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Trade Policy Uncertainty, China-US Trade War and Stock Liquidity in China: The Moderating Role of Digital Transformation

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Abstract: The China–U.S. trade war sharply increased trade policy uncertainty (TPU), raising concerns about market functioning when policy regimes become unstable. Using a firm-level panel of Chinese A-share listed companies, we examine whether TPU deteriorates stock liquidity. To address endogeneity that limits conventional fixed-effects regressions, we implement a propensity-score–matched (PSM) triple-differences design centered on TPU× TRW×Htech. We find that higher TPU during the trade war significantly worsens stock liquidity for high-tech firms and the conclusion is reliable across sever robust test. The effect is concentrated among smaller firms, non–state-owned enterprises, and manufacturing firms. Moreover, the adverse impact is attenuated for firms with greater digital transformation. Our findings provide credible evidence on how TPU translates into tighter trading conditions and offer policy and managerial implications for strengthening market resilience to external shocks.

Keywords: Trade policy uncertainty; Stock liquidity; China-US trade war; High-tech companies; Digital Transformation

1. Introduction

Since 2018, the China–U.S. trade war made trade policy uncertainty (TPU) a salient source of uncertainty for China's capital markets (Caliendo & Parro, 2023). Figure 1 plots a Chinese TPU (Davis et al., 2019) index and highlights two features: TPU rises markedly after the onset of the trade war, and it becomes substantially more volatile, with sharp spikes around key episodes. This pattern is consistent with the view that TPU is not simply the realization of tariff changes, but rather persistent ambiguity about the future trade-policy regime and its downside tail risks—ambiguity that can trigger repeated revisions in expectations about firms' cash flows and discount rates and, in turn, generate large stock price movements (Alessandria et al., 2025). Yet volatility is not our endpoint. A more consequential channel is market quality: when uncertainty increases, information asymmetry tends to intensify and risk-bearing becomes more costly, weakening the supply of immediacy. The result is poorer quote quality—wider bid–ask spreads, larger price impacts, and thinner depth—and, ultimately, lower stock liquidity (Chung & Chuwonganant, 2014). This motivates our central question: does higher TPU erode stock liquidity in China, and is this effect amplified after the trade war and particularly for high-tech firms?

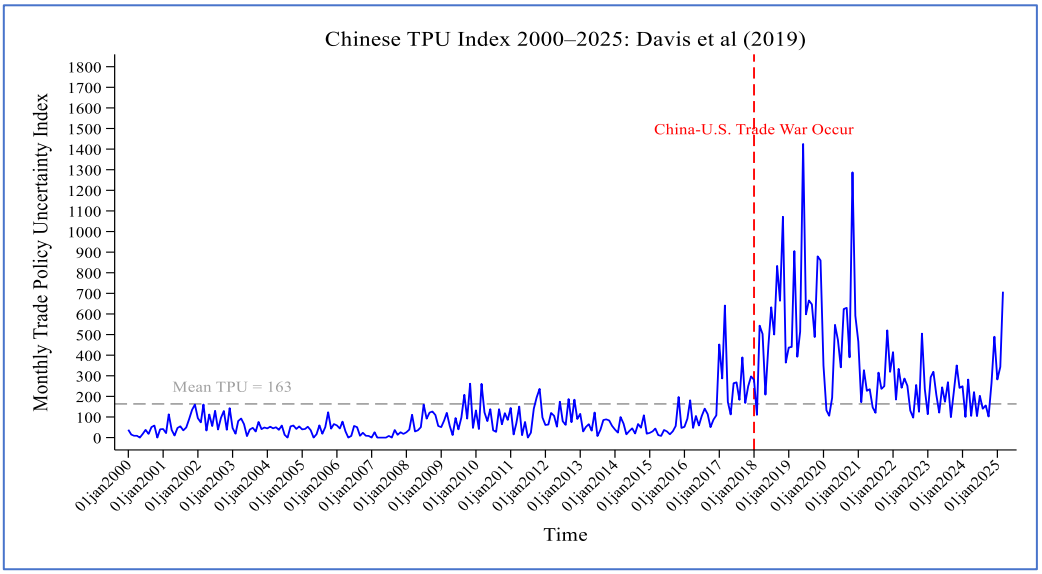


Figure 1 Trade Policy Uncertainty Index of China (Davis et al., 2019).

Stock liquidity is a central margin of market quality: it captures whether investors can trade quickly at low cost and with limited price impact (Amihud, 2002). Liquidity

matters not only because it governs trading frictions and price discovery, but also because it is closely tied to the cost of capital, risk sharing, and the efficiency with which capital is allocated (Acharya & Pedersen, 2005). A large literature shows that liquidity responds to information frictions (e.g., asymmetric information and disagreement) (Cujean & Praz, 2015; Wang et al., 2022), risk (e.g., volatility and tail risk) (Acharya & Pedersen, 2005), and the risk-bearing capacity (Amihud & Mendelson, 1986) and funding constraints of intermediaries (Li & Luo, 2019). Against this backdrop, policy uncertainty is a natural candidate for shifting trading conditions. Yet the empirical evidence has largely focused on broader measures of economic policy uncertainty (EPU) (Wang et al., 2022), while comparatively less is known about trade policy uncertainty (TPU)—a more directional source of uncertainty that is tightly linked to external demand and supply-chain risk. Moreover, existing work on TPU has primarily studied real outcomes such as investment and trade (Handley & Limao, 2015), with much less attention to secondary-market trading conditions. As a result, evidence on whether TPU systematically erodes stock liquidity—especially in a setting with a sharp and salient shock such as the China–U.S. trade war—remains limited.

Further, because the trade war disproportionately targeted technology-intensive activities, high-tech firms offer a natural and testable margin of heterogeneity in the liquidity effects of TPU (Fajgelbaum & Khandelwal, 2022). First, their exposure to the trade war is typically higher and more observable: reliance on U.S.-linked revenues, cross-border supply chains, and critical imported inputs means that uncertainty about the trade-policy regime is more likely to translate into disruptions, delays, and costly re-optimization (Fazzari et al., 1988). Second, high-tech valuations tend to rest more on long-run growth opportunities and intangible capital, so increases in uncertainty and tail risks can trigger sharper revisions in expected cash flows and discount rates (Handley & Limao, 2015). Third, their information environment is often opaquer—R&D and technology choices are harder to verify—so higher uncertainty can aggravate adverse selection (Nagar et al., 2019), leading liquidity providers to widen spreads and reduce depth.

To identify the liquidity effects of TPU, standard fixed-effects regressions are limited: TPU is likely endogenous to unobserved firm shocks, and the trade-war period features broad, time-varying forces that can confound simple before–after comparisons. This study therefore moves beyond the conventional FE approach and use a DDD design, which DDD=TPU×TRW×Htech, exploiting (i) the variation in TPU, (ii) the timing of the trade war, and (iii) cross-sectional differences in high-tech status. To further mitigate selection on observables and improve covariate balance between firms with systematically different exposure to TPU, we implement a Propensity Score Matching (PSM) approach (Caliendo & Kopeinig, 2008), which reduces reliance on functional-form extrapolation and strengthens the credibility of the identifying comparison. This PSM-DDD structure nets out common macro shocks, persistent differences between high-tech and non–high-tech firms, and trade-war-period trends that differentially affect technology-intensive sectors, thereby sharpening causal interpretation relative to prior work.

Building on the identification strategy, this study next posits digital transformation as a potential resilience margin that may attenuate the liquidity consequences of TPU. One channel operates through the information environment: stronger digital capabilities can improve the timeliness and verifiability of disclosure and facilitate monitoring by intermediaries, potentially reducing information asymmetry and adverse selection in trading (Diamond & Verrecchia, 1991; Li & Zhang, 2025). A second channel is operational: digitalization may enhance supply-chain visibility and speed adjustment and recovery, thereby dampening the pass-through from trade-policy ambiguity to cash-flow risk (Li et al., 2025; Tian & Cui, 2025). These mechanisms motivate a testable expectation that the TPU–liquidity slope is weaker among more digitally transformed firms. Because digital transformation is not randomly assigned, we rely on lagged measures and robustness checks to limit a “better-firms” interpretation.

Using an unbalanced panel of China’s A-share firms from 2015–2022 (a symmetric four-year window around the 2018 trade-war onset), this paper implements PSM to improve the comparability between high-tech and non–high-tech firms and reduce selection on observables. We then estimate a triple-differences model with firm

and year fixed effects, complemented by an event-study parallel-trends check and a permutation-based placebo test. The results indicate that higher TPU during the trade-war period significantly reduces the liquidity of high-tech firms; results are consistent when using alternative liquidity measures. Heterogeneity is pronounced: the adverse effect is concentrated among smaller firms, non-SOEs, and manufacturing firms. Finally, the interaction between digital transformation and the DDD exposure term is positive, suggesting that more digitally transformed firms experience a weaker deterioration in liquidity when TPU rises.

This paper contributes along three cumulative dimensions. First, in the context of the trade-war shock, we quantify and establish a key empirical fact: increases in TPU significantly worsen stock liquidity for high-tech firms, providing clear and economically meaningful evidence on how trade-policy uncertainty translates into tighter trading conditions in capital markets. Second, rather than relying on conventional fixed-effects correlations, we exploit the trade-war escalation as a sharp temporal structure together with high-tech status as a meaningful exposure margin in a (PSM-)DDD and event-study framework; by differencing out common macro shocks, persistent firm-type differences, and trade-war-period sectoral trends, and by improving covariate balance through matching, this approach substantially mitigates endogeneity concerns stemming from unobserved firm shocks and delivers more credible causal evidence. Third, we incorporate digital transformation into the same empirical design and find that digital capabilities may act as a resilience margin that attenuates liquidity deterioration under elevated TPU, sharpening the managerial and policy implications for strengthening resilience to external shocks.

The remainder of the paper is organized as follows. Section 2 summarizes related literature on the China-US trade war, economic effect of TPU, the relationship between TPU and stock liquidity, and mitigating effect of digital transformation. Section 3 describes the data, variable constructions, and baseline methods. Section 4 presents the main results. The additional tests are reported in Section 5, and Section 6 concludes the study.

2. Literature review and hypothesis

2.1 China-US Trade War

The China–US trade war that began in 2018 marked a sharp break in the post-crisis evolution of global trade relations and quickly became a defining event for international economic policy (Fajgelbaum & Khandelwal, 2022). Existing work attributes the escalation to a bundle of structural frictions—China's expanding global presence, the bilateral trade imbalance, concerns over intellectual property protection, and the role of industrial policy—each of which was framed as conflicting with U.S. national economic interests (Benguria et al., 2022). In this sense, the trade war reflected not only a dispute over tariffs, but also a broader reorientation of bilateral relations toward strategic competition.

The conflict moved rapidly from rhetoric to policy implementation. On June 15, 2018, the United States announced the first list of Chinese products subject to a 25% tariff, covering up to US$50 billion, which is widely regarded as the start of the trade war. China responded with countermeasures of comparable scale and intensity, including tariffs on U.S. metal and agricultural products (Bown, 2019). Subsequent rounds of tariff announcements and retaliation deepened the confrontation and disrupted the established bilateral trade architecture, with spillovers to the broader global trading system (Caliendo & Parro, 2023). More broadly, the episode reinforced a shift toward less predictable trade relations at the global level.

