Financial Sanction Spillovers and Firm Interdependence

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Abstract

States increasingly outsource coercion to the market, using sanctions to deter private actors from dealing with blacklisted entities. Despite the key role of such intermediaries, research on economic statecraft is ambiguous about the effect and boundaries of such actions on market participants. We analyze the impact of the Trump administration's actions against Chinese tech giant Tencent. Leveraging an event-study, we find that sanctions negatively impact targets and spread to co-nationals. We also test a novel spillover mechanism: firm interdependence. Tencent acts 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 interdependencies into theories of economic statecraft, especially as export controls, sanctions, and tariffs target industries marked by highly complex supply and financial chains.

Data and replication materials: Replication files are available in the *JOP* Dataverse (https://dataverse.harvard.edu/dataverse/jop). The empirical analysis has been successfully replicated by the *JOP* replication analyst.

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Short title: Financial Sanction Spillovers and Firm Interdependence

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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, 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 the millennium.[3] 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.[4] 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 for revenue may be hindered as well (Ahn and Ludema, 2020; Stone,

[1] Suzanne Lynch, "European ambassadors urge US to support lifting of sanctions on Aughinish owner," *Irish Times*, January 12, 2019. https://www.irishtimes.com/business/manufacturing/european-ambassadors-urge-us-to-support-lifting-of-sanctions-on-aughinish-owner-1.3756231.

[2] Thomas Wilson, "German Industry Sounds Alarm That Rusal Sanctions Pain Is Coming," *Bloomberg*, April 19, 2018. https://www.bloomberg.com/news/articles/2018-04-19/german-industry-sounds-alarm-that-rusal-sanctions-pain-is-coming.

[3] "The Treasury 2021 Sanctions Review," *US Treasury*, October 2021. https://home.treasury.gov/system/files/136/Treasury-2021-sanctions-review.pdf.

[4] For notable exceptions, see Katzenstein (2015); Early and Preble (2020).

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.

Despite the growing consensus linking financial intermediaries to economic statecraft, research is still ambivalent as to how market actors price risk in the face of economic coercion. In this *Short Article*, we attempt to tease apart discrete channels and test them empirically. In particular, we analyze several mechanisms that reoccur in the political risk literature and could explain the transmission between state coercion and market response; (1) the direct channel (whether sanctions negatively impact targeted firms) and (2) the categorical channel (whether firms from the same country as the target suffer). Extending work on weaponized interdependence, with its sensitivity to economic network relations, we offer an additional novel hypothesis that suggests increased political risk based on firm interdependencies. We expect that market actors may view risks associated with (a) the product channel (whether firms that rely on products made by the targeted firm suffer) (b) 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 app WeChat in 2020.

The ban offers several important methodological advantages as compared to existing sanctions research. First, it provides a methodological toolkit to open 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 offers a comparatively clean market signal to test the product and investment channels. In late July 2020, rumors swirled that Trump would target TikTok after the app was used to build political momentum against his re-election campaign. WeChat and its owner Tencent, by contrast, were unexpected targets. Our media analysis (Online Appendix B) shows that, in the week before the announcement, there was scant media attention to WeChat or its parent company Tencent and potential sanctions on TikTok got three times more news coverage. This coverage gap disappeared (in fact, *reversed*) only after Trump's expansive executive order included Tencent. At this point, a notable political risk consultant concluded "I think it's going to be a challenge for any Chinese technology company operating in the US market"[5]. 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 (Gray, 2013; Brooks, Cunha, and Mosley, 2015).

The case is also well suited to test spillovers based on firm interdependencies. 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 product "chokepoints," 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 a 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 opportunities.

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 several discreate channels. Despite the heightened geopolitical environment, firms categorized as Chinese experienced abnormal returns that on average equaled up to $5 billion in capitalization losses. We further document that WeChat's central role in the Chinese digital ecosystem conditioned the spread of the targeted sanction: companies more reliant on the Tencent-owned product suffered average abnormal losses equivalent to $20 billion. But the spread of the sanction effect was not restricted to Chinese firms or those that rely on direct-to-consumer channels that WeChat enables: direct financial ties mattered as well. American and foreign firms with significant Tencent owner-

[5] Jodi Xu Klein, Coco Feng, and Tracy Qu, "As US broadens TikTok battle, tech firms such as WeChat and Zoom might have to pick sides," *myNews*, August 6, 2020. https://www.scmp.com/news/world/united-states-canada/article/3096222/us-broadens-tiktok-battle-tech-firms-such-wechat.

ship were immediately and negatively impacted, resulting in average abnormal losses of $1.5 billion.

Our findings have important empirical, theoretical and policy implications. Corporate finance research has long employed event study models to examine how markets price various types of risk—e.g., credit (Hand, Holthausen, and Leftwich, 1992), policy (Pastor and Veronesi, 2012), or ESG (Krüger, 2015). Political scientists have recently applied this design to understand international legal rulings (Kucik and Pelc, 2016; Voeten, 2025), regulations (Wilf, 2016), or elections (Aklin, 2018). We expand this methodological toolkit by adapting it to understand economic coercion. Theoretically, the paper highlights the need for scholarship to incorporate firm interdependencies into theories of economic statecraft and political risk, especially as export controls, sanctions, and tariffs target industries marked by highly complex supply chains and financial flows. Both product and financial centrality have become potential levers of statecraft. For policymakers, our research draws attention to equity markets as an important source of economic statecraft with potentially unanticipated consequences. US control over the reserve currency is rightfully regarded as the bedrock of its coercive capabilities. But in recent years we have seen growing prospects of conflict in equity markets: an additional vector of economic interdependence. Our paper suggests that these financial sanctions have a more expansive effect and that the market reaction may boomerang back on some American companies. The potential for such unintended consequences would be particularly high in the US-China relationship given the high levels of interlinked investments.

1 Case Description: Sanctioning WeChat

On August 6th 2020, the Trump Administration announced two executive orders targeting TikTok and WeChat.[6] After a 45 day transition period, any person subject to U.S. jurisdiction was

[6] "Executive Order on Addressing the Threat Posed by TikTok," *White House*, August 6, 2020. https://trumpwhitehouse.archives.gov/presidential-actions/executive-order-addressing-threat-posed-tiktok/; See Also, "Executive Order on Addressing the Threat Posed by WeChat," *White House*, August 6, 2020. https://trumpwhitehouse.archives.gov/presidential-actions/executive-order-addressing-threat-posed-wechat/

barred from making transactions on or with the two social media giants.[7] The administration argued that the apps collected vast swaths of data on its users and, given the national origins of the companies, provided means for the Chinese Communist Party to surveil American individuals and companies.

Despite on-going rumors that the Administration might target TikTok,[8] little discussion surrounded WeChat. Yet the August executive orders targeted the holding companies ByteDance (parent company of TikTok) and Tencent (parent company of WeChat). How far-reaching the ban would extend, potentially affecting other companies tied to Tencent, like Tesla, Snapchat, Activision Blizzard, and Epic Games, remained unclear.[9] Mike Murphy, writing for *MarketWatch*, said that the ban "could prove to have much farther-reaching effects than Trump may have anticipated" and rhetorically asked whether Donald Trump just blew up the video game industry given Tencent's ownership stakes in a wide range of popular video game companies.[10] A number of analysts saw this as the broadening of the US-China competition, with the US trying to deter future engagement with key actors from its rival:

> The move will also make foreign capitalists think twice about partnering with companies from the People's Republic. Beijing has invested a lot of political and economic capital incubating global tech champions, but Washington is now leveraging

[7] Swanson, Ana, Isaac, Mike, Mozur, Paul, "Trump Targets WeChat and TikTok, in Sharp Escalation with China," *The New York Times*, August 6, 2020. https://www.nytimes.com/2020/08/06/technology/trump-wechat-tiktok-china.html.

[8] Lorenz, Taylor, Browning, Kellen, Frenkel, Sheena. "TikTok Teens and K-Pop Stans Say They Sank Trump Rally," *The New York Times*, June 21, 2020. https://www.nytimes.com/2020/06/21/style/tiktok-trump-rally-tulsa.html. By July 2020, July 2020, Secretary of State Mike Pompeo announced that the US was considering banning TikTok. See also Online Appendix B.

[9] Swanson, Ana, "Trump's Orders on WeChat and TikTok Are Uncertain. That May Be the Point," *The New York Times*, August 7, 2020. https://www.nytimes.com/2020/08/07/business/economy/trump-executive-order-tiktok-wechat.html.

[10] Murphy, Mike., "Trump's ban against WeChat owner Tencent could have huge implications for U.S. companies," *MarketWatch*, August 8, 2020. https://www.marketwatch.com/story/trumps-order-against-wechat-owner-tencent-could-have-huge-implications-for-us-companies-2020-08-06.

its regulatory advantages over internet infrastructure and operating systems to contain those ambitions.[11]

2 Argument and Research Design

The WeChat ban offers important empirical ground to study one of the key outstanding puzzles in the burgeoning work on economic statecraft. Work on weaponized interdependence, in general, and financial sanctions, in particular, relies on the notion that private sector intermediaries (e.g., investors on stock markets) transmit state policy actions into economic coercion (Farrell and Newman, 2019; Early and Preble, 2020). Intermediaries face direct compliance risks (i.e. doing business with a target) but also indirect risks that stem from harm to their reputation related to conducting business with potential future targets or with those that have a relationship with the target. Economic intermediaries may respond to these direct and indirect risks, serving as chokepoints that cut off resources to suspicious firms. In other words, economic statecraft often relies on activating political risk to discipline market behavior (McDowell, 2021). That said, this literature has largely black-boxed the firm-level dynamics of how state pressure might ripple through markets and how intermediaries might interpret these risks (Gjesvik, 2023).

