
	(1) AR	(2) CAR	(3) AR	(4) CAR	(5) AR	(6) CAR
Pre-sanctions:						
Wed, Aug 05 2020	-0.801	-0.801	-0.251	-0.251	0.153	0.153
	(0.512)	(0.512)	(1.028)	(1.028)	(0.582)	(0.582)
Thu, Aug 06 2020	-0.348	-1.149	-1.346	-1.597	-0.534	-0.380
	(0.400)	(0.638)	(0.693)	(1.387)	(0.618)	(0.766)
Post-sanctions:						
Fri, Aug 07 2020	-1.775*	-2.924*	-2.212*	-3.809*	-3.419*	-3.799*
	(0.594)	(0.784)	(0.788)	(1.372)	(0.870)	(1.212)
Mon, Aug 10 2020	-0.260	-3.184*	-1.515	-5.325*	-0.759	-4.558*
	(0.354)	(0.909)	(0.838)	(1.692)	(0.689)	(1.667)
Tue, Aug 11 2020	-0.592	-3.776*	-1.967*	-7.292*	-0.845	-5.403*
	(0.427)	(1.023)	(0.891)	(2.183)	(0.765)	(2.328)
Wed, Aug 12 2020	-0.185	-3.961*	1.387	-5.905*	1.750*	-3.653
	(0.415)	(1.100)	(0.724)	(2.063)	(0.611)	(2.206)
Thu, Aug 13 2020	0.495	-3.465*	-0.265	-6.170*	-1.311*	-4.963*
	(0.431)	(1.200)	(0.683)	(2.098)	(0.494)	(2.387)
Fri, Aug 14 2020	-1.203*	-4.669*	-1.551	-7.721*	-2.706*	-7.669*
	(0.498)	(1.399)	(0.867)	(2.462)	(0.667)	(2.550)
N of firms	95	95	19	19	19	19

* $p < 0.05$
Average *Abnormal Returns* (AR) and *Cumulative Abnormal Returns* (CAR) to firms in each sample per day. Standard errors of the mean reported in parentheses. P-values computed from a two-tailed test of difference from zero for the average against a standard normal distribution. Estimation window starts 30 days and ends 3 days before US sanctions. Market models estimated using the LASSO and individual S&P 500 constituents as predictors, selected using 5-fold cross validation. Data exclude firms whose market models resulted in an R^2 smaller than 0.10

Table D.17: The spillover effect of US sanctions against Tencent. 3-fold LASSO estimation window

	Chinese firms		Tencent-owned firms		WeChat-reliant firms	
	(1) AR	(2) CAR	(3) AR	(4) CAR	(5) AR	(6) CAR
Pre-sanctions:						
Wed, Aug 05 2020	-0.824	-0.824	-0.868	-0.868	-0.229	-0.229
	(0.482)	(0.482)	(1.364)	(1.364)	(0.603)	(0.603)
Thu, Aug 06 2020	-0.626	-1.450*	-1.821	-2.688	-0.230	-0.460
	(0.436)	(0.613)	(1.073)	(1.784)	(0.692)	(0.818)
Post-sanctions:						
Fri, Aug 07 2020	-2.365*	-3.814*	-2.215*	-4.903*	-2.713*	-3.172*
	(0.436)	(0.745)	(1.120)	(1.681)	(0.724)	(0.963)
Mon, Aug 10 2020	-0.391	-4.205*	-0.058	-4.961*	-0.278	-3.451*
	(0.409)	(0.871)	(1.406)	(1.628)	(0.464)	(1.253)
Tue, Aug 11 2020	-0.894	-5.099*	-2.890*	-7.851*	-0.634	-4.085*
	(0.484)	(1.109)	(0.993)	(1.755)	(0.469)	(1.521)
Wed, Aug 12 2020	0.123	-4.976*	0.696	-7.155*	2.073	-2.011
	(0.391)	(1.224)	(0.912)	(1.623)	(1.338)	(1.583)
Thu, Aug 13 2020	3.595	-1.380	1.051	-6.104*	-1.748*	-3.759*
	(3.022)	(3.261)	(1.821)	(1.990)	(0.627)	(1.506)
Fri, Aug 14 2020	-1.154	-2.534	0.944	-5.160	-2.665*	-6.424*
	(0.800)	(2.852)	(2.875)	(4.275)	(0.697)	(1.612)
N of firms	100	100	15	15	17	17