These policy shocks were followed by visible adjustments in bilateral trade flows. As illustrated in Figure 2, both exports and imports recorded negative year-on-year growth in early 2019, accompanied by a rapid narrowing of the trade surplus (Chen et al., 2023). Official Chinese statistics indicate that total China–US trade in 2019 fell to US$541.38 billion, a year-on-year decline of 14.5%. Within this total, China's imports from the United States were US$122.71 billion (−20.9% year-on-year), while China's exports to the United States were US$418.67 billion (−12.5% year-on-year). These contractions implied a direct revenue shock for export-oriented sectors and,

simultaneously, higher operating costs as firms navigated tariff schedules and compliance burdens (Bown, 2019; Handley et al., 2024).

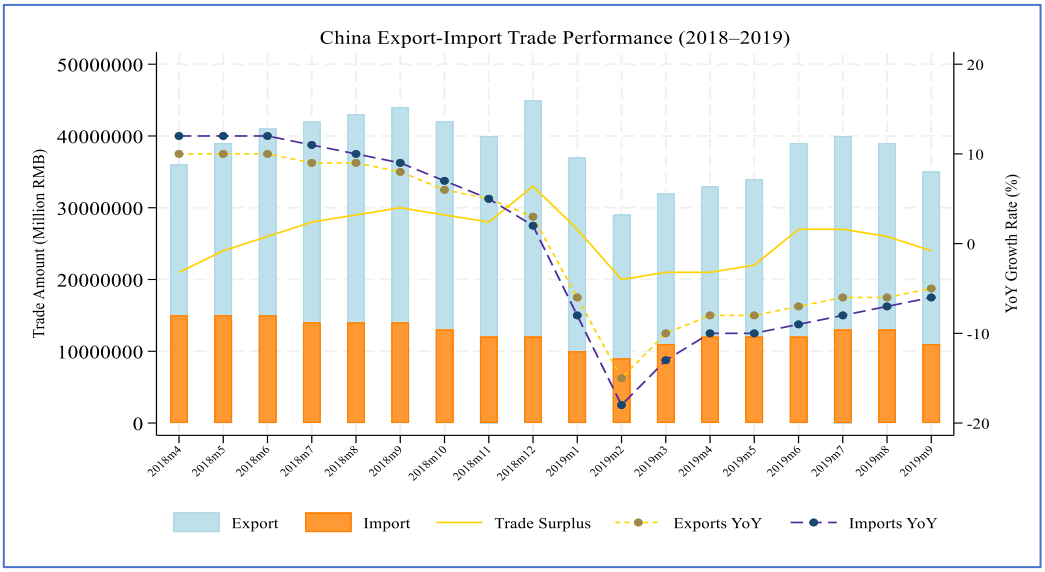


Figure 2 Trade Dynamics Between China and the U.S. After 2018 Trade War

Although bilateral trade volumes began to recover in 2020, the confrontation itself persisted, and firms continued to face a policy environment characterized by elevated friction and repeated revisions to market access conditions (Liu & Woo, 2018). The trade war therefore operated not as a one-off tariff change, but as a sustained sequence of policy moves that complicated firms' long-horizon planning. Consistent with research on the irreversibility of international investment, such policy conflict can distort firms' investment timing and disrupt longer-run sourcing and production arrangements (Handley & Limão, 2022).

A distinctive feature of the China–US trade war was its strong technology dimension. Beyond tariffs, the United States tightened restrictions on technology transfer and cross-border technological collaboration, raising barriers for Chinese firms in advanced sectors and reshaping incentives for innovation and industrial upgrading (Wu, 2018). In response, China placed greater weight on domestic innovation capacity and strategic self-sufficiency in areas such as semiconductors, new energy, AI, quantum technologies, and 5G, with potential long-run implications for industrial structure and China's position in global value chains (Caliendo & Parro, 2023). The episode also coincided with intensified scrutiny of Chinese firms in overseas markets, prompting a search for alternative destinations and reinforcing policy initiatives that emphasize the

domestic market as a central pillar while maintaining external linkages (Jiang & Yu, 2021; Wang et al., 2023). Building on the event background above, we treat 2018 as the onset of the trade-war shock and define the policy-period indicator (TRW) accordingly in the empirical analysis that follows.

2.2 TPU and Its Economic Effect

Trade policy is a central source of uncertainty about an open economy's external demand, costs, and market access conditions (Liu & Woo, 2018). When trade rules are clear and stable, they anchor expectations and reduce background risk. When rules are discretionary, frequently revised, or weakly communicated, trade policy becomes a recurring shock that raises volatility (Handley & Limão, 2022). A key insight in this literature is that uncertainty depends less on whether a policy stance is "pro-" or "anti-" trade, and more on the credibility and continuity of the regime (Handley & Limão, 2017). Limited transparency, inconsistent enforcement, and weak forward guidance increase the perceived probability of abrupt changes in tariffs, quotas, and trade agreements (Caldara et al., 2020). Following Handley and Limao (2015), we use trade policy uncertainty (TPU) to denote the ex-ante risk that prospective trade-policy actions alter the conditions under which firms make production, trade, and investment decisions.

TPU is closely related to, but conceptually distinct from, broader economic policy uncertainty (EPU) (Baker et al., 2016). EPU captures uncertainty about the fiscal, monetary, and regulatory environment and is known to depress investment and raise market volatility (Baker et al., 2016). TPU is narrower in scope, focusing on the stability of trade rules—tariffs, trade agreements, and non-tariff barriers (Handley & Limão, 2022). Importantly, TPU is not redundant even when EPU is accounted for. Trade-policy shocks operate through channels that are specific to external market access, marginal trade costs, and supply-chain resilience, which are only imperfectly reflected in aggregate macro-policy uncertainty (Caldara et al., 2020; Handley et al., 2020). As a result, trade-policy episodes can generate concentrated real and financial losses in trade-exposed sectors even after controlling for broad policy uncertainty (Benguria et al., 2022).

The economic effects of TPU arise at both the macro and the micro level. At the macro level, TPU disrupts trade by raising the perceived risk of future trade costs, which can reduce imports and exports and reallocate trade across partners (Handley, 2014; Handley & Limão, 2022). TPU can also trigger swings in commodity prices and input costs, thereby compressing profit margins, especially in industries with high import content (Bown, 2019). It may further affect exchange rates and capital flows, altering the financial performance of internationally exposed firms (Fajgelbaum & Khandelwal, 2022). Consistent with these mechanisms, empirical studies link higher TPU to weaker employment outcomes, lower foreign direct investment, and slower economic growth (Carballo et al., 2018, 2022).

At the micro level, TPU affects firm decisions through real-options and balance-sheet channels. When investment is partially irreversible, uncertainty increases the value of waiting and can delay or scale down long-horizon projects (Handley & Limão, 2017, 2022). TPU can also tighten financing conditions as lenders become more risk-sensitive, raising the cost of capital and suppressing expansion (Li & Zhang, 2025). Operationally, TPU complicates supply-chain planning and market development, particularly for firms with cross-border production networks (Handley & Limão, 2022; Li et al., 2025). Innovation responses are more ambiguous. Uncertainty can induce managerial short-termism and reduce incentives for risky R&D (Yang & Xie, 2024). At the same time, under persistent external constraints, firms may redirect effort toward domestic substitution and technological self-sufficiency (Fajgelbaum & Khandelwal, 2022). Overall, the literature views TPU as a first-order determinant of real activity and risk exposure, with implications that can propagate into financial markets through fundamentals and risk premia (Caldara et al., 2020).

Taken together, the literature portrays TPU as a distinct and economically meaningful source of uncertainty that reshapes firms' real decisions and risk exposure through trade-specific channels (Caldara et al., 2020). These effects are likely to be especially salient in episodes of heightened trade frictions, when market access conditions and trade costs are repeatedly reassessed. Motivated by this framework, the next section turns to the capital-market implications and reviews how TPU, in the

context of the China–US trade war, can translate into differences in stock liquidity across firms.

2.3 Relationship between TPU and Stock Liqudity during the China-US Trade War

Stock liquidity is an equilibrium manifestation of trading frictions (Amihud, 2002; Amihud & Mendelson, 1986). It summarizes the cost of immediacy—the price investors pay to transact quickly. In canonical market microstructure models, liquidity supply is jointly constrained by two forces: adverse-selection risk generated by asymmetric information and inventory risk/risk-capital constraints faced by liquidity providers (Glosten & Milgrom, 1985; Stoll, 1978). When informed trading becomes more likely and information risk rises, or when intermediaries' risk-bearing capacity tightens and risk capital becomes scarce, market-making and other liquidity provision contract (Li et al., 2019). Trading frictions increase, and market liquidity deteriorates. This delivers a clear implication: uncertainty shocks that systematically worsen the information environment or raise risk-bearing costs have a solid theoretical basis for reducing liquidity (H. Liu et al., 2025).

Against this background, trade policy uncertainty (TPU) provides a natural lens for understanding liquidity dynamics during the China-US trade war (Wang et al., 2022). TPU is not about whether policy is "pro-" or "anti-" trade. It is about the credibility, continuity, and predictability of the trade-policy regime (Alessandria et al., 2025). When trade rules are revised more frequently, enforcement is more discretionary, and forward guidance is weak, firms face an ex-ante risk that future market access conditions and marginal trade costs will shift discretely (Handley et al., 2020; Handley & Limão, 2017, 2022). The U.S.–China trade war in 2018 is a prototypical regime-shock episode in this sense (He et al., 2021). Repeated policy moves and renegotiation cycles increased uncertainty about the policy path, undermining stable expectations and amplifying the economic salience of TPU for corporate decisions and risk exposure (Caliendo & Parro, 2023).

The literature further suggests two microstructure-consistent mechanisms through which TPU can depress stock liquidity. First, TPU widens the set of plausible future cash-flow and cost paths (Obenpong Kwabi et al., 2024). It increases valuation

uncertainty and disagreement, and it raises the value of private information in price formation (Li & Zhang, 2025). This intensifies adverse selection and discourages liquidity provision (Easley & O'hara, 2004). Second, TPU elevates tail risk in earnings and cash flows and heightens risk-premium volatility (H. Liu et al., 2025). This raises the compensation required by liquidity providers for bearing inventory risk (Stoll, 1978). When capital constraints and risk limits bind more tightly and financing conditions become more restrictive, liquidity supply is more easily compressed and trading frictions are more readily amplified (Brunnermeier & Pedersen, 2009). Accordingly, the negative effect of TPU on liquidity should be stronger precisely when information frictions are more severe or risk-bearing capacity is scarcer.

These channels are likely to be amplified for high-tech firms during the trade war because “high-tech” proxies for differential exposure to policy bindingness (Caliendo & Parro, 2023). The trade war did not operate solely through tariffs. It also featured technology-related restrictions and complementary measures that are more likely to bind in technology-intensive segments(Fajgelbaum & Khandelwal, 2022). As a result, high-tech firms are more exposed to discrete shocks in effective market access, critical input availability, and compliance costs (Caldara et al., 2020). Moreover, high-tech valuations often load more heavily on intangibles and growth options (Graham & Harvey, 2001), making them more sensitive to policy-driven shifts in the distribution of longer-horizon cash flows. Stronger policy bindingness combined with greater forward-looking sensitivity implies that (Baker et al., 2016), when TPU rises, both information risk and risk-bearing costs increase more for high-tech firms than for other firms, leading to a more pronounced deterioration in liquidity (Handley & Limão, 2022). Motivated by this framework, we propose the following hypothesis:

Hypothesis 1. During the trade war, TPU significantly decreased stock liquidity for high-tech firms.