We draw on research concerned with political risk to consider various channels by which state coercion may shape the behavior of economic intermediaries. The simplest is the direct effect i.e. that sanctions undermine the market opportunities of targets. A second channel (categorical *heuristics*) comes from the political risk literature on credit rating. Heuristics could include a country or firm's region, international organization membership, or the nationality of their main creditors (Gray, 2013; Grittersová, 2014). Brooks, Cunha, and Mosley (2015), for example, demonstrate that market actors often attribute political risk by lumping countries together in categorical baskets. Taking the insights of research on weaponized interdependence seriously, which highlight the key role that economic networks play in coercion, we develop a third novel pathway based on *firm interdependencies*. The logic is that intermediaries might

[11] Pete Sweeney, "Breakingviews – Trump's swipe at Tencent hits China's softest spot," *Retuers*, August 7, 2020. https://www.reuters.com/article/breakingviews/breakingviews-trumps-swipe-at-tencent-hits-chinas-softest-spot-idUSKCN2530PX/.

not only price risk directly to the target or heuristically based on categorical baskets but also based on how material consequences to the target might ricochet through their market relationships to other firms. In particular, we propose a product pathway (i.e. companies that use core products of the target) and an investment pathway (i.e. companies that receive funding from the target). The assumption is that coercion generates spillovers which will follow the network of firm interdependencies of the target.

Most quantitative studies on the effect of sanctions study country-level flows, which can yield confounded estimates of political risk and would struggle at teasing apart these different channels (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 daily *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 firm groups (sample selection is in Appendix A). First, we study Tencent's stock directly.[12] Second, we examine 208 US-traded Chinese firms to assess nationality-based categorical spillovers. We focus on a nationality heuristic given that the sanctions took effect during the ratcheting up of US efforts to stymie Chinese, rather than general, technological development. Third, we study 38 US-traded firms that rely on Tencent's WeChat app for revenue, capturing firm interdependencies at the product level. Fourth, we include 29 US-traded firms in which Tencent held shares pre-sanctions, capturing firm interdependencies via investment ties. Our samples partly overlap, but the latter two also include non-Chinese firms like Tesla, Spotify, Activision Blizzard, and Sea Limited.

Our identification hinges on accurate counterfactual firm-level daily *Returns*, estimated using a market model, i.e. a baseline quantifying the relationship between *Returns* of a single firm

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

and those of the market, fit on pre-sanction data ("estimation window"). Once estimated, we use this model to predict a firm's *Returns*. We stretch this prediction outside of the estimation window, in an "event window" that shortly follows and that includes the sanctions. Expected *Returns* 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.[13]

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. Instead, 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, which is appropriate given that there was no anticipation that sanctions would involve Tencent. We estimate parameter λ, which determines how the LASSO shrinks coefficients of non-predictive constituents towards zero, with a 15-fold cross-validation (CV). CV splits the data into 15 folds and iteratively uses 14 folds to train the model with a given λ, using the remaining fold to calculate the validation error. The model selects the one λ that minimizes the average validation error across all folds. A higher number of CV folds reduces bias but can increase variance as the number of observations per fold shrinks. We maintain this high number of folds as it yields stronger predictive power (see Appendix C). We discard firms whose estimation window yielded market models with an R2 below 0.10. Appendices F and G show robustness to all these choices, including the number of CV folds.

[13] Appendix C describes the design. In Appendix E, we use alternative estimation strategies and tests for statistical significance, including regression, parametric, and non-parametric tests used in corporate finance.

3 Results

Observed and counterfactual *Returns* of Tencent (Figure 1, left panel), are remarkably similar before sanctions. On the sanction day, AR drop by 8.36pp (right panel), statistically significant with p-value = 0.009 (computed via permutation inference, see Appendix D). Thus, the targeted sanction was highly effective. The negative effect was not limited to the sanction day, as CAR remained negative for the entire trading week (and longer in the year, see Appendix H). Thus, stock values did not easily rebound from the sanction.

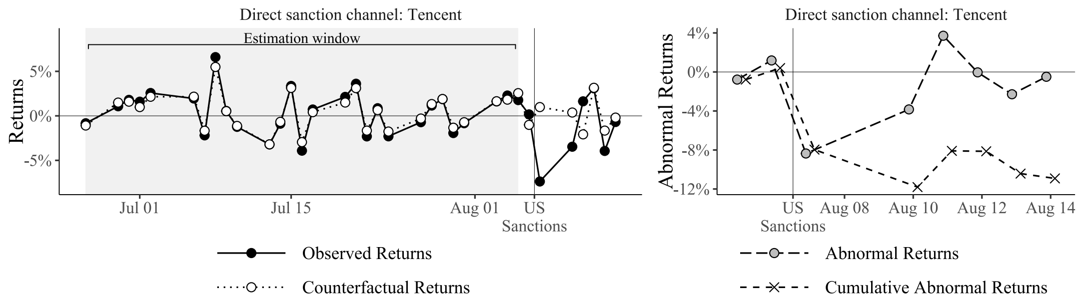

FIGURE 1: Stock Returns, Counterfactual Returns, AR, and CAR for Tencent before and after US sanctions
Alt text: Two-panel figure showing Tencent's stock reaction to U.S. sanctions. Observed versus counterfactual returns drop sharply at the announcement, and abnormal and cumulative abnormal returns turn strongly negative and remain below zero afterward.

Effects were also not limited to the direct target. Figure 2 displays results for the three samples of US-traded firms (top panel: Chinese firms; middle panel: WeChat-reliant; bottom panel: Tencent-owned). Observed average *Returns* follow a similar path to counterfactuals before the event (left panels) but drop well below them following sanctions, in all samples. This confirms negative spillover effects of sanctions via the categorical channel (top panel) and via firm interdependencies created by the product and investment channels (middle and bottom panels). When looking at average AR (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, which should bias against finding an effect. Product and investment channels generated 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].

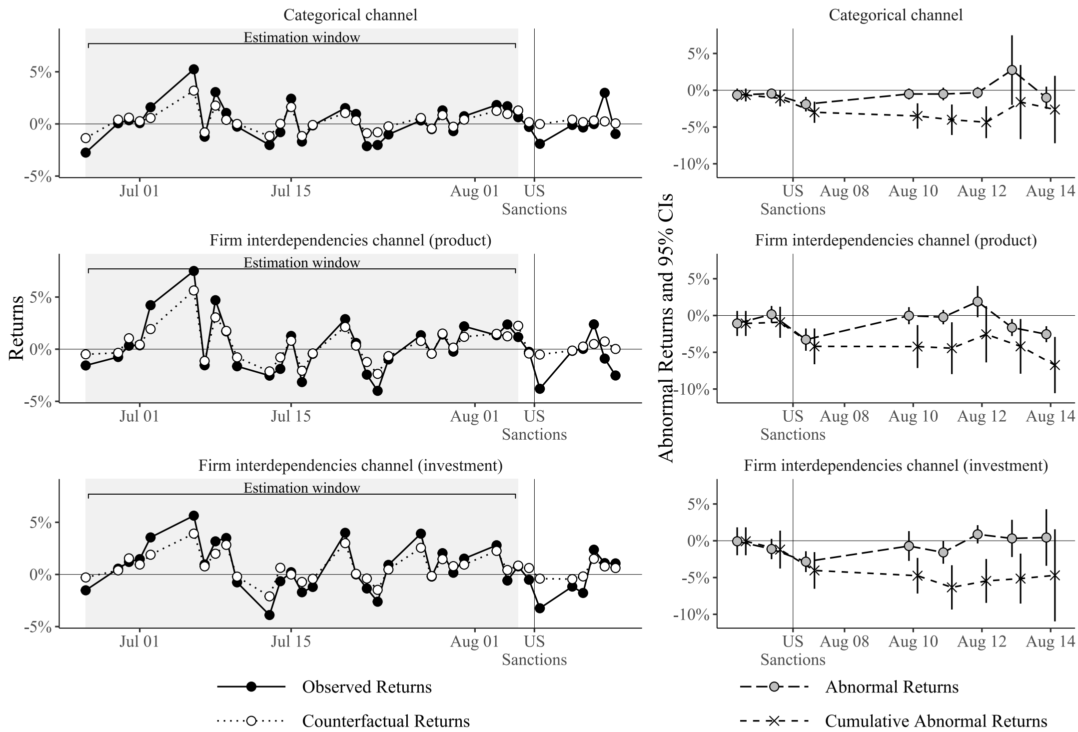

FIGURE 2: Stock Returns, Counterfactual Returns, AR, and CAR to US-traded firm who are Chinese (top), WeChat-reliant (middle), and Tencent-owned (bottom) before and after US sanctions targeting Tencent.
Alt text: Two-panel figure showing stock market effects of Chinese firms, firms reliant on WeChat, and Tencent-owned firms after U.S. sanctions. Observed versus counterfactual returns diverge sharply at the sanction announcement, and abnormal and cumulative abnormal returns become negative and remain below zero in the days that follow.

Spillovers were not limited to the immediate day following US executive orders. We observe significant and negative CAR spillover effects in the trading week after sanctions. Firm interdependence diffused political risk not just on the sanction day and market prices did not fully rebound after the sanctions. Tencent-owned and WeChat-reliant firms experienced the strongest cumulative losses, underperforming US market expectations by 4.35pp [-7.12; -1.59] (August 14) and 6.56pp [-10.2; -2.87] (August 13), respectively. Firm interdependencies seem to propagate a stronger effect than co-nationality. In Appendix H, we reach similar conclusions when considering long-term CAR effects detected more than a year after the sanctions.

4 Conclusions

Powerful states increasingly turn firms into foot soldiers as they weaponize the global economy. Nevertheless, research on economic statecraft often black-boxes the role of these companies, leaving questions as to why they may or may not impose economic costs on targets.

We fill this gap by extending the market event study design for abnormal stock returns estimation, which has become a mainstay in corporate finance (and more frequently in political science), to better understand economic statecraft. While this method is not geared to identifying long-term effects, it reveals direct and indirect mechanisms of coercion. As the stock price fundamentally reflects how investors view the future earnings prospects of a firm, the reductions in prices illustrate a broad acceptance that sanctions will undercut a company's profitability. The stock price matters for the functioning of the firm. Price reductions limit the ability of the firm to raise capital and grow and, given our focus on tech firms, also substantially impact the management and founders of these firms. Ultimately, our market study of the WeChat ban finds evidence to support categorical spillovers: all Chinese firms were negatively impacted. But spillovers were not limited to nationality. We find significant support for spillovers via firm interdependencies, as companies with a product or an investment tie to Tencent were most severely hit. Remarkably, as we report in Appendix H, we find evidence that the stock market effect is not limited to the short term but is quite durable.