* $p < 0.05$
Average *Abnormal Returns* (AR) and *Cumulative Abnormal Returns* (CAR) to firms in each sample per day. Standard errors of the mean reported in parentheses. P-values computed from a two-tailed test of difference from zero for the average against a standard normal distribution. Estimation window starts 30 days and ends 3 days before US sanctions. Market models estimated using the LASSO and individual S&P 500 constituents as predictors, selected using 3-fold cross validation. Data exclude firms whose market models resulted in an R^2 smaller than 0.10

D.3.4 Using OLS instead of the LASSO for estimating market models

Finally, here we replicate our analysis when considering an altogether different estimation strategy for obtaining our market models. Instead of relying on the LASSO and individual S&P 500 constituents on the right-hand side of the market models, we just include an aggregated market-wide index (the S&P 500 index itself) and perform the estimation using OLS. The estimation window starts 180 days before and ends 3 days before US sanctions, as this choice results in the best-fitting market models, on average (see Figure B.2). Results, reported in Table D.18, are broadly consistent with our main results.

Table D.18: The spillover effect of US sanctions against Tencent. OLS market models, estimation window starts 180 days before sanctions

	Chinese firms		Tencent-owned firms		WeChat-reliant firms	
	(1) AR	(2) CAR	(3) AR	(4) CAR	(5) AR	(6) CAR
Pre-sanctions:						
Wed, Aug 05 2020	1.072*	1.072*	1.623*	1.623*	1.163*	1.163*
	(0.298)	(0.298)	(0.784)	(0.784)	(0.365)	(0.365)
Thu, Aug 06 2020	-0.290	0.782	-0.750	0.873	-0.111	1.052
	(0.407)	(0.521)	(0.743)	(0.930)	(0.499)	(0.667)
Post-sanctions:						
Fri, Aug 07 2020	-2.510*	-1.728*	-3.860*	-2.987*	-3.598*	-2.547*
	(0.431)	(0.518)	(0.648)	(0.901)	(0.626)	(0.839)
Mon, Aug 10 2020	-0.570	-2.298*	-2.821*	-5.808*	-0.466	-3.012*
	(0.354)	(0.585)	(0.808)	(1.006)	(0.490)	(1.028)
Tue, Aug 11 2020	0.744*	-1.553*	-0.780	-6.588*	0.206	-2.806*
	(0.328)	(0.705)	(0.460)	(1.234)	(0.326)	(1.192)
Wed, Aug 12 2020	0.594	-0.960	0.913	-5.675*	1.165	-1.640
	(0.394)	(0.766)	(0.796)	(1.042)	(0.820)	(1.358)
Thu, Aug 13 2020	0.187	-0.773	-0.585	-6.261*	-0.661	-2.302
	(0.401)	(0.952)	(0.558)	(1.058)	(0.347)	(1.341)
Fri, Aug 14 2020	-1.026*	-1.799	-0.777	-7.037*	-2.325*	-4.627*
	(0.323)	(1.089)	(0.565)	(1.314)	(0.494)	(1.416)
N of firms	77	77	18	18	27	27

* $p < 0.05$
Average *Abnormal Returns* (AR) and *Cumulative Abnormal Returns* (CAR) to firms in each sample per day. Standard errors of the mean reported in parentheses. P-values computed from a two-tailed test of difference from zero for the average against a standard normal distribution. Estimation window starts 180 days and ends 3 days before US sanctions. Market models estimated using OLS and aggregate S&P 500 index as predictor. Data exclude firms whose market models resulted in an R^2 smaller than 0.10

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