2.4 Moderating Effect of Digital Transformation

Digital transformation can influence market liquidity by reshaping how firm information is generated, verified, and disseminated (Li & Zhang, 2025; Stoll, 2003). In market microstructure, trading frictions are pinned down by adverse-selection risk

from information asymmetry and by liquidity providers' risk-bearing and inventory constraints (Wang et al., 2022). When information becomes timelier and easier to verify, adverse selection recedes and liquidity supply becomes more resilient (Diamond & Verrecchia, 1991; Stoll, 1978). Digital transformation delivers these improvements by upgrading internal data systems, standardizing information production and reporting, and expanding disclosure channels(McAffee et al., 2011). Investors can then acquire and validate information at lower cost and update beliefs faster (Easley & O'hara, 2004), which compresses the role of private-information advantages in price formation.

This logic yields a first moderating mechanism. Trade-policy shocks tend to widen disagreement about firms' cost structures, market access, and future cash flows. That raises the value of private information and intensifies adverse selection in trading. By improving transparency and traceability, digital transformation can strengthen the information environment when policy uncertainty is high and thereby dampen the liquidity deterioration induced by TPU (Easley & O'Hara, 2004; Kyle, 1985; Goldfarb & Tucker, 2019). The implication is testable. The buffering effect should be strongest in high-TPU periods, when investors' demand for credible, high-frequency signals is greatest. It should also be more pronounced when the pre-shock information environment is weaker, because the marginal gain from verification is larger.

A second moderating mechanism operates through risk-bearing constraints (Brunnermeier & Pedersen, 2009; Chung & Chuwonganant, 2014). TPU can increase cash-flow uncertainty and tail risk, raising the inventory-risk compensation required by intermediaries and other liquidity suppliers (Stoll, 1978). When funding conditions tighten, liquidity becomes more fragile because funding liquidity and market liquidity reinforce each other (Brunnermeier & Pedersen, 2009). Digital transformation can reduce this fragility by improving firms' operational adaptability. Stronger data capabilities and digital coordination allow faster adjustments in sourcing, inventories, pricing, and customer allocation under policy stress (Browder et al., 2024). This stabilizes realized outcomes relative to worst-case scenarios, lowers the perceived probability of extreme downside states, and weakens the pass-through from TPU to

risk-bearing costs (Denis & Kannan, 2013). In turn, it attenuates the contraction in liquidity supply.

During the China–US trade war, this mechanism is likely to be especially pronounced for high-tech firms (Fajgelbaum & Khandelwal, 2022) because innovation-side uncertainty is quickly capitalized into valuation disagreement and tail-risk pricing. Export controls, licensing restrictions, and constraints on critical intermediates increase the risk of R&D disruption (Alessandria et al., 2025) and widen uncertainty about innovation payoffs (Chen et al., 2023), which amplifies disagreement about long-horizon cash flows and technology paths and raises both information risk and the risk compensation demanded by liquidity suppliers (Caldara et al., 2020). Digital transformation offsets this transmission by strengthening innovation resilience: data-driven R&D management and digital coordination accelerate learning and iteration, facilitate key-technology substitution (Browder et al., 2024) and product upgrading, and reduce reliance on constrained external technologies and inputs (Goldfarb & Tucker, 2019). These innovation gains help stabilize expectations and compress left-tail risk(Hobbs et al., 2017), thereby lowering adverse-selection pressures and inventory-risk premia, so liquidity supply contracts less when TPU rises. Overall, this study proposed the flowing hypothesis:

Hypothesis 2: During the China–US trade war, Digital Transformation can effectively mitigate the deteriorated liquidity induced by(Li & Luo, 2019; Wang et al., 2022; Zhang et al., 2023) TPU.

3. Data and empirical strategy

3.1 Data and sample selection

Firm-level financial and market data are drawn from CSMAR database for Chinese listed companies. The monthly China trade policy uncertainty (TPU) index is obtained from the country-specific Economic Policy Uncertainty database (http://www.policyuncertainty.com) developed by Baker, Bloom, and Davis (2016). We take 2018—the onset of the China–US trade war—as the benchmark year and study a

symmetric window spanning four years before and after the shock, yielding a sample period from 2015 to 2022. To limit the influence of data irregularities, we implement two standard filters: we drop observations with missing values and winsorized all continuous variables at the 1st and 99th percentiles. The resulting dataset is an unbalanced firm-year panel. Before propensity score matching, it contains 26,537 annual observations. All empirical analyses are conducted in Stata 18, and estimated using **reghdfe** command.

3.2 variable definition

3.2.1 Dependent variables: stock Liqudity

Existing literature (Li & Luo, 2019; Wang et al., 2022; Zhang et al., 2023) has compared firm-level measures of liquidity and identified the illiquidity ratio proposed by Amihud (2002)Amihud (2002) as one of the most appropriate proxies for capturing stock liquidity in the context of China's capital markets. This measure effectively reflects the combined effects of transaction costs and price impact associated with trading activity. Drawing on the methodology introduced by Amihud (2002), this paper constructs a firm-level stock illiquidity indicator, calculated in accordance with Equation (1).

$$ILLIQ_{i,t} = \frac{1}{D_{i,t}} \sum_{d=1}^{D_{i,t}} \sqrt{\frac{|r_{i,t,d}|}{V_{i,t,d}}} \quad (1)$$

In the above expression, $|r_{i,t,d}|$ denotes the absolute return of firm *i* on trading day *d* of year *t*, calculated with reinvested cash dividends. $V_{i,t,d}$ represents the trading volume of firm *i* on the same day, measured in millions of RMB, while $D_{i,t}$ denotes the total number of trading days for firm *i* in year *t*. Intuitively, the ratio $|r_{i,t,d}|/V_{i,t,d}$ captures the return volatility per unit of trading volume for stock i on a given day. Averaging this ratio over all trading days within the year yields a standard illiquidity measure. A higher ILLIQ value implies a greater price impact per unit of trading volume, indicating higher transaction costs for investors and, consequently, lower stock liquidity; the reverse also holds. To enhance the interpretability of empirical results, this study defines the stock liquidity measure, denoted as Liquid, as the negative of the illiquidity index. The calculation is formalized as follows:

$$Liquid = -ILLIQ \quad (2)$$

Accordingly, a higher value of the Liquid variable indicates a greater degree of stock liquidity at the firm level. In addition, this study uses the Amihud et al. (1997) liquidity ratio (LR) as the alterative dependent variable.

3.2.2 Independent variables: the DDD item

Another key variable is TPU. We use the monthly China TPU Index, as a proxy for TPU, grounded in the work of Davis et al. (2019). This measure has been widely adopted in the empirical literature on policy uncertainty and trade shocks, which facilitates comparison across studies (C. Liu et al., 2025; Ren et al., 2022). It quantifies uncertainty-related concepts since 2000 using two mainland Chinese newspapers, People's Daily and Guangming Daily. To capture broader trends, the monthly China TPU Index is aggregated into an annual index by applying a weighted average method, and then the natural logarithm of the annual index was calculated.

Our variable of interest is the triple-difference term **DDD**. We construct it in two steps. We start from the standard difference-in-differences (DID) logic widely used in empirical policy evaluation (Angrist & Pischke, 2009). DID compares changes in outcomes before and after a policy shock between treated and control units, thereby differencing out time-invariant unobservable and isolating the variation attributable to the policy environment. This framework supports a causal interpretation under a parallel-trends assumption (Callaway & Sant’ Anna, 2021).

Building on the literature that studies the economic effects of trade policy uncertainty (TPU) in China’s post-WTO environment (Bianconi et al., 2021), we examine how TPU affects the stock liquidity of Chinese listed firms during the China–US trade war. We first form the DID component TPU × TRW, where TPU denotes the trade policy uncertainty index and TRW is an indicator for the trade-war period. This interaction captures the trade-war regime shift in policy uncertainty.

We then introduce cross-sectional treatment intensity through high-tech status. As Chinese firms advanced rapidly in strategic sectors—such as artificial intelligence, semiconductors, 5G communications, and renewable energy—the U.S. technological lead came under greater pressure. During the trade war, high-tech firms were more

likely to be directly exposed to tariffs, export controls, and restrictions on technology cooperation, while non-high-tech firms faced comparatively weaker trade-policy pressure (Caliendo & Parro, 2023). To leverage this differential exposure, we define Htech as an indicator for whether a firm belongs to the high-tech sector, following the classification criteria of Peng and Mao (2017). We then interact high-tech status with the trade-war TPU component to obtain the triple-difference specification:

$$DDD = TPU \times TRW \times Htech \quad (3)$$

This DDD design isolates the incremental effect of trade-war TPU on stock liquidity for high-tech firms relative to non-high-tech firms, while mitigating confounding forces that are common across firms or constant within firms over time.

3.2.3 Moderating variable

Consistent with the conceptual definition of firm digital transformation, we follow Zhang et al. (2021) and construct a firm-year proxy (DIG) from the year-end intangible-asset disclosures in listed firms' annual reports. Specifically, we identify intangible-asset line items that are plausibly related to digital technologies. An item is classified as a "digital-technology intangible asset" if its description includes keywords such as "software," "network," "client," "management system," or "smart platform," or if it is associated with digital-technology patents. We then sum all digital-technology intangible assets within the same firm-year and scale the total by the firm's overall intangible assets for that year. A higher share indicates a greater accumulation of digital-related technological assets and, hence, a higher degree of digital transformation.

3.2.4 Control variables

This study includes a standard set of firm-level controls that capture size, leverage, asset composition, ownership concentration, managerial incentives, and operating efficiency. Size is measured as the natural logarithm of annual total assets. Lev is defined as total liabilities at year-end scaled by year-end total assets. To proxy for asset tangibility and capacity constraints, FIXED is net fixed assets divided by total assets, and Intangible is net intangible assets divided by total assets. We further control for working-capital intensity using INV, defined as net inventory over total assets. To account for governance and control rights, Herfindahl10 is the sum of squared

ownership shares of the firm's top ten shareholders, capturing the concentration of equity holdings. Mshare measures managerial equity incentives, defined as the fraction of shares held by directors, supervisors, and senior executives relative to total shares outstanding. Finally, ATO captures operating efficiency and asset utilization, measured as operating income divided by average total assets. The main variables are surmised in Table 1 and a descriptive statistics analysis in Table 2.