Theoretically, our emphasis on firm interdependencies has important implications on how market concentration or investor relations interact with economic statecraft. In China, virtually all consumers, and thereby direct-to-consumer businesses, use WeChat while its parent company Tencent has operated like a sprawling venture capitalist helping develop the Chinese tech ecosystem. Our findings indicate that, when such key players are targeted, the damage extends far beyond the parent firm, negatively impacting companies commercially or financially tied to the target (e.g., relying on its products or having it as a shareholder). Such patterns of cross-firm ownership are prevalent across several countries and even the United States where the Big 3 Asset Managers now control roughly 20% of each S&P500 company. To understand coercion effectiveness or escalation dynamics, scholars will need to address issues of industrial concentration and investor relationships.

Finally, our evidence underscores that economically interdependent US companies also suffered from US coercion. For policymakers, our evidence suggests that sanctions senders require a high level of market expertise to avoid blow back on national companies. Given the complexity of supply chains and financial flows, efforts to use sanctions, export controls or tariffs in highly interdependent sectors could have far reaching spillovers. Such spillovers could become particularly salient in coercion episodes between the US and China, where many sectors are marked by technical and intricate market relationships. Limited market expertise could also raise the specter of a new era of rent seeking: an important next step in the statecraft research agenda is to understand how potential substitute firms win—what strategies they deploy to build up substitution potential, under what conditions are they deemed adequate by the markets, and whether this incentivizes them to lobby in favor of sanctions.

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References

Ahn, Daniel P, and Rodney D Ludema. 2020. "The sword and the shield: The economics of targeted sanctions." *European Economic Review* 130: 103587.

Aklin, Michaël. 2018. "How robust is the renewable energy industry to political shocks? Evidence from the 2016 US elections." *Business and Politics* 20 (4): 523–552.

Brooks, Sarah M, Raphael Cunha, and Layna Mosley. 2015. "Categories, creditworthiness, and contagion: How investors' shortcuts affect sovereign debt markets." *International Studies Quarterly* 59 (3): 587–601.

Early, Bryan R, and Keith A Preble. 2020. “Enforcing US economic sanctions: Why whale hunting works.” *The Washington Quarterly* 43 (1): 159–175.

Farrell, Henry, and Abraham L Newman. 2019. “Weaponized interdependence: How global economic networks shape state coercion.” *International Security* 44 (1): 42–79.

Gjesvik, Lars. 2023. “Private infrastructure in weaponized interdependence.” *Review of International Political Economy* 30 (2): 722–746.

Gray, Julia. 2013. *The company states keep: International economic organizations and investor perceptions*. Cambridge University Press.

Grittersová, Jana. 2014. “Transfer of reputation: Multinational banks and perceived creditworthiness of transition countries.” *Review of International Political Economy* 21 (4): 878–912.

Hand, John RM, Robert W Holthausen, and Richard W Leftwich. 1992. “The effect of bond rating agency announcements on bond and stock prices.” *The Journal of Finance* 47 (2): 733–752.

Katzenstein, Suzanne. 2015. “Dollar unilateralism: the new frontline of national security.” *Ind. LJ* 90: 293.

Kerner, Andrew. 2014. “What we talk about when we talk about foreign direct investment.” *International Studies Quarterly* 58 (4): 804–815.

Krüger, Philipp. 2015. “Corporate goodness and shareholder wealth.” *Journal of Financial Economics* 115 (2): 304–329.

Kucik, Jeffrey, and Krzysztof J Pelc. 2016. “Do international rulings have spillover effects?: The view from financial markets.” *World Politics* 68 (4): 713–751.

McDowell, Daniel. 2021. “Financial sanctions and political risk in the international currency system.” *Review of International Political Economy* 28 (3): 635–661.

Morse, Julia C. 2019. “Blacklists, market enforcement, and the global regime to combat terrorist financing.” *International Organization* 73 (3): 511–545.

Newman, Abraham L, and Qi Zhang. 2024. "Secondary effects of financial sanctions: Bank compliance and economic isolation of non-target states." *Review of International Political Economy* 31 (3): 995–1021.

Pastor, Lubos, and Pietro Veronesi. 2012. "Uncertainty about government policy and stock prices." *The Journal of Finance* 67 (4): 1219–1264.

Stone, Mark. 2016. "The Response of Russian security prices to economic sanctions: policy effectiveness and transmission." *US Department of State Office of the Chief Economist Working Paper* .

Verdier, Pierre-Hugues. 2022. "Sanctions overcompliance: What, why, and does it matter?" *NCJ Int'l L.* 48: 471.

Voeten, Erik. 2025. "Do domestic climate rulings make climate commitments more credible? Evidence from stock market returns." *The Journal of Politics* 87 (4): 000–000.

Wilf, Meredith. 2016. "Credibility and distributional effects of international banking regulations: evidence from us bank stock returns." *International Organization* 70 (4): 763–796.

Biographical statements

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Online Appendix
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A Sample selection and data sources

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

A.1 Sample 1: US-traded Chinese firms

First, we built a sample identifying Chinese firms trading on US exchanges. This is not a straightforward task, 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.

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. The 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 the "China Concepts Stock" list and the Compustat firms headquartered in China or in popular foreign jurisdictions. Matches are US-traded firms which are, potentially, Chinese actors. We manually coded as Chinese each of the matching firms if they met *at least* one of three conditions:

1. The firm is headquartered in mainland China
2. The firm's primary assets or its primary business sources of revenue are in mainland China
3. The firm's *controlling* shareholder is a Chinese firm

Availability of stock prices data further restricted the number of firms. The final set comprised 208 firms.

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

Next, we built a sample of US-traded firms which Tencent had stakes in, Chinese or not. Drawing from a database on Tencent ownership provided by Itjuzi[1] (a data service provider of venture capital in China), we built a list 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%. We found 17 companies not included in sample 1. 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. The final set comprised 29 firms.

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

We coded whether each firm in sample 1 or 2 relies on the main app provided by Tencent and targeted by the US executive orders, WeChat, as part of its core business for revenue generation. We initially coded this manually by researching the business models of each of the firms under study. 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 provide a list of WeChat-reliant Chinese firms and our initially manual list was fully covered with some extraneous firms included by the AI algorithm. Sample 3 comprises 38 firms.

A.4 Sample baseline: S&P 500 constituents

We also obtained information on S&P 500 constituents to support our estimation strategy. For this step, we use the Refinitiv API to download information on constituents. This yields 455 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 relied 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	145	69.71%
CRSP	62	29.81%
Yahoo! Finance	1	0.48%
Total:	**208**	**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	455	100.00%
Total:	**455**	**100.00%**

Stock data in our three samples of interest come from Compustat if firms trade common stocks on US stock exchanges (respectively, 69.71%, 82.76%, and 89.47%). Firms that trade ADRs do not report stock prices on Compustat. We drew price data from the Center for Research in Security Prices (CRSP). For a minority that is not present in CRSP (including Tencent itself), we used a Yahoo! Finance API. Finally, we obtained all stock prices for the 455 S&P 500 constituents from the Refinitiv python API. We then computed, for every firm (or S&P 500 constituent), stock *Returns* as daily percentage change in closing stock prices between two trading days.

B Media coverage of sanctions against TikTok/ByteDance and WeChat/Tencent

Here we provide evidence that, in August 2020, US media sources anticipated the upcoming Trump administration's sanctions against TikTok and its owner ByteDance but did not anticipate that WeChat and its owner Tencent would also be targeted. We conducted a Factiva search for the number of articles in US newspapers mentioning "sanctions" and any of "TikTok," "ByteDance," "WeChat," or "Tencent" in the week leading up to Trump's sanctions (August 7) and in the two following days. Results are in the left-hand panel of Figure B.1. Over the entire week preceding US sanctions, TikTok and its owner ByteDance experienced the vast majority of news. Before the sanctions episode, there was scarce coverage of WeChat/Tencent in conjunction with sanctions but that coverage caught up with that of TikTok/ByteDance following the sanctions themselves, when article counts rise to comparable levels for both pairs of companies and products. On the right-hand side, we report the ratio between the coverage of TikTok or ByteDance (in connection with sanctions) and that of WeChat or Tencent (in connection with sanctions). Over the entire week before sanctions, TikTok/ByteDance constantly experienced about 3 times as large a coverage, in connection with sanctions than WeChat/Tencent. This gap disappeared, and even reversed, following actual sanctions.

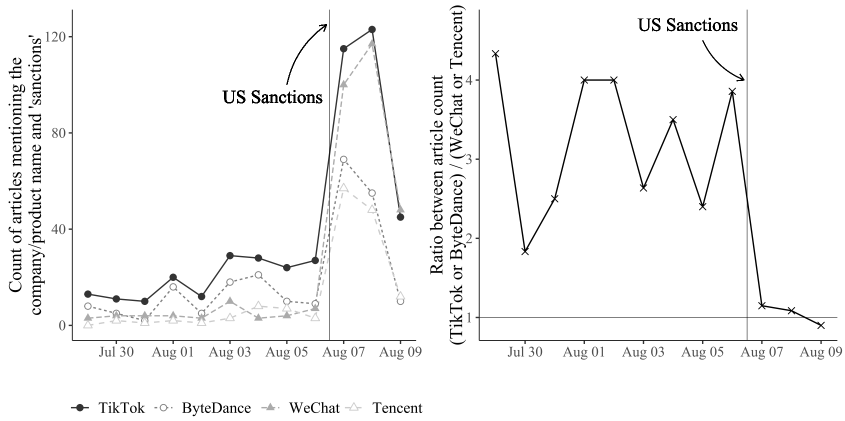

FIGURE B.1: Media coverage of sanctions against Chinese tech companies in the run-up to US Executive Order. Left-hand panel: number of articles mentioning "sanctions" and any of "TikTok," "ByteDance," "WeChat," or "Tencent". Right-hand panel: ratio between the number of articles mentioning "sanctions" and "TikTok" or "ByteDance" and the number of articles mentioning "sanctions" and "WeChat" or "Tencent". Source: Factiva

C Estimation window

C.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[2] *Returns* before and after the event (US sanctions). We compare observed and counterfactual *Returns* to estimate whether (and how) the event affected risk, as investors priced it.

