

Digital Innovation, Government Support Credibility, and Stock Returns: Evidence from China^{*}

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Abstract

Government support can reduce innovation risk, but dependence on that support creates exposure to whether governments can credibly sustain their commitments. Using digital innovation in China, we show that digital patent intensity (DPI) predicts higher future stock returns, with the premium stronger where provincial governments emphasize digital development and face lower fiscal pressure, and weaker when policy uncertainty rises. Around the first publicly disclosed LGFV shadow-debt default in 2017, high-DPI firms underperform and subsequently experience larger increases in accounts receivable and interest expense. DPI also predicts digital subsidies and government procurement, linking innovation to government-supported cash flows. The premium is unrelated to analyst forecast errors, does not concentrate around earnings announcements, and does not reverse. Government support thus changes the source of innovation risk rather than eliminating it.

Keywords: Digital Innovation; Government Support Credibility; Policy Uncertainty; Stock Returns; China

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1 Introduction

Government support can make digital innovation more valuable: subsidies finance investment that capital markets are reluctant to fund, and public procurement creates demand for digital products before private markets do. But the same support creates a new source of risk. Once a firm’s innovation payoffs run through government-related payment channels, the firm becomes exposed to the government’s ability and willingness to honor its commitments. Government support thus both protects innovative firms and makes them vulnerable. This paper asks how capital markets price this dual exposure, and it answers in a setting where the exposure is particularly salient: digital innovation in China.

Digital innovation is the natural place to look for this tension. Digital technologies, such as artificial intelligence, cloud computing, and big data, are general-purpose technologies whose payoffs are more scalable, more uncertain, and more dependent on complementary infrastructure and demand than those of traditional innovation (Yoo et al., 2012; Hirshleifer et al., 2018). Precisely because of this dependence, the pricing of digital innovation reflects not only what a firm invents but also the institutional environment in which the invention is deployed (Syverson, 2011). In China especially, but increasingly in the United States and Europe, the state defines that environment: government support through subsidies, public procurement, and policy directives shapes both the level of digital innovation and its economic payoff. China provides an especially important setting: in 2023, invention patents approved in China’s core digital economy industries totaled 406,000, representing 44.1% of domestic grants and 45.7% of comparable patents worldwide,¹ and in financial technology

¹Statistical Analysis Report on the Patents of the Core Industries of the Digital Economy (2024), China National Intellectual Property Administration (CNIPA). See https://www.cnipa.gov.cn/art/2024/7/29/art_88_193995.html.

China has overtaken the United States to lead global patent filings, with state-owned banks among the most prolific filers.² The exposure is also unusually visible to investors there: in China’s “government-centric” financial market, policy signals and government decisions are an important part of investors’ information set (Pan and Peng, 2025).

The mechanism we propose has two sides. On the benefit side, government subsidies alleviate capital constraints and reduce information frictions (Howell, 2017; Lim et al., 2018; Beraja et al., 2025), and government procurement provides stable, state-backed demand that reduces commercialization risk. These channels can crowd out competitors who lack access to public resources (Kalouptsi, 2018; Rotemberg, 2019), reinforcing the competitive advantage of supported firms. On the risk side, the same dependence ties firm outcomes to the state’s fiscal condition: when fiscal capacity tightens or support is scaled back, firms reliant on government-linked revenues may experience rising accounts receivable, higher borrowing costs, and declining valuations (Hu et al., 2025; Pastor and Veronesi, 2012). Recent evidence from China’s credit market shows that such support is directly priced: bailout expectations make SOE bonds more valuable, particularly when liquidity deterioration raises default risk (Geng and Pan, 2024).

This two-sided structure has asset-pricing implications that guide how we read the evidence. Shocks to support credibility are infrequent and discrete: support arrives steadily until a fiscal event disrupts it. Exposure to such risk is therefore compensated during periods when support remains credible; as perceived support risk rises, exposed firms are repriced downward, compressing realized returns; and when a credibility shock materializes, the exposure produces realized losses. If the digital innovation premium compensates for

²“China overtakes US in fintech patent filings to seize global lead,” *Nikkei Asia*, July 7, 2026. See <https://asia.nikkei.com/business/finance/china-overtakes-us-in-fintech-patent-filings-to-seize-global-lead>.

support-credibility risk, the realized premium should be earned in tranquil states, compress as policy uncertainty rises, and turn into losses around a credibility shock - the structure of a peso-problem premium (Rietz, 1988; Barro, 2006). This is the pattern we find.

Throughout the paper, we use *government support credibility* as the overarching concept, and we measure its two components separately: the government’s *willingness* to support digital innovation, proxied by the digital focus of provincial policy agendas, and its *capacity* to support, proxied by provincial fiscal pressure. *Policy uncertainty* is an aggregate state variable that captures investors’ confidence in support, and the 2017 default of a local government financing vehicle (LGFV) provides a shock to perceived *government payment reliability*. These four elements organize the empirical design: cross-sectional splits on willingness and capacity, time-series conditioning on uncertainty, and an event study around the shock.