Table 1 List of variables definition and measurement

Variables	Definition/measurement	Source
Liquid	$-ILLIQ_{i,t} = -\frac{1}{D_{i,t}}\sum_{d=1}^{D_{i,t}}\sqrt{\frac{\lvert r_{i,t,d}\rvert}{V_{i,t,d}}}$	CSMAR
DDD	TPU×Period×HighTech	
Htech	The high-tech industry is 1, otherwise it is 0 (Peng & Mao, 2017)	
period	The value is 0 before 2018, and the value is 1 after 2018.	
Size	natural logarithm of annual total assets	
Lev	Total liabilities at the end of the year / total assets at the end of the year	
FIXED	Net fixed assets / total assets	
Intangible	Net intangible assets / total assets	
INV	Net inventory / total assets	
Herfindahl10	The sum of the squares of the shareholding ratios of the top 10 shareholders of the company	
Mshare	Number of shares held by directors, supervisors and senior managers / total number of shares	
ATO	Operating income / average total assets	
DIG	Digital-technology intangible assets/ the total intangible assets (Zhang et al., 2021)	
TPU	Following Davis et al. (2019) construct an index of TPU for China based upon mainland newspapers. Specifically, using the weighted frequency count of publications on policy-related economic uncertainty in two most authoritative newspapers on the Chinese mainland (Renmin Daily and Guangming Daily), China's TPU index is constructed.	https://www.policyuncertainty.com/china_monthly.html

Table 2 Descriptive statistics analysis

VARIABLES	(1) N	(2) mean	(3) SD	(4) min	(5) max
Liquid	26,537	-0.070	0.450	-27.165	-0.000
DDD	26,537	0.237	0.486	-0.526	1.841
DIG	26,509	0.132	2.931	0.000	1.000
TPU	26,537	0.287	0.793	-1.688	1.841
Htech	26,537	0.614	0.487	0.000	1.000
period	26,537	0.649	0.477	0.000	1.000
Size	26,537	22.300	1.316	17.641	28.636
Lev	26,537	0.417	0.199	0.008	0.998
FIXED	26,537	0.205	0.155	0.000	0.954
Intangible	26,537	0.047	0.060	0.000	0.938
INV	26,537	0.136	0.124	0.000	0.931
Herfindahl10	26,537	0.153	0.112	0.000	0.810
Mshare	26,537	14.323	19.499	0.000	89.990
ATO	26,537	0.647	0.532	-0.048	12.373

3.3 Empirical model and methods

3.3.1 The basically model

In markets with informational frictions, liquidity is an equilibrium outcome that depends on how easily investors can infer fundamentals from public signals (Amihud, 2002; Stoll, 1978). When external policy uncertainty rises, managers face stronger incentives to delay disclosure and to bundle information releases, and investors face greater difficulty distinguishing transitory noise from persistent shocks. These forces widen information asymmetry and increase adverse-selection risk, which reduces the willingness of liquidity suppliers to provide immediacy (Glosten & Milgrom, 1985). Financial Market Microstructure Theory (Stoll, 2003) therefore predicts that policy uncertainty worsens market depth and raises trading frictions, lowering liquidity. In addition, trade-policy shocks can increase disagreement and risk aversion. Investors rebalance toward safety and shorten horizons. This raises risk-bearing costs in secondary markets and further depresses liquidity. Together, these channels imply that the escalation of TPU during the China–US trade war should be associated with a deterioration in stock liquidity for HighTech firms that are more exposed to the trade-war shock. We summarize this relation in reduced form as:

$$Liquid = F(DDD, CONTROL) \quad (4)$$

where DDD captures differential exposure to TPU during the trade-war period and CONTROL denotes other determinants of liquidity, including Size, Lev, FIXED, Intangible, INV, Herfindahl10, Mshare, ATO. Based on the DDD framework, we estimate the effect of trade-war TPU on firm-level liquidity using the following fixed-effects regression:

$$Liquid_{itj} = \beta_0 + \beta_1 DDD_{it} + \beta_2 CONTROL_{it} + u_t + \gamma_i + \epsilon_{it} \quad (5)$$

where *i* indices' firms and *t* indexes years. Firm fixed (u_t) effects absorb all time-invariant differences across firms, while year fixed effects (λ_t) capture aggregate shocks common to all firms, including shifts in the average level of TPU. We focus on β_1, the coefficient on the triple interaction. If trade-war TPU reduces liquidity for the treated firms relative to the control group, β_1 should be negative and statistically significant.

3.3.2 Parallel trend test model

The credibility of the DDD design hinges on the parallel-trends assumption. Parallel trends means that, absent the trade-war shock, treated and control firms would have exhibited similar trajectories in the outcome variable (here, stock liquidity Liquid). Any systematic divergence should emerge only after the escalation of trade policy uncertainty (TPU) during the trade-war period. To assess this identifying condition and to trace the dynamic response, we estimate an event-study version of the baseline DDD specification:

$$Liquid_{itj} = \beta_0 + \sum \beta_t \left(TPU_t \times Htech_{it} \times 1\{t = t_0 + k\}\right) + \beta_X CONTROL_{it} + \epsilon_{it} \quad (6)$$

Here, t_0 denotes the reference year for the onset of the trade war (2018 in our setting), and $1\{t = t_0 + k\}$ is an event-time indicator for year t relative to t_0. HighTech identifies treated firms, and TPU_t is the annual trade policy uncertainty index. Firm fixed effectsu_i absorb all time-invariant heterogeneity across firms, and year fixed effects$\gamma_t$absorb aggregate shocks common to all firms. Under parallel trends, the pre-treatment coefficients (k<0) should be small and statistically indistinguishable from zero. A systematic departure from zero after the onset (k≥0) indicates that the trade-war TPU shock differentially affects treated firms. Because Liquid is increasing

in liquidity, we expect the post-onset coefficients to be negative if TPU during the trade war depresses liquidity for treated firms relative to controls.

3.3.3 Moderating effect model

To test whether digital transformation mitigates the adverse liquidity effect of trade-war TPU, we augment the baseline DDD specification by introducing a measure of digital transformation (DIG) and its interaction with the DDD exposure term. We estimate:

$$Liquid_{it} = \beta_0 + \beta_1 DDD_{it} + \beta_2 (DDD_{it} \times DIG_{it}) + \beta_3 DIG_{it} + \beta_4 CONTROL_{it} + \epsilon_{it} \quad (7)$$

Here, we focus on β_2, the coefficient on the interaction term. If digital transformation strengthens the information environment and lowers trading frictions, it should buffer liquidity against TPU shocks. In that case, the negative DDD effect should be attenuated for firms with higher DIG, so β_2 is expected to be positive and statistically significant. The coefficient β_1 captures the average DDD effect at a given level of DIG; because Liquid is increasing in liquidity, we expect β_1 in the baseline.

4. Empirical results

4.1. Propensity Score Matching (PSM) Procedure

In this study, we use PSM to construct a matched sample for the empirical analysis. In observational data, treatment is typically not randomly assigned, so treated and control units can differ systematically in baseline characteristics that also shape outcomes. Simple mean comparisons or regressions with limited controls may therefore confound the treatment effect with selection. To address this identification concern, we use propensity score matching (PSM) (Caliendo & Kopeinig, 2008; Rosenbaum & Rubin, 1983): we first estimate each unit's propensity score—the predicted probability of treatment—as a function of pre-treatment covariates, and then match treated units to control units with similar scores within the region of common support. By improving covariate balance and comparability across groups, PSM reduces bias from observable confounders and strengthens the causal interpretation of the estimated average treatment effect under a selection-on-observables assumption.

In our setting, HighTech is the treatment indicator, capturing whether a firm holds a distinct status (high-tech vs. non-high-tech) that can affect firms' resources, information environment, and market attention, and thus the outcome variable (stock Liqudity). We define firms with HighTech=1 as the treated group and firms with HighTech=0 as the control group. We implement PSM using psmatch2: we first estimate each firm's propensity score based on the pre-treatment covariates in all control variables: Size, Lev, FIXED, Intangible, INV, Herfindahl10, Mshare, ATO, and then perform 1:1 nearest-neighbor matching (neighbor (1)) without replacement (no replacement), imposing a caliper of 0.1 (caliper (0.1)) to ensure close matches within the region of common support. Using the matched sample, we estimate the treatment effect on stock liquidity and report the average treatment effect (ATE) in Table 3. The T-stat value of ATT is 3.320, bigger than 1.67. That means the matching is successful.

Table 3 Average Treatment Effect

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Liquid	Unmatched	-0.076	-0.060	-0.0159	0.005	2.090
	ATT	-0.048	-0.064	0.0163	0.011	3.320

To assess whether PSM improves the comparability of treated and control units, we conduct standard post-matching balance diagnostics. We report covariate means for the treated and control groups before matching (Unmatched) and after matching (Matched), together with standardized percent bias and the corresponding t-tests, and we also plot standardized biases (Figure 3). The balance results (Table 4 and Figure 3) indicate that matching substantially reduces differences in most covariates, with standardized biases moving closer to zero. For example, the standardized bias in Size falls from -44.2 to 14.1, a 68.0% reduction. Figure 3 provides a visual summary of these diagnostics: black dots denote pre-matching bias, crosses denote post-matching bias, and the vertical dashed line marks zero. Most covariates shift markedly toward zero after matching, suggesting improved balance and greater comparability between the two groups, which strengthens the credibility of subsequent treatment-effect estimates. If a small number of covariates remain meaningfully imbalanced, we address this in

robustness checks by tightening the caliper, using alternative matching procedures, or imposing additional restrictions.

Table 4 Covariate balance test— Unmatched vs Matched

Variable	Status (U/M)	Treated mean	Control mean	% bias	% reduct |bias|	t-stat	p-value	V(T)/ V(C)
Size	U	22.076	22.656	-44.2	68.0	-35.79	0.000	0.71*
	M	22.590	22.405	14.1		9.97	0.000	0.99
Lev	U	0.383	0.471	-44.5	59.2	-35.68	0.000	0.83*
	M	0.478	0.443	18.2		12.85	0.000	0.74*
FIXED	U	0.197	0.217	-12.8	47.4	-10.56	0.000	0.52*
	M	0.230	0.220	6.7		4.46	0.000	0.62*
Intangible	U	0.041	0.055	-21.4	79.6	-18.43	0.000	0.19*
	M	0.048	0.045	4.4		3.95	0.000	0.71*
INV	U	0.125	0.152	-19.9	66.6	-16.98	0.000	0.24*
	M	0.144	0.136	6.6		4.92	0.000	0.42*
Herfindahl10	U	0.139	0.174	-30.8	81.0	-25.00	0.000	0.67*
	M	0.163	0.156	5.9		3.96	0.000	1.14*
Mshare	U	17.152	9.830	38.8	45.0	30.29	0.000	1.32*
	M	7.247	11.271	-21.3		-16.47	0.000	0.54*
ATO	U	0.635	0.664	-5.3	36.9	-4.39	0.000	0.43*
	M	0.701	0.682	3.3		2.14	0.033	0.55*

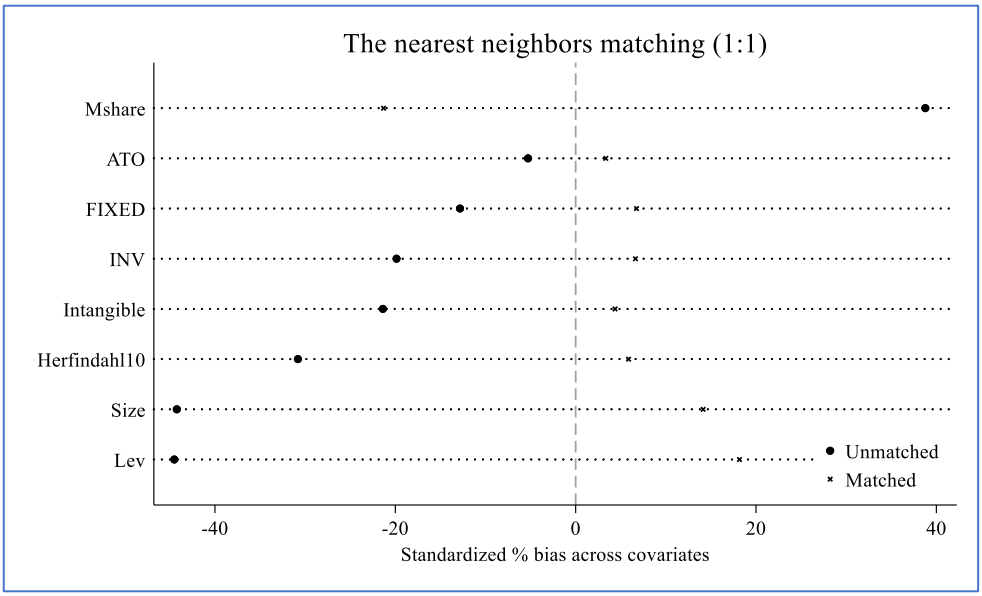


Figure 3 The balance check results of PSM

Consistent with these balance diagnostics, matching also affects the effective sample size. Because matches must satisfy common support and the caliper restriction, observations without suitable counterparts are dropped. As a result, the sample used for

estimation falls from 26,537 observations in the full sample to 15,926 observations in the matched sample. This matched sample forms the basis for our subsequent treatment-effect estimates and robustness analyses.