The design estimates counterfactual *Returns*, for each firm, as an expectation based on overall market trends. To do so, we divided the *Returns* to every firm in two windows: an "estimation window" (entirely preceding the event) and an "event window" (which shortly follows and includes the US sanctions). Figure C.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). We tested different estimation windows and event windows lengths. We also considered symmetrical or asymmetrical event windows around the event (Section G).

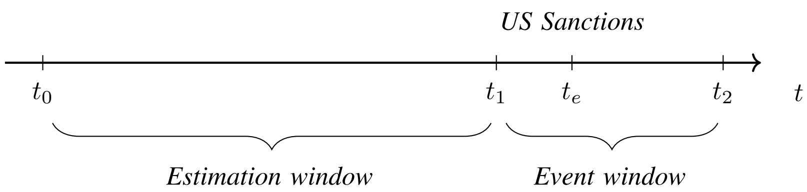

FIGURE C.1: Research design: Estimation and event window

We used 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 estimated one model per firm, all estimand parameters are specific to a given firm *i* (hence the subscripts).

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

[2] We explicitly call "counterfactuals" the predicted *Returns* from market models, consistently with a large literature in corporate finance and international business studies that uses the same causal terminology and intends the design as one allowing identification (e.g., Eden et al., 2022, 805). Castro-Iragorri (2019) also shows that the "counterfactuals" obtained from event studies market models are as precise as those that causal designs like synthetic control methods or difference-in-differences yield.

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 considered span over 180 trading days (six months) and the number of S&P 500 constituents is 455, such a model would have more predictors than observations. To obviate the problem we used 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. Equation 1 represents it with 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).[3] The optimal set of weights assigns a 0-weight to non-predictive S&P 500 constituents, effectively excluding them from the market model of that firm. That is, we custom-built an index explaining each firms' *Returns* with the weighted most predictive S&P 500 constituents.

Once a single market model per firm is estimated via the LASSO, we used it to predict *Returns* to that firm. Such expectation represents counterfactual *Returns*, given that it is derived from market models that entirely predate US sanctions, at a time when information relative to this event was not anticipated. Equation 2 represents this step, where $\hat{\alpha}_i$ and $\hat{\boldsymbol{\beta}}_i$ and optimal sets of weight ($\tilde{\boldsymbol{w}}_i$) have been estimated through the LASSO. We obtained expected (counterfactual) *Returns* over both estimation and event windows. In the estimation window, such expectation is useful to gauge the aggregate quality of the fit obtained from the LASSO (Equation 1). When extended "out of sample" and into the event window, instead, expectations are used for estimating event effects.

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

We then focused on event window data ($t_1 \leq t \leq t_2$) and obtained two firm-level measures of interest: *Abnormal Returns* (AR) and *Cumulative Abnormal Returns* (CAR) as in Equation 3. AR are daily differences between observed and expected *Returns*, representing the daily gap between observations and counterfactuals. CAR are the running sum of AR for a given firm over the event window. They are useful to evaluate if firms rebounded from a negative (positive) event effect.

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

Finally, we studied daily average AR and CAR before and after the event. We did so by computing daily averages and 95% confidence intervals (CIs) using standard errors of the mean (and a 1.96 critical value). We tested whether daily estimated average AR and CAR are distinguishable from zero at an alpha of 0.05 (or whether 95% CIs overlap with 0). In robustness tests, we modelled AR and CAR in fixed effect regression models and in parametric and non-parametric event tests (Section E).

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

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

In order to fit our market models, we needed to make modelling choices and fine-tune hyper parameters. First, we chose to use the LASSO (and individual S&P 500 constituents), as opposed to ordinary least squares (OLS) market models on aggregated market-wide indexes. A second choice, specific to the LASSO, was the number of cross-validation (CV) folds imposed to define the parameter λ determining the set of weights $\tilde{\boldsymbol{w}}$ of Equation 2. A third choice, for both OLS and LASSO, was the length of the estimation window.

We present the average model fit of all combinations of market models we estimated when varying modelling choices along these three dimensions. We selected the single modelling choice that yields the best average model fit: market models estimated using the LASSO, with 15-folds CV, and estimation windows of 30 days. Our main results are based on these hyper parameters. We show robustness to other modelling choices in Section G.

We evaluated 15 sets of individual firm-specific market models. 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, or 15 folds. For estimation window lengths (both LASSO and OLS), we evaluated windows

[3] CV produced 95 parameters λ determining the set of weight $\boldsymbol{w}$. We selected the λ yielding the minimum mean cross-validated error.

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 $\times$ 4 possible CV choices). We estimated one market model per firm in these 15 combinations.

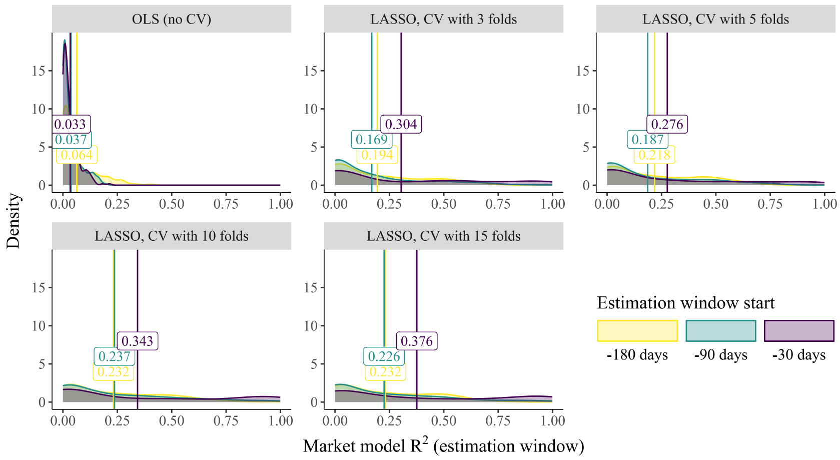

FIGURE C.2: Distribution of R^2 of market models estimated when varying modelling choices. Average R^2 reported as vertical lines

Figure C.2 shows 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 performed significantly better than OLS. For any given estimation window length, a LASSO model with 3-folds CV always yielded average R^2 that are at least $3\times$ (180 days) and at most $9\times$ (30 days) larger than OLS. Increasing the number of LASSO CV folds, moreover, further improved model fit. In terms of estimation window lengths, instead, we find that the shortest windows always performed better, on average, for the LASSO. This is not true for OLS.

We selected the LASSO with 15-fold CV and estimation window starting 30 days before the US sanctions as our preferred estimation choice. This model choice yielded significantly better model performance than traditional OLS market models. The average R^2 of our best-performing LASSO market model choice is 0.376, more than $5\times$ 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 0.064.

We tested robustness by considering alternatives to these modelling choices in Section G. We considered the best fitting alternatives. We varied 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 varied CV choices by selecting estimates from LASSO models with 3, 5, and 10 folds (and estimation windows starting 30 days before the event). For varying modelling strategy, we considered estimates from OLS models with estimation windows starting 180 days before the event. Finally, we also showed that our results do not hinge on ending the estimation window 3 trading days before the US sanctions (on Tuesday August 4, 2020). We replicated our analysis using 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 C.3 plots the LASSO-weighted coefficients (the $\tilde{\boldsymbol{w}}_i\hat{\boldsymbol{\beta}}_i$ from Equation 2) obtained from our preferred LASSO specification. We excluded firms whose market model results in R^2 lower than 0.10, as they do not enter our analyses (except in Table F.1). 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 size growing 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 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 the fit between observed and counterfactual *Returns* in Figure 1 of the main text shows, this market model creates extremely accurate expectations (R^2 is 0.96).

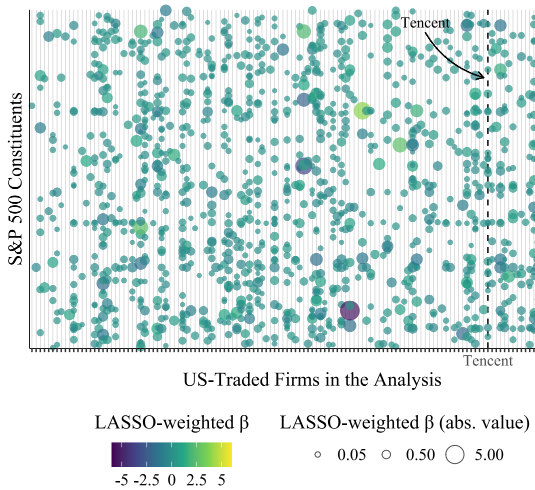

FIGURE C.3: LASSO-estimated coefficients from firm-specific market models estimated with 15-fold CV and estimation windows starting 30 trading days before US sanctions. Excludes firms whose market models results in R^2 lower than 0.10

D Event window

D.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 produced an extremely close fit between observed and counterfactual *Returns* (R^2 for this model is 0.96). Observed *Returns*, then, dropped by 8.36 percentage points below market expectations immediately following the event. Although AR bounced back relatively quickly, CAR remained significantly negative. Multiplying the AR loss on the sanctions day (-8.36pp, or -0.0836) by Tencent's stock price before the event ($72.6) and number of outstanding shares (9.6B), we estimate a market capitalization loss of about $58B. That is, Tencent realized $58B less in market capitalization than it was expected, based on broader market characteristics, on the day of the sanctions.

Was the AR loss suffered by Tencent statistically distinguishable from zero? Because the estimate is relative to a single firm, we could not compute p-values or confidence intervals by means of standard errors and conventional hypothesis-testing. We thus proceeded 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 resorted to 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 un-impacted 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 did so by repeating our estimation procedure on each one of the "donors" in the pool of firms that generated Tencent's counterfactual returns. That is, we repeated our procedure for each of the S&P 500 individual constituents, whose LASSO market models we fitted by using the remaining constituents.