4.2 Effect of TPU on stock liquidity during the China-US trade war

To study whether the liquidity consequences of trade policy uncertainty (TPU) are heterogeneous across firms during the trade war, we focus on high-tech firms as a group that is plausibly more exposed to policy-driven shocks. Conceptually, a rise in TPU during the trade-war period increases uncertainty about future payoffs and the policy environment. This may widen valuation disagreement, intensify information asymmetries, and raise the compensation investors require to intermediate trades. The resulting deterioration in trading conditions is expected to manifest as lower market depth, higher effective trading costs, and weaker trading activity—i.e., reduced liquidity. These effects should be particularly salient for high-tech firms, whose cash flows and investment plans are more sensitive to policy risk and whose innovation and capital expenditures often involve greater irreversibility. Taken together, this framework motivates the expectation that TPU during the trade war is associated with a less favorable liquidity environment for high-tech firms and results are reported in Table 5.

In table 5, Columns (1)– (4) report PSM–DDD estimates with Liquid as the dependent variable, where the triple interaction DDD is the key regressor. In the baseline specification without additional controls (Column (1)), the DDD coefficient is −0.041 with a t-statistic of −4.12 (significant at the 1% level). Adding the full set of firm controls but excluding firm and time fixed effects (Column (2)) yields a smaller estimate of −0.022 (t = −1.79, significant at the 10% level). When we further include firm fixed effects (Column (3)), the estimate remains negative at −0.016 (t = −2.40, significant at the 5% level). Our most demanding matched-sample specification with both firm and time fixed effects (Column (4)) delivers a DDD coefficient of −0.039 (t = −4.57, significant at the 1% level). Column (5) reports the corresponding standard DDD regression using the full sample of 26,009 observations. The DDD estimate is −0.084 (t = −8.32, significant at the 1% level), providing a useful benchmark against the matched-sample results.

Based on Column (4) of Table 3, which includes both firm and time fixed effects, the triple-difference term DDD (TPU × Period × HighTech) is −0.039 (t = −4.57). This implies that, during the trade-war period, higher TPU is associated with an additional decline in stock liquidity for high-tech firms relative to the benchmark group. Using the descriptive statistics in Table 2, the standard deviation of TPU is 0.793, so a one–standard-deviation increase in TPU corresponds to an estimated liquidity change of about −0.031. This magnitude is economically meaningful: it is roughly 6.9% of the standard deviation of Liquid (0.450) and about 44% of the absolute value of the mean of Liquid (−0.070). Moreover, high-tech firms account for 61.4% of the sample (mean of HighTech_1 = 0.614), and the trade-war period covers 64.9% of observations (mean of Period = 0.649), suggesting that this effect applies to a large share of firms and time periods in the data.

Our setting explicitly links the TPU shock to the trade-war episode. Handley and Limão (2022) emphasize that events such as the 2018 trade war can raise TPU and make its effects empirically salient (Fajgelbaum & Khandelwal, 2022). Their framework highlights a simple mechanism. When key decisions involve sunk or partly irreversible costs, uncertainty creates an option value of waiting and lowers current investment and adjustment (Handley, 2014; Handley & Limao, 2015). A central object is policy tail risk—how downside policy risk maps into profits.

This logic is especially relevant for high-tech firms. These firms often rely on technology adoption, customization, and other activities with sunk costs. In the input-adoption setting discussed by Handley et al. (2024), tariff-increase risk lowers the value of adoption and reduces adoption because firms prefer to wait (Handley et al., 2024). During the trade war, higher TPU therefore implies larger and more asymmetric risks for the payoff process of high-tech firms. Financial markets can translate this into lower liquidity. The information environment deteriorates. Disagreement rises. Liquidity providers face greater adverse-selection and inventory risk (Glosten & Milgrom, 1985). Trading becomes less deep and more costly. The broader implication is that trade-war TPU affects not only real decisions, but also market quality. High-tech exposure makes this channel stronger.

Table 5 TPU and stock Liquidity: Benchmark results [DV: Liquid]

VARIABLES	(1) DV= Liquid	(2) DV= Liquid	(3) DV= Liquid	(4) DV= Liquid	(5) DV= Liquid
DDD	-0.041***	-0.022*	-0.016**	-0.039***	-0.084***
	[-4.12]	[-1.79]	[-2.40]	[-4.57]	[-8.32]
Size		0.034***	0.050***	0.046***	0.069***
		[14.46]	[7.36]	[5.74]	[7.85]
Lev		-0.037**	0.085***	0.074**	0.012
		[-2.41]	[2.79]	[2.41]	[0.36]
FIXED		0.018	0.042	0.040	0.098**
		[1.05]	[0.98]	[0.93]	[2.03]
Intangible		0.090*	0.261**	0.252**	0.091
		[1.67]	[2.50]	[2.42]	[0.84]
INV		0.038*	-0.006	-0.002	-0.047
		[1.67]	[-0.12]	[-0.03]	[-0.83]
Herfindahl10		-0.135***	-0.221***	-0.199***	-0.360***
		[-5.70]	[-3.38]	[-2.97]	[-4.63]
Mshare		-0.001***	-0.001***	-0.001**	-0.003***
		[-4.60]	[-2.93]	[-2.20]	[-5.61]
ATO		-0.006	-0.017	-0.017	-0.049***
		[-1.35]	[-1.57]	[-1.64]	[-3.91]
Constant	-0.045***	-0.789***	-1.185***	-1.077***	-1.492***
	[-28.67]	[-15.49]	[-7.61]	[-6.03]	[-7.62]
			Model Criteria		
Observations	15,926	16,456	15,926	15,926	26,009
R-squared	0.218	0.019	0.218	0.223	0.221
Time-FE	YES	NO	NO	YES	YES
Firm-FE	YES	NO	YES	YES	YES

Note: T-statistics in brackets. *** p<0.01, ** p<0.05, * p<0.1

4.3 Validity of the DDD Specification

4.3.1 Parallel trend test

To investigate the parallel-trends assumption underlying our DDD design, we estimate an event-study specification that traces the dynamic effects around the onset of the trade war. Table 6 reports the corresponding estimates for stock liquidity (DV = Liquid). The specification is estimated on the matched sample with 15,926 observations (R-squared = 0.215).

The pre-treatment coefficients provide no evidence of differential pre-trends between the treated and control groups. The estimates for pre_3 (0.017, t = 0.58), pre_2 (−0.030, t = −1.09), and pre_1 (0.037, t = 0.92) are all small in magnitude and

statistically indistinguishable from zero. This pattern indicates that, prior to the trade-war shock, the evolution of liquidity is comparable across groups.

Table 6 Parallel trend test [DV: Liquid]

VARIABLES	(1) DV=Liquid
pre_3	0.017
	[0.58]
pre_2	-0.030
	[-1.09]
pre_1	0.037
	[0.92]
current	-0.101***
	[-3.86]
post_1	-0.065***
	[-2.67]
post_2	-0.072***
	[-2.81]
post_3	-0.167***
	[-4.37]
post_4	-0.174***
	[-4.43]
Constant	-0.063***
	[-8.26]
Model Criteria	
Observations	15,926
R-squared	0.215
Time-FE	NO
Firm-FE	YES

Note: T-statistics in brackets. *** p<0.01, ** p<0.05, * p<0.1

In contrast, the coefficients turn sharply negative at the onset of the trade war and are statistically strong, indicating a clear post-shock divergence between treated and control firms. The contemporaneous effect (current) is −0.101 (t = −3.86), significant at the 1% level, pointing to an immediate deterioration in liquidity in the trade-war year. The post-treatment effects remain negative and are also significant at the 1% level throughout: post_1 = −0.065 (t = −2.67), post_2 = −0.072 (t = −2.81), post_3 = −0.167 (t = −4.37), and post_4 = −0.174 (t = −4.43). Moreover, the magnitudes become substantially larger in later periods, suggesting that the trade-war shock is not merely transitory but instead generates a persistent—and strengthening—liquidity

deterioration relative to the control group. Results above all are supported the parallel-trends assumption.

Figure 4 provides a graphical summary of the event-study estimates in Table 6. The vertical dashed line marks 2018, the onset of the China–US trade war, and the horizontal dashed line denotes the zero-effect benchmark. The pre-treatment coefficients (pre_3, pre_2, pre_1) fluctuate narrowly around zero and their confidence intervals overlap zero, visually reinforcing the absence of differential pre-trends between treated and control firms. Starting in the trade-war year (current), the point estimates shift clearly below zero and remain negative thereafter. The decline becomes more pronounced in the later post periods (post_3 and post_4), suggesting that the liquidity impact of TPU is not only immediate but also persistent and increasingly negative over time. Overall, Figure 1 aligns closely with Table 6: no pre-trend differences before the shock, followed by a clear post-shock divergence.