Figure D.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 assessed 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. To calculate the probability of observing an effect as large as that experienced by Tencent, under the null hypothesis, we computed a test statistic for Tencent and for the other placebo firms. We adopted the statistic that was proposed by Abadie, Diamond, and Hainmueller

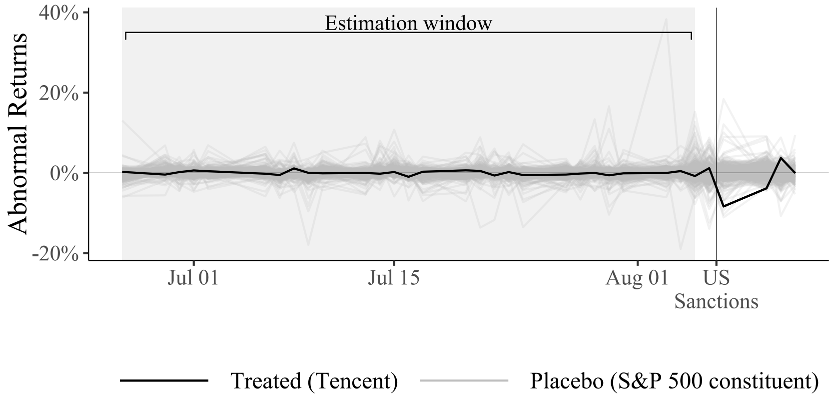

FIGURE D.1: The effect of US sanctions on *Abnormal Returns* to Tencent and to placebo S&P 500 constituents

(2015) for a synthetic control design. First we computed, 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 C.1) and T indicates the number of days between t_0 and $t_e - 1$. Because we computed the post-event RMSPE only on the day of the event, RMSPE_{1i} simplifies to the absolute value of the difference between observed and counterfactual *Returns* on the event day (that is, absolute AR).

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

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 defined 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 D.2. As the plot shows, Tencent's 8.36 percentage points loss in AR on August 07, 2020 results in the fifth most extreme test statistic when considering AR to the S&P 500. That is, there were only four firms out of 456 (455 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 4/455 = 0.009.

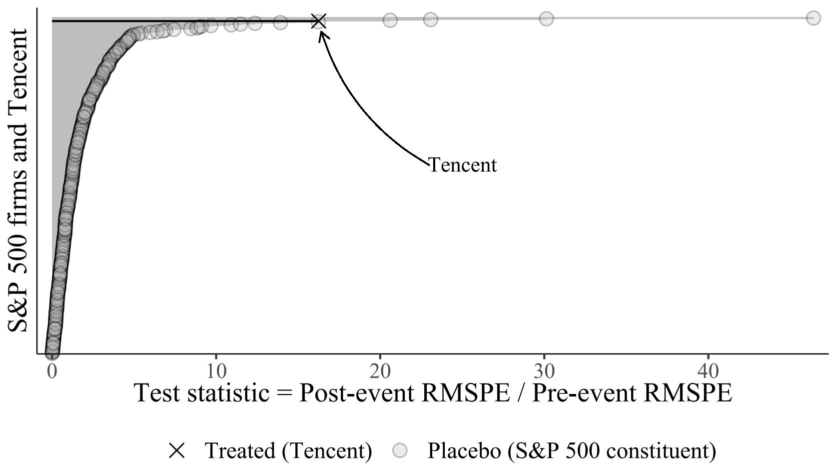

FIGURE D.2: Placebo test of significance for the effect of US sanctions on *Abnormal Returns* to Tencent on August 07, 2020

A closer investigation reveals that the high test statistics for the top four firms were, in fact, due to unrelated events occurring on August 07, 2020. UPS (NYSE: UPS) announced the adoption of an additional delivery fee, likely resulting in a surge in profit, due to intensified delivery requests caused by the COVID-19 pandemic[4] while Tripadvisor (NASDAQ: TRIP), Illumina (NASDAQ: ILMN), and Teradata (NYSE: TDC) announced their second-quarter revenues for the year. Tripadvisor and Illumina announced net losses due to the impact of the COVID-19 pandemic, whereas Teradata announced positive earnings.[5]

D.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 D.1.

We compute individual market capitalization losses for the three samples of firms, on the day of sanctions, by multiplying the number of outstanding shares, the price at closing on the day before the sanctions, and the estimated percentage abnormal returns (divided by 100). We, then, average such individual capitalization losses and calculate an average loss of $5B for US-traded Chinese firms, $2B for Tencent-owned companies, and $20B for WeChat-reliant firms. That is, on average these companies realized $5B, $2B, and $20B less in market capitalization than what was expected based on broader market trends, on the day of the sanctions.

[4] See: https://www.cnbc.com/2020/08/07/ups-tacks-on-additional-fees-as-it-faces-a-flood-of-packages-during-pandemic.html.
[5] 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).

Table D.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	-0.646	-0.646	-0.073	-0.073	-1.080	-1.080
	(0.446)	(0.446)	(0.968)	(0.968)	(0.869)	(0.869)
Thu, Aug 06 2020	-0.453	-1.099	-1.123	-1.196	0.163	-0.917
	(0.343)	(0.562)	(0.705)	(1.314)	(0.579)	(1.077)
Post-sanctions:						
Fri, Aug 07 2020	-1.895*	-2.993*	-2.841*	-4.037*	-3.280*	-4.198*
	(0.507)	(0.733)	(0.723)	(1.271)	(0.771)	(1.240)
Mon, Aug 10 2020	-0.507	-3.501*	-0.714	-4.752*	-0.026	-4.223*
	(0.384)	(0.879)	(1.032)	(1.235)	(0.593)	(1.489)
Tue, Aug 11 2020	-0.511	-4.012*	-1.586*	-6.338*	-0.223	-4.446*
	(0.440)	(1.056)	(0.783)	(1.535)	(0.498)	(1.797)
Wed, Aug 12 2020	-0.339	-4.351*	0.877	-5.461*	1.890	-2.556
	(0.394)	(1.102)	(0.634)	(1.522)	(1.087)	(1.950)
Thu, Aug 13 2020	2.746	-1.605	0.318	-5.143*	-1.639*	-4.195*
	(2.411)	(2.571)	(1.292)	(1.732)	(0.590)	(1.897)
Fri, Aug 14 2020	-1.017	-2.622	0.442	-4.700	-2.544*	-6.739*
	(0.768)	(2.339)	(1.962)	(3.194)	(0.554)	(1.951)
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

E Robustness: Alternative event tests

E.1 Regressions with firm-fixed effects

As an alternative to estimating spillover effects as sample averages of AR and CAR in the event window, we fitted linear regressions of AR and CAR. We fitted models with firm fixed effects (FE) and clustered standard errors at the firm level. We explained AR using a binary variable with value 1 only on the day of US sanctions (August 07, 2020). We explained 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 considered a symmetrical event window around the day of the sanctions, starting two days before and ending two days after. Results, in Table E.1, are broadly consistent with what we detected when studying sample averages.

Table E.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	-1.366*		-1.967*		-2.989*	
	(0.550)		(0.887)		(0.901)	
Post-event		-2.630*		-4.408*		-3.290*
		(0.657)		(1.084)		(1.028)
Num.Obs.	625	625	110	110	120	120
R2	0.254	0.723	0.161	0.709	0.363	0.799
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 when we changed the length of the event window to start and end four days before and after sanctions (Table E.2). Finally, we obtained similar results with non-symmetrical event windows. In Table E.3, we show similar results with an event window starting two days before and ending four days after the sanctions.

Table E.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	-2.348*		-2.238*		-3.432*	
	(0.587)		(0.846)		(0.889)	
Post-event		-2.192*		-4.168*		-2.370*
		(0.840)		(1.251)		(0.959)
Num.Obs.	1125	875	198	154	216	168
R2	0.109	0.435	0.083	0.647	0.134	0.723
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 E.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	-1.943*		-2.457*		-3.128*	
	(0.648)		(0.888)		(0.883)	
Post-event		-2.420*		-4.511*		-2.925*
		(0.859)		(1.198)		(1.143)
Num.Obs.	875	875	154	154	168	168
R2	0.139	0.430	0.110	0.656	0.195	0.771
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

E.2 Parametric event tests

As alternative ways to estimate event effects, in Tables E.4, E.5, and E.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 considered 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).

We found consistent evidence with that above. Our estimates generally pass these tests returning statistically significant results. Results were less strong for the test by Boehmer, Masumeci, and Poulsen (1991) in the case of Tencent-owned firms where, however, limited sample sizes reduce the extent to which we can make substantive evaluations from this demanding test (N = 22).

Table E.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	-1.304	-5.102*	-2.734*	-2.532*	-3.444*	-0.202	-2.684*
Thu, Aug 06 2020	-0.391	-1.528	-0.819	-1.028	-3.807*	-0.351	-0.799
Post-sanctions:							
Fri, Aug 07 2020	-1.861	-7.280*	-3.901*	-3.467*	-45.715*	-2.249*	-3.806*
Mon, Aug 10 2020	-0.799	-3.128*	-1.676	-1.758	-18.385*	-1.192	-1.643
Tue, Aug 11 2020	-0.356	-1.393	-0.746	-0.667	-23.750*	-0.984	-0.716

* $p < 0.05$
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 E.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	-0.270	-0.502	-0.497	-0.261	2.463*	0.199	-0.488
Thu, Aug 06 2020	-1.160	-2.161*	-2.138*	-1.553	-0.819	-0.153	-2.097*
Post-sanctions:							
Fri, Aug 07 2020	-2.123	-3.954*	-3.912*	-2.628*	-18.635*	-1.369	-3.818*
Mon, Aug 10 2020	-0.298	-0.555	-0.549	-0.295	-16.409*	-0.996	-0.539
Tue, Aug 11 2020	-1.773	-3.302*	-3.267*	-1.692	-1.166	-0.433	-3.207*

* $p < 0.05$
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 E.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	-1.860	-5.219*	-3.065*	-1.953	-19.961*	-1.838	-3.010*
Thu, Aug 06 2020	0.501	1.406	0.826	0.776	18.680*	1.835	0.811
Post-sanctions:							
Fri, Aug 07 2020	-2.905	-8.150*	-4.786*	-3.337*	-42.468*	-2.682*	-4.617*
Mon, Aug 10 2020	0.117	0.329	0.193	0.174	-24.171*	-1.190	0.187
Tue, Aug 11 2020	-0.072	-0.203	-0.119	-0.115	0.957	0.177	-0.117

* $p < 0.05$
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

E.3 Non-parametric event tests

In Tables E.7, E.8, and E.9 we present results obtained using non-parametric event tests for US-traded Chinese, Tencent-owned, and WeChat-reliant firms, respectively. We considered 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).

We found 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 E.8) where our statistical power is significantly limited.

Table E.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	-2.057*	-2.187*	-0.838	-0.982	-0.982	3108.000*
Thu, Aug 06 2020	-0.984	-1.113	-0.309	-0.116	-0.116	3546.000
Post-sanctions:						
Fri, Aug 07 2020	-4.383*	-4.512*	-2.162*	-2.580*	-2.580*	2101.000*
Mon, Aug 10 2020	-0.268	-0.398	0.044	-0.299	-0.299	3521.000
Tue, Aug 11 2020	1.878	1.749	1.015	0.681	0.681	4118.000

* $p < 0.05$
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 E.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	-0.853	-0.916	-0.322	0.230	0.230	123.000
Thu, Aug 06 2020	-0.853	-0.916	-0.644	-0.768	-0.768	84.000
Post-sanctions:						
Fri, Aug 07 2020	-1.706	-1.769	-1.287	-2.225*	-2.225*	56.000*
Mon, Aug 10 2020	-2.132*	-2.195*	-0.965	-0.795	-0.795	88.000
Tue, Aug 11 2020	-1.279	-1.342	-0.965	-1.130	-1.130	87.000

* $p < 0.05$
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 E.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	-1.633	-1.453	-1.029	-1.186	-1.186	79.000*
Thu, Aug 06 2020	0.816	0.999	0.771	0.671	0.671	190.000
Post-sanctions:						
Fri, Aug 07 2020	-2.449*	-2.270*	-1.543	-2.069*	-2.069*	45.000*
Mon, Aug 10 2020	-1.225	-1.044	-0.514	-0.436	-0.436	136.000
Tue, Aug 11 2020	0.408	0.590	0.257	0.112	0.112	153.000

* $p < 0.05$
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

F Robustness: Inclusion and exclusion of firms from the samples

F.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 F.1 we relaxed this choice and considered all firms. Results are, again, broadly consistent with earlier findings. In this test that considers firms with poorly-estimated counterfactuals, negative CAR were significantly large for a longer time and at least until August 14, 2020.

Table F.1: 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	0.001	0.001	-0.545	-0.545	0.108	0.108
	(0.431)	(0.431)	(0.856)	(0.856)	(1.312)	(1.312)
Thu, Aug 06 2020	-2.039	-2.038	-1.494*	-2.038	0.085	0.194
	(1.282)	(1.251)	(0.589)	(1.196)	(0.464)	(1.339)
Post-sanctions:						
Fri, Aug 07 2020	-3.541*	-5.741*	-2.789*	-4.827*	-3.021*	-2.828
	(1.285)	(2.454)	(0.728)	(1.276)	(0.934)	(2.002)
Mon, Aug 10 2020	-1.043	-6.784*	-1.035	-5.861*	-0.337	-3.164
	(0.902)	(3.062)	(0.971)	(1.685)	(0.812)	(2.649)
Tue, Aug 11 2020	-1.926*	-8.710*	-1.669*	-7.531*	-1.535	-4.700*
	(0.907)	(3.734)	(0.785)	(1.843)	(0.977)	(2.393)
Wed, Aug 12 2020	-0.058	-8.768*	0.451	-7.080*	1.097	-3.603
	(0.335)	(3.639)	(0.549)	(2.022)	(0.778)	(2.707)
Thu, Aug 13 2020	1.982	-6.786	-0.075	-7.154*	-0.647	-4.250
	(1.494)	(3.830)	(1.003)	(2.226)	(0.771)	(2.939)
Fri, Aug 14 2020	-0.710	-7.496*	-0.349	-7.503*	-3.075*	-7.325*
	(0.607)	(3.678)	(1.535)	(3.252)	(0.597)	(3.033)
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

F.2 Exclusion of firms experiencing unrelated events

We repeated 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 reduced our sample size, shrinking the sample of US-traded Chinese firms from 125 to 99, 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 were able to detect a significant effect of the event on AR and CAR for *all* samples (Table F.2). We still detected significant negative CAR up until August 14, 2020 for the first and third sample, but not for the second one (negative and statistically significant CAR until August 12, 2020).

Table F.2: 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	-0.483	-0.483	0.226	0.226	0.049	0.049
	(0.488)	(0.488)	(1.619)	(1.619)	(0.603)	(0.603)
Thu, Aug 06 2020	-0.417	-0.899	-2.351	-2.125	-0.062	-0.012
	(0.371)	(0.569)	(1.380)	(2.101)	(0.797)	(0.786)
Post-sanctions:						
Fri, Aug 07 2020	-1.983*	-2.883*	-3.435*	-5.560*	-3.081*	-3.094*
	(0.430)	(0.800)	(1.303)	(2.492)	(0.952)	(1.402)
Mon, Aug 10 2020	-0.331	-3.213*	0.702	-4.858*	-0.066	-3.160
	(0.429)	(0.972)	(2.077)	(2.362)	(0.783)	(1.828)
Tue, Aug 11 2020	-0.439	-3.653*	-2.340	-7.198*	0.234	-2.925
	(0.516)	(1.231)	(1.539)	(3.000)	(0.656)	(2.223)
Wed, Aug 12 2020	-0.694	-4.347*	0.685	-6.512*	1.254	-1.671
	(0.360)	(1.263)	(1.070)	(2.964)	(0.659)	(2.015)
Thu, Aug 13 2020	0.686	-3.660*	2.512	-4.000	-1.374*	-3.045
	(0.484)	(1.357)	(2.864)	(3.088)	(0.501)	(1.959)
Fri, Aug 14 2020	-0.112	-3.772*	1.404	-2.596	-3.277*	-6.322*
	(0.758)	(1.696)	(4.771)	(6.985)	(0.800)	(2.230)
N of firms	99	99	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.

F.3 Exclusion of one firm at the time (jackknife test)

We excluded one firm from each sample at the time and re-performed our main analysis iteratively. Here we report average AR and 95% CIs on the day of the US sanctions (August 07, 2020) as coefficient plots (Fiure F.1). We report one point estimate and CI for each iteration of our procedure. We also report the estimated average AR from the full sample (in red, estimates from Table D.1). We found 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.

F.4 Exclusion of firms in the interdependence channel test from categorical channel test

Our samples partly overlap: some of the US-traded Chinese firms also use WeChat in their business model or are (partly) Tencent-owned. In an effort to keep categorical and interdependence spillover effects distinct, we split the 125 US-traded Chinese firms in the categorical channel sample between the 30 companies who have product or investment ties with Tencent and the 95 who do not. Unfortunately, the small size of the WeChat-reliant and Tencent-owned samples (N = 24 and 22) prevented us from distinguishing categorical effects for those groups. Table F.3 reports the results. Chinese firms without a product or investment tie to Tencent (columns 3-4) still experienced negative and statistically significant AR and CAR, confirming that a categorical effect is detectable even when excluding firms that might have experienced an interdependence effect via WeChat-reliance or Tencent-ownership. Unsurprisingly, firms subject to both categorical and interdependence spillover effects (columns 1-2) experienced much stronger and significant negative effects on AR and CAR.

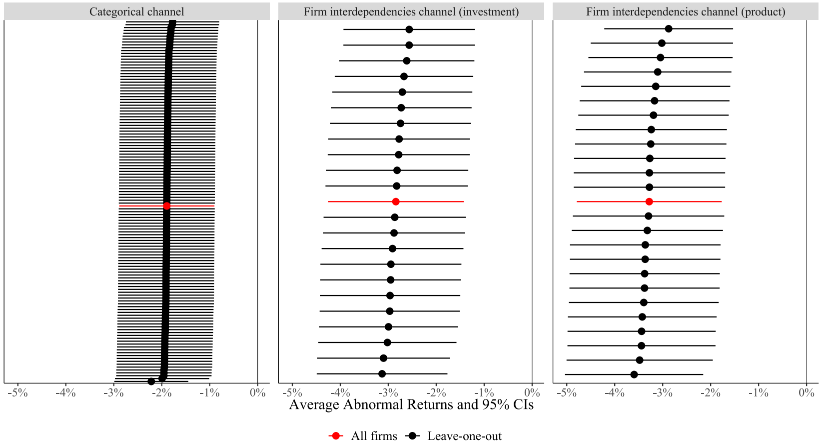

FIGURE F.1: Average AR from a jackknife test on August 07, 2020. Exclusion of one firm at the time from each sample

Table F.3: The spillover effect of US sanctions against Tencent. Exclusion of firms experiencing interdependencies effects from US-traded Chinese

	Product/investment tie		No interdependencies	
	(1) AR	(2) CAR	(3) AR	(4) CAR
Pre-sanctions:				
Wed, Aug 05 2020	-1.214	-1.214	-0.467	-0.467
	(0.879)	(0.879)	(0.518)	(0.518)
Thu, Aug 06 2020	-0.104	-1.318	-0.563	-1.030
	(0.544)	(1.156)	(0.419)	(0.646)
Post-sanctions:				
Fri, Aug 07 2020	-3.323*	-4.641*	-1.444*	-2.473*
	(0.643)	(1.227)	(0.630)	(0.880)
Mon, Aug 10 2020	0.133	-4.507*	-0.710	-3.183*
	(0.839)	(1.302)	(0.430)	(1.083)
Tue, Aug 11 2020	-0.963	-5.471*	-0.368	-3.551*
	(0.614)	(1.576)	(0.546)	(1.298)
Wed, Aug 12 2020	1.858*	-3.613*	-1.033*	-4.584*
	(0.896)	(1.718)	(0.412)	(1.349)
Thu, Aug 13 2020	-1.134	-4.747*	3.971	-0.613
	(1.012)	(1.794)	(3.151)	(3.334)
Fri, Aug 14 2020	-1.391	-6.138*	-0.899	-1.512
	(1.484)	(2.598)	(0.899)	(2.964)
N of firms	30	30	95	95

* $p < 0.05$
Average *Abnormal Returns* (AR) and *Cumulative Abnormal Returns* (CAR) to US-traded Chinese firms per day, distinguishing whether firms could experience interdependencies effects (either for being Tencent-owned or WeChat-reliant). 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

G Robustness: Alternative choices for estimating market models

G.1 Estimation window lengths

We show results obtained when estimating *Returns* in market models that considered an estimation window starting 180 days before US sanctions. Estimation windows ended 3 days before US sanctions and market models were estimated using 15-fold LASSO CV. Results (Table G.1) were similar to those above, although CAR were significant only for the Tencent-owned sample. Then, we did the same but started our estimation windows 90 days before sanctions. Results (Table G.2) generate similar considerations.