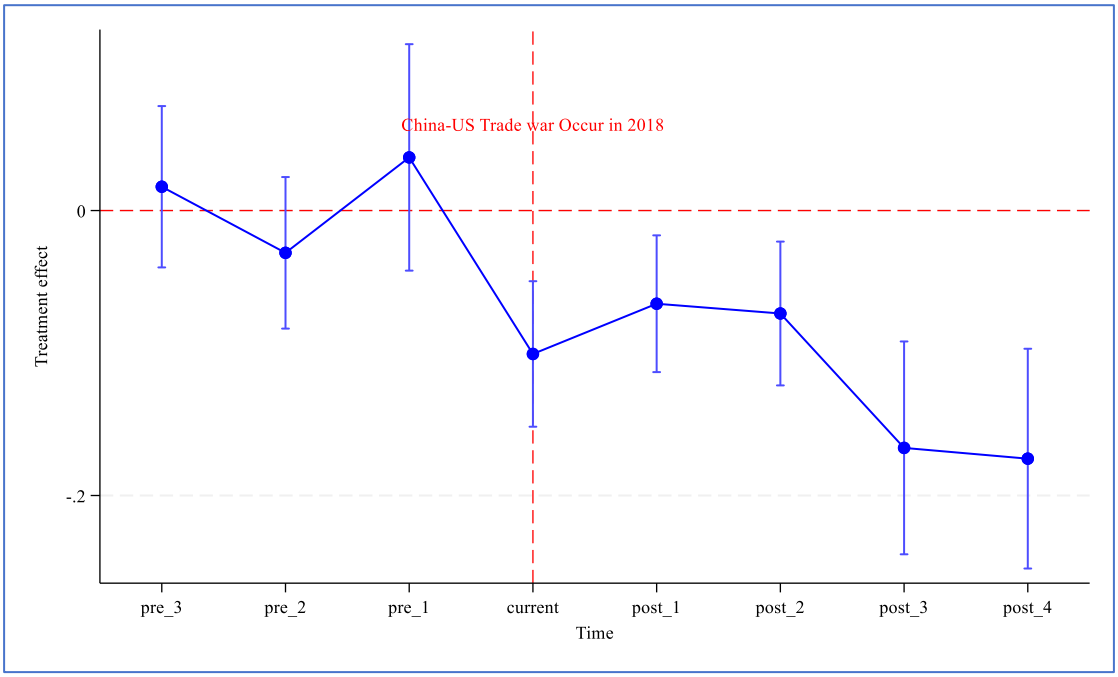


Figure 4 The dynamic effect of the impact of TPU on stock liquidity

4.3.2 Placebo Test

To assess whether our baseline DDD estimate could be generated by chance under random assignment, we implement a permutation-based placebo exercise. We keep TPU and the trade-war timing variable Period fixed, randomly reassign firms to the

treated group, and re-estimate the baseline DDD specification in each replication. We then collect the coefficient on the triple interaction DDD and its statistical significance. Figure 5 summarizes the placebo distribution. The x-axis reports the estimated placebo DDD coefficients, and the red curve plots their kernel density. The blue dots report the associated p-values (left axis), with the horizontal dashed line marking the 5% threshold ($p = 0.05$). The vertical dashed line indicates the baseline DDD estimate (about −0.039). The placebo coefficients are tightly clustered around zero and form an approximately symmetric, bell-shaped distribution, with most draws falling between roughly −0.02 and 0.013. Consistent with this pattern, the bulk of placebo regressions is statistically insignificant at conventional levels. By contrast, the baseline estimate lies far in the left tail of the placebo distribution, well outside its typical range. Taken together, this evidence suggests that our main DDD effect is unlikely to be driven by random assignment and strengthens the credibility of the causal interpretation.

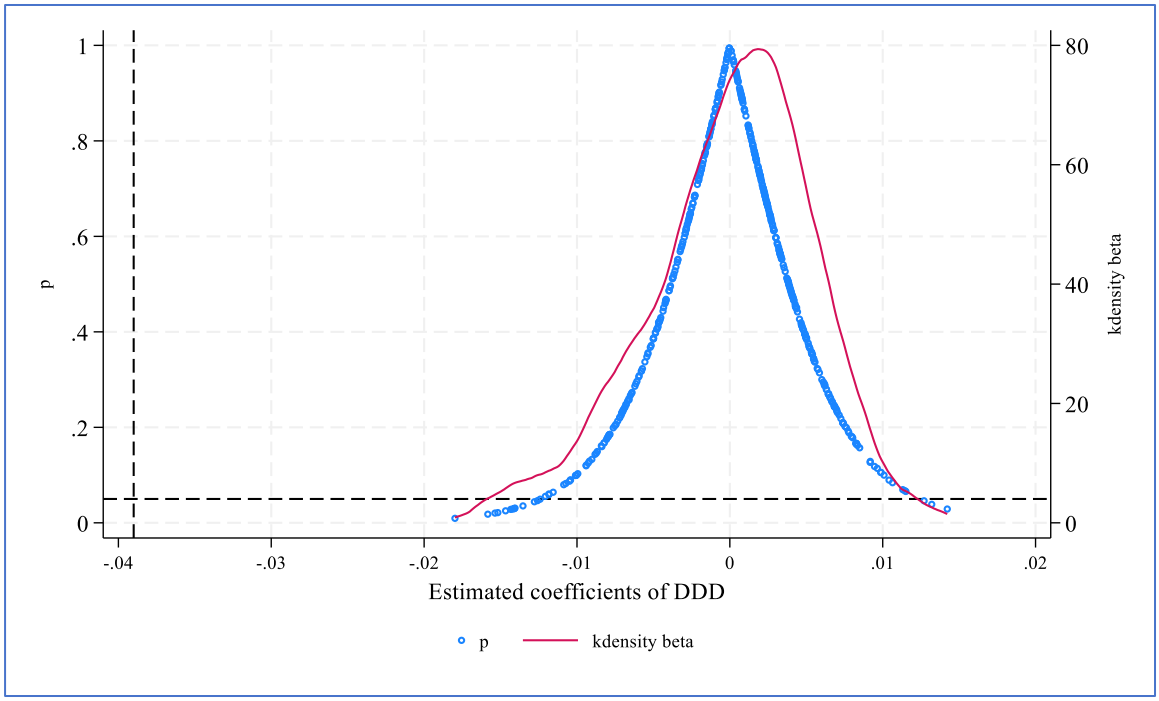


Figure 5 Placebo Test

4.4 Robustness check

4.4.1 Replace the measurement of stock liquidity

Table 7 re-estimates the baseline DDD specification using the Amihud and Mendelson (1986) liquidity ratio (LR) as the dependent variable, replacing Liquid.

Columns (1)– (3) report PSM–DDD estimates on the matched sample, while Column (4) reports the corresponding standard DDD estimate using the full sample.

Table 7 Change core variable measurement [DV=LR]

	(1)	(2)	(3)	(4)
VARIABLES	DV=LR	DV=LR	DV=LR	DV=LR
DDD	-9.966***	-11.952***	-3.092***	-6.545***
	[-9.44]	[-12.36]	[-3.14]	[-8.65]
Size		-33.440***	-35.856***	-34.100***
		[-94.47]	[-39.45]	[-51.83]
Lev		75.091***	56.633***	51.424***
		[31.92]	[16.20]	[20.32]
FIXED		23.258***	8.329*	6.987*
		[9.13]	[1.72]	[1.95]
Intangible		4.315	35.931***	24.688***
		[0.53]	[3.02]	[3.08]
INV		0.471	-23.824***	-24.776***
		[0.14]	[-4.27]	[-5.87]
Herfindahl10		93.234***	108.485***	105.808***
		[26.27]	[14.16]	[18.25]
Mshare		-0.070***	-0.091	-0.085**
		[-2.78]	[-1.58]	[-2.49]
ATO		-3.835***	-11.084***	-12.027***
		[-5.72]	[-9.20]	[-12.78]
Constant	-104.030***	597.586***	666.854***	631.292***
	[-187.04]	[77.82]	[32.66]	[43.18]
		Model Criteria		
Observations	16,453	16,453	15,926	26,009
R-squared	0.005	0.413	0.767	0.761
Time-FE	YES	YES	YES	YES
Firm-FE	YES	NO	YES	YES

Note：t-statistics in brackets. *** p<0.01, ** p<0.05, * p<0.1.

Across all specifications, the coefficient on the triple interaction DDD is negative and statistically strong. In Column (1), the baseline regression without additional controls yields DDD = −9.966 (t = −9.44), significant at the 1% level. Column (2) adds the full set of controls and continues to show a highly significant effect, −11.952 (t = −12.36; 1% level). Column (3) further tightens the specification by absorbing both firm and time fixed effects and still delivers a negative and significant estimate, −3.092 (t = −3.14; 1% level). The full-sample benchmark in Column (4) remains negative and precisely estimated as well, −6.545 (t = −8.65; 1% level). These results show that the

core finding is robust to an alternative, widely used liquidity proxy: when liquidity is measured by LR, the estimated DDD effect remains negative and highly significant, supporting the conclusion that trade-war TPU is associated with a deterioration in stock liquidity for the HighTech firms rather than reflecting measurement-specific noise.

4.4.2 Other determinants on stock liquidity

Table 8 augments the baseline PSM–DDD specification with several plausible confounders—COVID-19, the global supply-chain crisis, tariff pass-through capacity, and export exposure—to rule out competing explanations. All columns use Liquid as the dependent variable and include both firm and year fixed effects. Across these progressively richer specifications, the triple interaction DDD remains negative and precisely estimated, indicating that the adverse liquidity effect associated with trade-war TPU is not driven by omitted shocks captured by these alternative determinants.

Column (1) controls for COVID-19 by adding a dummy equal to one in 2020–2022 and zero otherwise. The DDD estimate remains −0.038 (t = −4.31). The COVID dummy itself is −0.013 (t = −1.14) and statistically insignificant, suggesting that the baseline effect does not hinge on pandemic-period variation once firm heterogeneity and common time shocks are absorbed.

Column (2) controls for supply-chain risk by introducing SCR, a dummy equal to one in 2021–2023 and zero otherwise. The DDD coefficient is essentially unchanged at −0.041(t = −4.77). SCR enters with a modest negative coefficient, −0.023 (t = −1.92, marginal at the 10% level), consistent with some liquidity pressure during the supply-chain crisis. Importantly, including SCR does not attenuate the DDD effect, implying that our main estimate is not simply capturing supply-chain disruptions.

Column (3) adds TRSF. During the China–US trade war, a firm's ability to pass tariff-induced cost increases on to end consumers played a pivotal role in determining its exposure to risk (Amiti et al., 2019). To capture this pass-through capacity, this study introduces the tariff pass-through rate (TRSF) as a proxy variable, reflecting a firm's ability to transmit external cost shocks downstream. The variable is constructed as follows:

$$TRSF_{i,t} = \frac{1}{1-gpm_{i,t}} \quad (8)$$

Where gpm denotes the gross profit margin of firm i in year t. The DDD coefficient remains −0.039 (t = −4.56). TRSF is −0.005 (t = −0.79) and insignificant, indicating that controlling for pass-through capacity does not alter the sign or precision of the DDD estimate.

Column (4) further controls for firms' export exposure. The DDD estimate again remains −0.039 (t = −4.56), while the export measure is −0.001 (t = −0.88) and insignificant. This pattern suggests that the baseline effect is not mechanically driven by differences in export intensity.

Column (5) includes COVID, SCR, TRSF, and export exposure jointly. The DDD coefficient remains −0.043 (t = −4.58), significant at the 1% level. The added determinants are not statistically significant in this saturated specification—COVID (0.009, t = 0.53), SCR (−0.030, t = −1.60), TRSF (−0.005, t = −0.76), and exports (−0.001, t = −0.80). Taken together, Table 8 shows that the negative DDD effect is robust to a broad set of alternative determinants, strengthening the credibility of the baseline interpretation.