Table G.1: 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	0.762	0.762	0.046	0.046	2.183	2.183
	(0.564)	(0.564)	(0.956)	(0.956)	(1.382)	(1.382)
Thu, Aug 06 2020	0.533	1.295	-1.359	-1.313	-0.075	2.108
	(0.628)	(1.051)	(0.751)	(1.381)	(0.495)	(1.409)
Post-sanctions:						
Fri, Aug 07 2020	-1.405	-0.110	-2.665*	-3.978*	-2.537*	-0.429
	(0.776)	(1.686)	(0.675)	(1.363)	(0.985)	(2.197)
Mon, Aug 10 2020	0.111	0.000	-1.989*	-5.966*	-0.323	-0.752
	(0.576)	(2.171)	(0.741)	(1.591)	(0.737)	(2.814)
Tue, Aug 11 2020	0.422	0.422	-1.565*	-7.531*	-0.822	-1.575
	(0.624)	(2.616)	(0.782)	(2.095)	(0.897)	(2.110)
Wed, Aug 12 2020	0.983	1.405	0.533	-6.998*	1.424	-0.151
	(0.634)	(3.118)	(0.564)	(2.189)	(0.743)	(2.424)
Thu, Aug 13 2020	1.118	2.523	-0.410	-7.408*	-0.476	-0.627
	(0.629)	(3.648)	(0.473)	(2.044)	(0.347)	(2.592)
Fri, Aug 14 2020	0.201	2.724	-1.183*	-8.592*	-2.245*	-2.872
	(0.813)	(4.247)	(0.494)	(2.320)	(0.450)	(2.633)
N of firms	127	127	26	26	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 G.2: 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	1.040	1.040	-0.254	-0.254	1.211	1.211
	(1.092)	(1.092)	(1.136)	(1.136)	(1.603)	(1.603)
Thu, Aug 06 2020	-1.317	-0.276	-1.185	-1.440	-0.296	0.915
	(1.378)	(1.142)	(0.885)	(1.370)	(0.536)	(1.601)
Post-sanctions:						
Fri, Aug 07 2020	-2.874*	-3.150	-2.416*	-3.855*	-2.517*	-1.602
	(1.180)	(2.057)	(0.748)	(1.377)	(0.981)	(2.402)
Mon, Aug 10 2020	1.014	-2.136	-1.398	-5.253*	0.189	-1.413
	(0.962)	(2.074)	(0.983)	(1.573)	(0.712)	(2.959)
Tue, Aug 11 2020	1.024	-1.112	-0.807	-6.060*	-1.003	-2.416
	(0.902)	(2.384)	(0.640)	(1.775)	(0.936)	(2.248)
Wed, Aug 12 2020	0.984	-0.128	0.150	-5.910*	1.284	-1.132
	(0.798)	(2.770)	(0.723)	(1.819)	(0.832)	(2.601)
Thu, Aug 13 2020	1.466	1.338	-0.704	-6.614*	-0.626	-1.758
	(0.872)	(3.427)	(0.608)	(1.757)	(0.404)	(2.801)
Fri, Aug 14 2020	0.296	1.634	-1.254	-7.867*	-2.497*	-4.254
	(0.911)	(4.079)	(0.718)	(2.055)	(0.500)	(2.789)
N of firms	113	113	22	22	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

G.2 Estimation window ending

We replicated our analysis employing our preferred estimation window (starting 30 days before US sanctions), with LASSO and 15-fold CV market models, but stopping the estimation window 5 days before US sanctions (instead of 3). Results (Table G.3) are consistent with those in our main analysis.

Table G.3: 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	-1.029*	-1.029*	-1.157	-1.157	-0.800	-0.800
	(0.446)	(0.446)	(1.253)	(1.253)	(0.904)	(0.904)
Thu, Aug 06 2020	-0.014	-1.043	-1.022	-2.179	0.963	0.163
	(0.401)	(0.633)	(0.659)	(1.541)	(0.720)	(1.073)
Post-sanctions:						
Fri, Aug 07 2020	-2.168*	-3.211*	-2.748*	-4.928*	-2.990*	-2.827*
	(0.511)	(0.782)	(0.718)	(1.659)	(0.725)	(1.279)
Mon, Aug 10 2020	-0.404	-3.616*	-1.141	-6.068*	-0.494	-3.322
	(0.421)	(0.960)	(1.261)	(2.169)	(0.839)	(1.971)
Tue, Aug 11 2020	-0.428	-4.043*	-1.215	-7.283*	0.125	-3.197
	(0.486)	(1.104)	(0.835)	(2.259)	(0.365)	(1.969)
Wed, Aug 12 2020	0.008	-4.036*	0.586	-6.697*	1.284*	-1.912
	(0.327)	(1.161)	(0.721)	(2.321)	(0.514)	(2.090)
Thu, Aug 13 2020	2.896	-1.139	0.251	-6.446*	-1.384*	-3.297
	(2.446)	(2.636)	(1.301)	(2.569)	(0.423)	(2.136)
Fri, Aug 14 2020	-1.041	-2.180	-0.163	-6.609	-2.437*	-5.734*
	(0.773)	(2.409)	(2.040)	(3.983)	(0.704)	(2.544)
N of firms	123	123	22	22	25	25

* $p < 0.05$
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

G.3 Number of LASSO cross-validation folds

We replicated the analysis but changed the number of folds for the CV procedure employed by the LASSO to consider 10 (Table G.4), 5 (Table G.5), and 3 (Table G.6) folds. All estimation windows had the same hyper-parameters selected in our main study: they started 30 days before and ended 3 days before the US sanctions. Results were, once again, consistent with those presented in our main text.

Table G.4: 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	-0.939	-0.939	-0.270	-0.270	-0.494	-0.494
	(0.486)	(0.486)	(0.911)	(0.911)	(0.879)	(0.879)
Thu, Aug 06 2020	-0.588	-1.526*	-1.284	-1.555	-0.021	-0.514
	(0.361)	(0.598)	(0.701)	(1.249)	(0.653)	(1.071)
Post-sanctions:						
Fri, Aug 07 2020	-2.024*	-3.551*	-2.708*	-4.263*	-3.405*	-3.919*
	(0.545)	(0.749)	(0.760)	(1.323)	(0.825)	(1.429)
Mon, Aug 10 2020	-0.541	-4.092*	-0.662	-4.925*	-0.437	-4.356*
	(0.402)	(0.905)	(1.024)	(1.384)	(0.602)	(1.791)
Tue, Aug 11 2020	-0.690	-4.782*	-1.621*	-6.547*	-0.301	-4.657*
	(0.487)	(1.124)	(0.764)	(1.640)	(0.487)	(2.076)
Wed, Aug 12 2020	-0.384	-5.166*	0.870	-5.677*	1.095	-3.562
	(0.370)	(1.155)	(0.596)	(1.637)	(0.654)	(2.224)
Thu, Aug 13 2020	2.998	-2.169	0.136	-5.541*	-1.160*	-4.723*
	(2.717)	(2.877)	(1.295)	(1.802)	(0.518)	(2.198)
Fri, Aug 14 2020	-0.958	-3.127	0.380	-5.162	-2.697*	-7.419*
	(0.856)	(2.593)	(1.879)	(3.169)	(0.644)	(2.219)
N of firms	111	111	23	23	21	21

* $p < 0.05$
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 G.5: 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	-0.806	-0.806	-0.565	-0.565	-0.067	-0.067
	(0.492)	(0.492)	(1.049)	(1.049)	(0.645)	(0.645)
Thu, Aug 06 2020	-0.557	-1.363*	-1.234	-1.799	-0.657	-0.723
	(0.374)	(0.604)	(0.670)	(1.433)	(0.617)	(0.910)
Post-sanctions:						
Fri, Aug 07 2020	-1.946*	-3.308*	-2.455*	-4.254*	-3.400*	-4.123*
	(0.564)	(0.749)	(0.755)	(1.425)	(0.791)	(1.243)
Mon, Aug 10 2020	-0.276	-3.585*	-1.519	-5.773*	-0.486	-4.609*
	(0.359)	(0.875)	(0.851)	(1.756)	(0.689)	(1.675)
Tue, Aug 11 2020	-0.693	-4.278*	-2.061*	-7.834*	-0.926	-5.535*
	(0.479)	(1.027)	(0.953)	(2.345)	(0.749)	(2.325)
Wed, Aug 12 2020	-0.067	-4.344*	1.186	-6.648*	2.792*	-2.743
	(0.468)	(1.136)	(0.725)	(2.285)	(1.195)	(2.395)
Thu, Aug 13 2020	0.329	-4.015*	-0.417	-7.065*	-1.691*	-4.434
	(0.427)	(1.245)	(0.737)	(2.434)	(0.606)	(2.426)
Fri, Aug 14 2020	-1.209*	-5.224*	-1.363	-8.428*	-2.776*	-7.210*
	(0.487)	(1.450)	(0.836)	(2.845)	(0.625)	(2.559)
N of firms	99	99	19	19	20	20

* $p < 0.05$
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 G.6: 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	-0.989*	-0.989*	-0.702	-0.702	-0.188	-0.188
	(0.483)	(0.483)	(1.236)	(1.236)	(0.585)	(0.585)
Thu, Aug 06 2020	-0.646	-1.635*	-1.470	-2.172	-0.250	-0.438
	(0.409)	(0.595)	(0.982)	(1.652)	(0.687)	(0.802)
Post-sanctions:						
Fri, Aug 07 2020	-2.459*	-4.094*	-2.637*	-4.809*	-2.726*	-3.164*
	(0.420)	(0.719)	(1.016)	(1.576)	(0.717)	(0.965)
Mon, Aug 10 2020	-0.593	-4.687*	-0.553	-5.363*	-0.300	-3.464*
	(0.411)	(0.862)	(1.431)	(1.630)	(0.458)	(1.259)
Tue, Aug 11 2020	-0.920	-5.607*	-2.885*	-8.247*	-0.617	-4.081*
	(0.482)	(1.116)	(0.974)	(1.760)	(0.466)	(1.524)
Wed, Aug 12 2020	0.084	-5.523*	0.776	-7.472*	2.026	-2.055
	(0.389)	(1.233)	(0.895)	(1.653)	(1.285)	(1.554)
Thu, Aug 13 2020	3.349	-2.175	0.633	-6.839*	-1.634*	-3.689*
	(2.982)	(3.236)	(1.765)	(2.182)	(0.574)	(1.524)
Fri, Aug 14 2020	-1.221	-3.396	0.807	-6.032	-2.683*	-6.372*
	(0.799)	(2.856)	(2.679)	(4.220)	(0.700)	(1.620)
N of firms	101	101	16	16	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

G.4 Using OLS instead of the LASSO for estimating market models

Finally, we replicated our analysis when considering an altogether different estimation strategy for obtaining our market models: OLS models with an aggregated market-wide index (the S&P 500 index itself). The estimation window started 180 days before and ended 3 days before US sanctions, as this choice resulted in the best-fitting market models on average (see Figure C.2). Results, reported in Table G.7, were broadly consistent with our main results.