Table 8 Other determinants [DV=Liquid]

	(1)	(2)	(3)	(4)	(5)
VARIABLES	DV=Liquid	DV=Liquid	DV=Liquid	DV=Liquid	DV=Liquid
DDD	-0.038***	-0.041***	-0.039***	-0.039***	-0.043***
	[-4.31]	[-4.77]	[-4.56]	[-4.56]	[-4.58]
Size	0.046***	0.047***	0.046***	0.047***	0.048***
	[5.81]	[5.85]	[5.77]	[5.81]	[5.92]
Lev	0.071**	0.069**	0.071**	0.074**	0.067**
	[2.33]	[2.26]	[2.31]	[2.42]	[2.18]
FIXED	0.041	0.041	0.039	0.040	0.041
	[0.96]	[0.97]	[0.92]	[0.95]	[0.97]
Intangible	0.251**	0.251**	0.252**	0.254**	0.253**
	[2.41]	[2.41]	[2.42]	[2.44]	[2.43]
INV	0.004	0.008	-0.003	0.001	0.008
	[0.08]	[0.17]	[-0.05]	[0.01]	[0.16]
Herfindahl10	-0.204***	-0.207***	-0.196***	-0.200***	-0.205***
	[-3.04]	[-3.09]	[-2.93]	[-2.99]	[-3.04]
Mshare	-0.001**	-0.001**	-0.001**	-0.001**	-0.001**
	[-2.13]	[-2.07]	[-2.18]	[-2.19]	[-2.06]

ATO	-0.017	-0.017	-0.017*	-0.016	-0.016
	[-1.60]	[-1.57]	[-1.65]	[-1.52]	[-1.47]
COVID	-0.013				0.009
	[-1.14]				[0.53]
SCR		-0.023*			-0.030
		[-1.92]			[-1.60]
Trsf			-0.005		-0.005
			[-0.79]		[-0.76]
SIN				-0.001	-0.001
				[-0.88]	[-0.80]
Constant	-1.088***	-1.095***	-1.080***	-1.100***	-1.116***
	[-6.08]	[-6.12]	[-6.04]	[-6.09]	[-6.17]
			Model Criteria		
Observations	15,926	15,926	15,926	15,926	15,926
R-squared	0.223	0.223	0.223	0.223	0.223
Time FE	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES

t-statistics in brackets *** p<0.01, ** p<0.05, * p<0.1

4.5 Endogeneity analysis

Our empirical strategy treats the rise in trade policy uncertainty during the U.S.–China trade war as a quasi-exogenous shock, while recognizing that China's TPU is a macro, news-based time series with rich dynamics and potential endogeneity. Crucially, our identification does not rely on movements in the level of TPU. Instead, it relies on differential exposure captured by the triple interaction. In the DDD framework, firm fixed effects absorb all time-invariant differences across firms, and year fixed effects absorb aggregate shocks common to all firms—including shifts in the average level of TPU and other macro disturbances. The triple interaction therefore exploits relative changes in trade-war-related exposure for treated firms, rather than TPU per se. The identifying assumption is that, conditional on fixed effects and controls, residual variation in DDD is orthogonal to unobserved firm-specific liquidity shocks.

Table 9 provides two complementary pieces of evidence that address simultaneity and reverse causality. First, Column (1) replaces contemporaneous TPU with its one-period lag and constructs the corresponding DDD (−1) term. The lagged triple interaction remains negative and precisely estimated: DDD (−1) = −0.040 (t = −3.42). The magnitude is close to the baseline estimates, which suggests that the main effect is

not driven by contemporaneous co-movement. This timing result reduces the scope for reverse causality—liquidity feeding back into a macro TPU index—and is consistent with a mechanism in which uncertainty affects firm decisions and trading conditions before showing up in liquidity outcomes.

Second, to further mitigate the concern that China's TPU might respond endogenously to domestic economic and financial conditions, Columns (2)– (3) implement a 2SLS strategy that uses the U.S. TPU index as an external source of variation and constructs the corresponding interaction DDD_US. A growing body of research documents the international spillover effects of U.S. trade policy uncertainty, which directly shape China's external trade environment and corporate strategies. For example, Yan et al. (2022) shows that fluctuations in U.S. TPU transmit to China's exports and investment, while Suwanprasert (2022) demonstrates that U.S. TPU shocks generate measurable spillover effects on foreign economies. At the micro level, Gao and Zhou (2025) highlight that firms embedded in global supply chains are particularly exposed to U.S. policy uncertainty. Collectively, these findings confirm that U.S. TPU systematically influences Chinese firms' trade prospects and disclosure behaviors, thereby serving as a theoretically valid and empirically relevant instrument for identifying the causal effect of TPU.

The first stage (Column (2)) shows that DDD_US is strongly and positively related to China's TPU, with a coefficient of 0.197 (t = 281.12), indicating substantial instrument relevance. In the second stage (Column (3)), the fitted TPU term (TPU_Hat) remains negative and statistically significant, −0.031 (t = −3.32). Importantly, the sign aligns with the baseline DDD results and the magnitude is of the same order as the main estimates (e.g., around −0.039 in the preferred specifications). In addition, the usual identification and weak-instrument diagnostics support the validity of the IV strategy. The Stock–Wright LM statistic equals 13.23 (Chi-sq (1) = 13.23, p = 0.0000), rejecting under-identification. The Anderson–Rubin Wald test yields F (1, 13,229) = 10.9 (p = 0.00), indicating that inference remains robust in the IV setting. Finally, the Cragg–Donald Wald F statistic is 216.38, comfortably above conventional weak-IV cutoffs, suggesting that the instrument is strongly relevant and not weak. These diagnostics

reduce concerns that the 2SLS estimates are driven by weak instruments or fragile identification. Taken together, the lag specification and the IV evidence substantially reduce endogeneity concerns and strengthen the causal interpretation of the trade-war TPU shock on stock liquidity.

Table 9 Endogeneity analysis

		(1)	(2)
VARIABLES	Liquidity	First Stage: TPU	Second Stage: Liquidity
DDD (-1)	-0.040***		
	[-3.42]		
DDD_US		0.197***	
		[281.12]	
TPU_Hat			-0.031***
			[-3.32]
Size	0.039***	-0.033***	0.046***
	[3.75]	[-10.79]	[5.74]
Lev	0.084**	-0.021*	0.074**
	[2.09]	[-1.83]	[2.43]
FIXED	0.030	-0.043***	0.039
	[0.51]	[-2.68]	[0.92]
Intangible	0.430***	0.040	0.253**
	[2.97]	[1.01]	[2.42]
INV	0.021	-0.123***	-0.002
	[0.33]	[-6.61]	[-0.05]
Herfindahl10	-0.177*	0.323***	-0.198***
	[-1.89]	[12.59]	[-2.96]
Mshare	-0.001	0.000	-0.001**
	[-1.49]	[1.29]	[-2.25]
ATO	-0.016	-0.008**	-0.017
	[-1.17]	[-2.08]	[-1.63]
Constant	-0.953***	0.645***	-1.079***
	[-4.03]	[9.44]	[-6.03]
		Model Criteria	
Observations	10,993	15,926	15,926
R-squared	0.201	0.952	0.222
Firm FE	YES	YES	YES
Time FE	YES	YES	YES
	Stock-Wright LM statistic: Chi-sq (1) = 13.23, P-val=0.0000		
	Anderson-Rubin Wald test: F (1,13229) =10.9 P-val=0.00		
	Cragg-Donald Wald F statistic: 79028.12>16.38		

4.6 Heterogeneous analysis

Table 10 examines heterogeneity in the baseline DDD effect along three dimensions—firm size, ownership, and industry—within the same identification framework. All specifications use Liquid as the dependent variable and include both firm and year fixed effects, so the estimates are identified from within-firm changes relative to common time shocks. The results therefore speak to which firms experience a sharper liquidity response when TPU rises during the trade-war period.

Along the size dimension (Columns 1–2), the negative effect is concentrated among smaller firms. For small firms, the coefficient on DDD is −0.095* (t = −4.00), indicating a sizeable and precisely estimated liquidity deterioration. For large firms, by contrast, the estimate is economically negligible and statistically indistinguishable from zero (0.001, t = 0.64). This pattern is consistent with the idea that policy uncertainty is more damaging in environments with tighter financial constraints and more severe information frictions. Smaller firms typically face higher sensitivity to downside risk and weaker liquidity provision, so increases in uncertainty can amplify disagreement about future cash flows and reduce market depth, translating into lower liquidity (Bernanke, 1983; Gulen & Ion, 2016).

Ownership heterogeneity (Columns 3–4) points to a similar asymmetry. For SOEs, the DDD coefficient is close to zero and insignificant (−0.001, t = −0.27). For non-SOEs, the estimate is negative and highly significant (−0.068*, t = −3.75). A natural interpretation is that SOEs are partially insulated from policy-risk shocks through stronger policy ties and softer financing constraints, which dampen perceived tail risk and stabilize liquidity provision. Non-SOEs, by contrast, rely more heavily on market-based funding and are more exposed to shifts in policy risk, so trade-war TPU translates more directly into liquidity deterioration (Faccio et al., 2006; Megginson & Netter, 2001).

Finally, industry heterogeneity (Columns 5–6) shows that the effect is more pronounced in manufacturing. The DDD coefficient is −0.057* (t = −4.66) for manufacturing firms, whereas the estimate for non-manufacturing firms is smaller and not statistically significant (−0.032, t = −0.73). This difference aligns with the trade-

war channel: manufacturing firms tend to be more directly exposed to tariffs, global input linkages, and supply-chain re-optimization. In such sectors, TPU is more likely to shift expectations about costs and demand and to worsen the information environment, increasing risk-bearing costs for liquidity suppliers and leading to larger liquidity declines (Amiti et al., 2019; Handley & Limão, 2022).

Table 10 Sub-sample analysis of firm size, ownership, and Manufacturing [DV: Liquid]

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLE	Small	Large	SOE	NSOE	Manaf	No-manf
DDD	-0.095***	0.001	-0.001	-0.068***	-0.057***	-0.032
	[-4.00]	[0.46]	[-0.27]	[-3.75]	[-4.66]	[-0.73]
Size	0.107***	0.031***	0.020***	0.060***	0.053***	0.043**
	[4.63]	[5.30]	[6.20]	[4.42]	[5.14]	[2.22]
Lev	0.159	-0.025	-0.033**	0.128	0.022	0.158**
	[1.29]	[-1.61]	[-2.14]	[1.32]	[0.75]	[2.21]
FIXED	0.122*	-0.006	-0.032	0.064	0.050	0.039
	[1.84]	[-0.62]	[-1.62]	[1.26]	[1.43]	[0.38]
Intangible	0.467	0.111	0.083	0.396*	0.057	0.578**
	[1.52]	[1.25]	[1.25]	[1.65]	[0.54]	[2.36]
INV	-0.041	-0.007	-0.005	-0.015	0.019	-0.026
	[-0.40]	[-0.41]	[-0.28]	[-0.20]	[0.41]	[-0.27]
Herfindah	-0.328**	-0.104**	-0.029	-0.254***	-0.127**	-0.369*
	[-1.99]	[-2.42]	[-1.00]	[-2.61]	[-2.43]	[-1.93]
Mshare	-0.001	-0.001	-0.000	-0.001	-0.002	0.000
	[-0.80]	[-1.05]	[-0.19]	[-1.04]	[-1.59]	[0.28]
ATO	-0.054**	-0.000	-0.000	-0.032**	-0.021	-0.019
	[-2.11]	[-0.13]	[-0.08]	[-2.03]	[-1.53]	[-0.96]
Constant	-2.379***	-0.708***	-0.467***	-1.403***	-1.199***	-1.066**
	[-4.90]	[-5.33]	[-6.65]	[-4.85]	[-5.19]	[-2.45]
			Model Criteria			
Observations	6,161	9,765	6,340	9,204	10,245	5,626
R-squared	0.228	0.246	0.319	0.225	0.253	0.216
Time-FE	YES	YES	YES	YES	YES	YES
Firm-FE	YES	YES	YES	YES	YES	YES

Robust t-statistics in brackets *** p<0.01, ** p<0.05, * p<0.1

4.7 Moderating effect analysis

Digital transformation can affect stock liquidity by reshaping how information is generated, processed, and transmitted. As firms digitize internal operations and external disclosure, investors can acquire and verify information more quickly and at lower cost,

which tends to reduce information asymmetry and, in turn, adverse-selection concerns in trading. In standard microstructure models, a more symmetric information environment supports greater market depth and lower trading frictions, thereby improving liquidity (Kyle, 1985). Building on this logic, digital transformation should be associated not only with higher liquidity on average, but also with greater resilience to macro uncertainty shocks, insofar as transparency improves and investors can price risk more efficiently. This motivates the moderating prediction that digital transformation attenuates the adverse liquidity effect captured by the DDD term (Goldfarb & Tucker, 2019; Kyle, 1985).