Table G.7: 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	0.937*	0.937*	0.504	0.504	1.324*	1.324*
	(0.396)	(0.396)	(0.892)	(0.892)	(0.551)	(0.551)
Thu, Aug 06 2020	-0.114	0.823	-0.354	0.150	-0.645	0.679
	(0.604)	(0.806)	(0.719)	(1.111)	(0.623)	(0.867)
Post-sanctions:						
Fri, Aug 07 2020	-2.675*	-1.852*	-2.583*	-2.433*	-3.355*	-2.677*
	(0.543)	(0.662)	(0.702)	(1.097)	(0.940)	(1.171)
Mon, Aug 10 2020	-0.091	-1.943*	-2.186*	-4.620*	0.335	-2.341
	(0.436)	(0.708)	(0.986)	(1.154)	(0.663)	(1.447)
Tue, Aug 11 2020	0.563	-1.379	-0.654	-5.273*	-0.065	-2.406
	(0.310)	(0.820)	(0.490)	(1.394)	(0.291)	(1.496)
Wed, Aug 12 2020	1.183*	-0.196	2.057*	-3.217*	1.190*	-1.217
	(0.296)	(0.870)	(1.009)	(1.216)	(0.360)	(1.334)
Thu, Aug 13 2020	0.263	0.067	0.456	-2.761*	-0.511	-1.728
	(0.604)	(1.173)	(0.531)	(1.238)	(0.515)	(1.361)
Fri, Aug 14 2020	-0.779	-0.712	0.141	-2.620	-1.555*	-3.283*
	(0.420)	(1.364)	(0.811)	(1.607)	(0.527)	(1.481)
N of firms	44	44	12	12	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 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

H Long-term effects

Figure H.1 shows CAR of Tencent following the US sanctions of August 2020 and until the end of August 2021. The figure shows that, even one month (Sep 2020), six months (Feb 2021), and one year (Aug 2021) after the sanctions, Tencent's title had not recovered from the losses. At the end of August 2021, cumulative losses to Tencent's title ranged in the order of -120%. Of course, it is impossible to attribute such a large negative effect *entirely* to the sanctions: over such a long time period, a firm experiences a myriad of events that accrue positive or negative AR and that, when summed up, determine CAR. To name a few negative and positive, Tencent was involved in a Chinese antitrust investigation and regulatory measures (late Spring 2021 and Summer 2021),[6] experienced record-high year-on-year revenue growth in the first and second quarters of 2021,[7] was involved in a sanctioned data breach (August 2021),[8] and even in a further executive order by the Trump administration reinforcing the August 2020 sanctions (January 2021).[9] With the caveat that we cannot really estimate the long-term effect of the August 2020 sanction on CAR, the figure *still* informs us that no event in the time span *of an entire year* managed to recover the loss experienced by Tencent with the US sanctions. To express such loss as

[6] See: https://www.reuters.com/world/china/exclusive-china-readies-tencent-penalty-antitrust-crackdown-sources-2021-04-29/ and https://www.axios.com/2021/07/12/china-tech-crackdown-huya-douyu.

[7] See: https://www.ig.com/en/news-and-trade-ideas/why-tencent-s-revenue-could-reach-all-time-high-in-2021-210524 and https://www.prnewswire.com/news-releases/tencent-announces-2021-second-quarter-and-interim-results-301357768.html.

[8] See: https://www.reuters.com/business/retail-consumer/china-ministry-targets-43-apps-including-tencents-wechat-2021-08-18/.

[9] See: https://trumpwhitehouse.archives.gov/presidential-actions/executive-order-addressing-threat-posed-applications-software-developed-controlled-chinese-companies/.

unrealized market capitalization, we multiply Tencent's stock price before the sanctions ($72.6) by the outstanding shares (9.6B) and by the CAR loss one year after the sanctions (-110pp, or -1.10). The unrealized capitalization gains (i.e., losses) amount to about $770B.

FIGURE H.1: Long-term *Cumulative Abnormal Returns* for Tencent, from August 05, 2020 to August 30, 2021

In a similar vein, we report long-term average CAR (and 95% CIs) for US-traded Chinese firms, WeChat-reliant firms, and Tencent-owned firms in Figure H.2. US-traded Chinese firms recovered from the sanction effect in the longer term. Instead, firms with product or investment ties to Tencent had not managed to recover from the losses experienced with the sanctions even after a year of trading. CAR losses ranged from about -100% (WeChat-reliant firms) to -200% (Tencent-Owned firms). Net of the above caveats—this long time period includes several events which we cannot really account for—this confirms the long-term damage experienced after the sanctions. It also confirms our main text finding that the categorical spillover effect operating at the level of firms' nationalities is weaker than the interdependence effect generated by product dependence and investment ties. To express such losses in terms of unrealized market capitalization, we multiply each firm's stock price before the sanctions by the number of outstanding shares and by the CAR loss one year after the sanctions. We, then, average the quantity by each sample and find long-term unrealized capitalization gains (i.e., losses) of about $142B for the categorical channel, $648B for the product channel, and $97B for the investment channel.

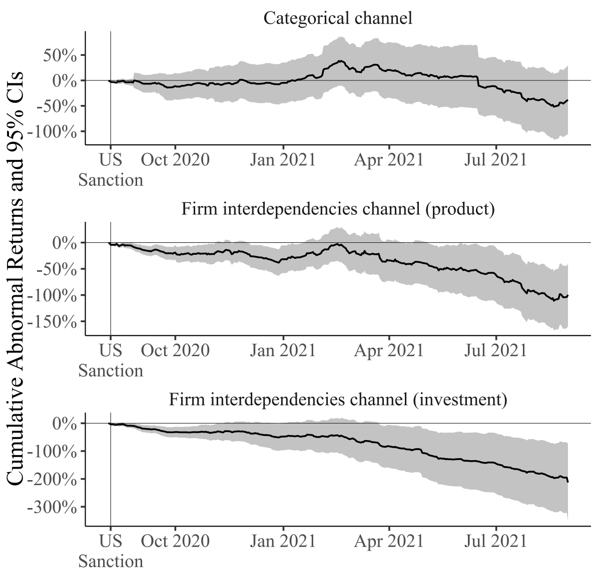

FIGURE H.2: Long-term average *Cumulative Abnormal Returns* and 95% CIs for firms traded in the US for Chinese firms (top), WeChat-reliant firms (middle), and Tencent-owned firms (bottom), from August 05, 2020 to August 30, 2021

References

Abadie, Alberto, Alexis Diamond, and Jens Hainmueller. 2015. "Comparative politics and the synthetic control method." *American Journal of Political Science* 59 (2): 495–510.

Aklin, Michaël. 2018. "How robust is the renewable energy industry to political shocks? Evidence from the 2016 US elections." *Business and Politics* 20 (4): 523–552.

Boehmer, Ekkehart, Jim Masumeci, and Annette B Poulsen. 1991. "Event-study methodology under conditions of event-induced variance." *Journal of Financial Economics* 30 (2): 253–272.

Brown, Stephen J, and Jerold B Warner. 1980. "Measuring security price performance." *Journal of Financial Economics* 8 (3): 205–258.

Brown, Stephen J, and Jerold B Warner. 1985. "Using daily stock returns: The case of event studies." *Journal of Financial Economics* 14 (1): 3–31.

Castro-Iragorri, Carlos. 2019. "Does the market model provide a good counterfactual for event studies in finance?" *Financial Markets and Portfolio Management* 33: 71–91.

Corrado, Charles J, and Terry L Zivney. 1992. "The specification and power of the sign test in event study hypothesis tests using daily stock returns." *Journal of Financial and Quantitative analysis* 27 (3): 465–478.

Cowan, Arnold Richard. 1992. "Nonparametric event study tests." *Review of Quantitative Finance and accounting* 2: 343–358.

Eden, Lorraine, Stewart R Miller, Sarfraz Khan, Robert J Weiner, and Dan Li. 2022. "The event study in international business research: Opportunities, challenges, and practical solutions." *Journal of International Business Studies* 53 (5): 803.

Kucik, Jeffrey, and Krzysztof J Pelc. 2016. "Do international rulings have spillover effects?: The view from financial markets." *World Politics* 68 (4): 713–751.

Lamb, Reinhold P. 1995. "An exposure-based analysis of property-liability insurer stock values around Hurricane Andrew." *Journal of Risk and Insurance* pp. 111–123.

McConnell, John J, and Chris J Muscarella. 1985. "Corporate capital expenditure decisions and the market value of the firm." *Journal of Financial Economics* 14 (3): 399–422.

Patell, James M. 1976. "Corporate forecasts of earnings per share and stock price behavior: Empirical test." *Journal of Accounting Research* pp. 246–276.

Tibshirani, Robert. 1996. "Regression shrinkage and selection via the lasso." *Journal of the Royal Statistical Society Series B: Statistical Methodology* 58 (1): 267–288.

Voeten, Erik. 2024. "Do domestic climate rulings make climate commitments more credible? Evidence from stock market returns." *The Journal of Politics* .

Wilcoxon, Frank. 1992. "Individual comparisons by ranking methods." In *Breakthroughs in statistics: Methodology and distribution*. Springer pp. 196–202.

Wilf, Meredith. 2016. "Credibility and Distributional effects of International Banking regulations: evidence from us Bank stock returns." *International Organization* 70 (4): 763–796.