Table 11 provides direct evidence consistent with this moderating channel. Column (1) reports a positive and statistically significant contemporaneous interaction between digital transformation and the DDD shock: DIG × DDD = 0.023 (t = 2.40), significant at the 5% level. The estimate implies that, during the trade-war period, firms with higher digital transformation experience a smaller TPU-induced decline in liquidity. The baseline effect remains negative and highly significant, with DDD = −0.014 (t = −2.59), significant at the 1% level. Column (2) shifts the moderator back by one year and yields a weaker, but still supportive, pattern: the lagged interaction remains positive and is marginally significant at the 10% level ((−1) DIG × DDD = 0.006, t = 1.66), while the DDD term continues to be negative and significant, DDD = −0.016 (t = −2.27; 5% level). Column (3) uses a two-year lag and the moderating effect disappears: (−2) DIG × DDD = −0.001 (t = −0.39), statistically indistinguishable from zero, even though the DDD term remains negative and marginally significant at the 10% level (DDD = −0.011, t = −1.71). Because the specifications impose a common set of controls and fixed effects (Time-FE and Industry-FE), these comparisons isolate how the timing of digital transformation maps into the TPU shock channel.

Table 11 Moderating effect analysis [DV: Liquidity]

VARIABLES	(1) DV=Liquid	(2) DV= Liquid	(3) DV= Liquid
DIG*DDD	0.023**		
	[2.40]		
DIG	0.001*		
	[1.83]		
(-1) DIG* DDD		0.006*	
		[1.66]	
(-1) DIG		0.000	
		[1.23]	
(-2) DIG* DDD			-0.001
			[-0.39]
(-2) DIG			0.001
			[1.56]
DDD	-0.014***	-0.016**	-0.011*
	[-2.59]	[-2.27]	[-1.71]
Size	0.044***	0.042***	0.042***
	[12.16]	[7.94]	[7.86]
Lev	-0.080***	-0.095***	-0.095***
	[-3.02]	[-2.62]	[-2.63]
FIXED	0.026	0.040*	0.032
	[1.52]	[1.81]	[1.46]
Intangible	0.092**	0.123***	0.107**
	[2.54]	[2.78]	[2.39]
INV	0.003	0.030	0.030
	[0.12]	[1.24]	[0.90]
Herfindahl10	-0.163***	-0.158***	-0.146***
	[-7.55]	[-5.19]	[-5.21]
Mshare	-0.001***	-0.001***	-0.001***
	[-5.61]	[-4.18]	[-4.07]
ATO	-0.014***	-0.011***	-0.017***
	[-3.81]	[-2.71]	[-3.16]
Constant	-0.981***	-0.929***	-0.922***
	[-12.56]	[-8.25]	[-8.13]
		Model Criteria	
Observations	26,509	18,922	18,800
R-squared	0.032	0.028	0.026
Time-FE	YES	YES	YES
Industry-FE	YES	YES	YES

Note: t-statistics in brackets. *** p<0.01, ** p<0.05, * p<0.1

The economic content of Columns (1)– (2) is straightforward: digital transformation offsets part of the trade-war liquidity deterioration associated with TPU. Using Column (1), a one-unit increase in DIG raises the estimated DDD effect by 0.023, mechanically reducing the magnitude of the implied liquidity decline. The dynamics are equally informative. The buffering role is strongest contemporaneously, weaker at a one-year lag, and essentially absent at a two-year lag. This time profile points to a short-horizon moderating effect: the liquidity-relevant benefits of digital capabilities are realized quickly—when uncertainty spikes and information frictions are most salient—but do not continue to strengthen in a mechanical way over longer horizons. A plausible interpretation is rapid market incorporation: once investors update about the informational advantages associated with digital capabilities, the incremental cushioning contribution becomes concentrated around the shock window.

From a theoretical perspective, the pattern is consistent with a mechanism in which digital transformation mitigates uncertainty-induced liquidity deterioration by improving the information environment precisely when policy risk is elevated. Trade-policy shocks widen the set of plausible cash-flow paths and can increase valuation disagreement, thereby intensify adverse selection and raise the risk-bearing costs of liquidity supply. Digital transformation can counteract these forces by enabling timelier and higher-frequency operational data, strengthening internal controls, and improving the credibility of external communication, all of which compress information gaps between informed and uninformed traders. It may also enhance firms' ability to adjust sourcing, inventory, and pricing under policy risk, stabilizing cash-flow expectations and reducing perceived tail risk. That the moderating effect attenuates with longer lags is consistent with a rapid-learning channel: once exposure and adaptive capacity are priced in, earlier digital transformation is less visible in subsequent years, even as the underlying DDD shock continues to weigh on liquidity.

6. Conclusion and policy implication

The escalation of the China–U.S. trade war in 2018 coincided with a sharp increase in trade policy uncertainty (TPU), amplifying uncertainty in financial markets and exposing firms to heightened external risk. This risk is plausibly more salient for technology-intensive firms, whose performance and valuation are more sensitive to disruptions in cross-border supply chains and to shifts in policy regimes. Motivated by these concerns, we use firm-level data and a triple-differences framework—augmented with propensity-score matching (PSM–DDD) and event-study diagnostics—to assess the liquidity consequences of TPU in China's capital market. The results show that rising TPU during the trade-war period significantly worsens stock liquidity for high-tech firms, and this conclusion remains robust across alternative liquidity measures, alternative definitions of high-tech status, and a battery of placebo and robustness tests. We further find that digital transformation can attenuate the adverse liquidity effect, consistent with the view that digital capabilities enhance firms' resilience when policy uncertainty is elevated. Heterogeneity analyses indicate that the negative effect is concentrated among smaller firms, non–state-owned enterprises, and manufacturing firms, groups that are likely to face tighter constraints and stronger exposure to trade frictions. Overall, these findings deepen our understanding of how trade-policy uncertainty materializes into deteriorating trading conditions, and highlight digital transformation as a potentially stabilizing force for market liquidity in the face of external shocks.

6.1 Policy Implication

This study proposes strategies for policymakers, enterprises, and investors to mitigate the liquidity consequences of trade policy uncertainty (TPU) in the capital market during episodes such as the China–U.S. trade war, which is widely viewed as a salient and multi-wave trade-policy shock (Caliendo & Parro, 2023; Fajgelbaum & Khandelwal, 2022). Moreover, given that TPU shocks are measurable and economically consequential in the data (Caldara et al., 2020), our heterogeneity results suggest that interventions should be targeted rather than uniform: the adverse liquidity

effects are more concentrated among smaller firms, non–state-owned enterprises, and manufacturing firms.

First, for the government, policymakers should prioritize improving the stability and predictability of the trade-policy environment. Strengthening the implementation of existing international trade commitments and enhancing timely communication with major trading partners can help anchor expectations and reduce uncertainty premia, thereby limiting the amplification of trade-policy shocks into market stress (Caliendo & Parro, 2023). In parallel, policies that support supply-chain resilience—especially for technology-intensive and manufacturing production networks—may further reduce the exposure of vulnerable firms to uncertainty-driven disruptions.

Secondly, financial regulators and exchanges should strengthen the institutional framework that supports market liquidity under stress. First, regulators can improve disclosure standards related to trade-policy exposure and supply-chain risk, increasing the comparability and timeliness of firm-level information when TPU rises (Caldara et al., 2020). Second, regulators may encourage more decision-useful reporting on digital transformation (e.g., operational digitalization, data governance, and supply-chain digital visibility), which can help market participants assess firms' resilience in high-uncertainty states. Third, exchanges can refine market microstructure tools—such as market-making incentives and transparency around liquidity provision—to prevent temporary shocks from translating into persistent illiquidity.

Third, firms should establish a strategic "uncertainty-response" mechanism, with particular attention to the groups identified as more exposed in the heterogeneity analysis. First, smaller firms and privately owned enterprises—especially in manufacturing and high-tech segments—should accelerate feasible digital upgrades that improve operational visibility and adjustment speed. Second, firms should strengthen investor-relations routines and risk communication, disclosing material exposures and mitigation actions in a timely and verifiable manner to stabilize expectations during uncertainty spikes. Third, firms should improve liquidity and financing contingency planning to avoid procyclical contractions that could compound market illiquidity.

Finally, investors should incorporate TPU exposure and firm resilience characteristics into portfolio allocation and risk management. In particular, investors may place greater weight on firms with stronger digital capabilities while applying more stringent scrutiny to trade-exposed small, non-SOE, and manufacturing firms, thereby improving portfolio robustness in periods of heightened policy uncertainty. More broadly, investor demand for standardized disclosure on trade exposure and digital capability can reinforce market discipline and improve information quality when uncertainty is elevated.

6.2 Limitations and future line of research

This study is not exempt from limitations. We rely on a particular TPU measure, and because the boundaries of trade policy uncertainty are inherently fuzzy, any single index may not fully capture the uncertainty firms face (Handley & Limão, 2022); future work could validate our findings using alternative constructions such as tariff-shift–based exposure, product-level tariff mappings, or textual measures from policy statements and enforcement actions. While our (PSM-)DDD design strengthens identification relative to conventional fixed-effects regressions, unobserved time-varying firm shocks and the trade war's multi-wave escalation may still leave residual endogeneity; future research could leverage more granular shock timing, higher-frequency market data, or additional quasi-experimental variation (e.g., instruments based on predetermined supply-chain links or tariff schedules).

Declaration of Competing Interest

The authors declare no conflict of interest.

Declaration of generative AI and AI-assisted technologies in the writing process.

During the preparation of this work ChatGPT is only used in the writing process to improve the readability and language of the manuscript. After using this, authors

reviewed and edited the content as needed and take full responsibility for the content of the published article.

Data availability

Data will be made available on request.

Ethical approval and informed consent

This article does not contain any studies with human participants performed by any of the authors.

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