This logic yields three testable predictions. First, if the market prices exposure to government-backed cash flows, firms with higher digital patent intensity should earn higher average returns; this premium should survive standard risk adjustments and should be specific to digital innovation rather than to general patenting activity. Second, the premium should track the credibility of the support behind it. For this to hold, DPI must first predict the actual allocation of digital subsidies and procurement contracts, the link that generates the exposure. Given that link, the premium should be strongest where willingness and capacity are high, should weaken when policy uncertainty is elevated, and should turn into losses when a shock disrupts expectations of government payment reliability, accompanied by deteriorating fundamentals for high-DPI firms. Third, if the premium compensates for this risk rather than mispricing, DPI should not predict analyst forecast errors, the premium should not concentrate around earnings announcements, and it should not reverse over longer horizons.

China provides variation along every dimension of this taxonomy. Digital innovation has been designated a national strategic priority, with the “Digital China” plan and the 15th Five-Year Plan committing substantial resources to digital transformation,³ and with about 1% of GDP directed to R&D subsidies between 2020 and 2023 (Fang et al., 2023). This national priority is reflected in provincial policy agendas, where digital transformation receives increasing emphasis on average (Figure 1). Yet provincial governments differ substantially in the strength of their policy support and in their fiscal capacity to sustain it, and China’s 2017 deleveraging campaign illustrates that support can be curtailed abruptly. This combination of ambitious policy commitments and episodes of fiscal stress generates the variation in support credibility that we exploit.

We measure digital innovation using digital patent intensity (DPI), defined as the number of digital patent applications filed over the prior 12 months scaled by firm market capitalization, constructed for all firms listed on the Main Board of China’s A-share market from 2009 to 2024. Because DPI has price in its denominator (raising, for example, the concern that it may mechanically predict returns), we devote substantial attention to validating the measure. In particular, the return predictability of DPI survives when patents are scaled by total assets instead of market capitalization, when patent grants replace applications, when DPI is orthogonalized with respect to market capitalization, and in double sorts that control for firm size. These results make it unlikely that the return predictability is mechanically generated by the scaling choice. Building on this validated measure, we present three sets of results.

First, higher DPI predicts higher future returns. The value-weighted long-short port-

³See <https://publicadministration.desa.un.org/good-practices-for-digital-government/compendium/overall-framework-digital-china-construction> and https://www.fmprc.gov.cn/eng/zy/jj/dstzgzz/dszs/202511/t20251103_11745957.html.

folio (top DPI quintile minus the zero-DPI bottom portfolio) earns a monthly return of 0.656% ($t = 3.16$), or 7.87% annualized, and the alpha survives every factor model we examine, including the China-specific benchmarks. Fama-MacBeth regressions with the standard cross-sectional controls further confirm the result. By contrast, non-digital patent intensity generates no comparable premium once we control for characteristics: the premium is specific to digital innovation.

Second, the premium tracks support credibility along each dimension of the taxonomy. DPI predicts both the likelihood and magnitude of digital subsidies and government digital procurement contracts, so high-DPI firms are systematically more exposed to government support. The implication for pricing is that the same characteristic that gives firms privileged access to government resources also loads them more heavily on the credibility of the government providing those resources. Consistent with this exposure being priced, the premium is concentrated in provinces whose governments emphasize digital development and is stronger in provinces with low fiscal pressure, with fiscal pressure damping the premium (without necessarily eliminating it). Conditioning on the residual Economic Policy Uncertainty index, the premium is earned in low-uncertainty months, with a seven-factor alpha of 0.97% per month, but is a statistically insignificant 0.24% when uncertainty is high. Around the first publicly disclosed default of LGFV shadow debt in December 2017, high-DPI firms underperformed low-DPI firms, with an equal-weighted long-short cumulative abnormal return of -2.166% ($t = -3.72$) over the $[-10, 5]$ event window and value-weighted magnitudes about twice as large, and subsequently exhibited larger increases in accounts receivable and cost of debt than low-DPI firms, patterns consistent with a fundamentals channel rather than with a purely price-based reaction.

Third, the premium does not appear to reflect a correction of biased expectations. DPI

is unrelated to analyst forecast errors, the premium does not concentrate around earnings announcement dates, and it does not reverse over horizons of up to 36 months. These tests address the most prominent mispricing channels (Chan et al., 2001; Eberhart et al., 2004; Cohen et al., 2013; Hirshleifer et al., 2013, 2018; Shu et al., 2022); while they cannot rule out every behavioral explanation, the evidence is more consistent with compensation for support-credibility risk than with the mispricing mechanisms examined.

Our study makes two contributions. First, we contribute to the literature on innovation and digital intangibles in asset pricing. Prior work links innovation and intangible assets to firm value and investment opportunities (Kogan et al., 2017; Peters and Taylor, 2017), and recent studies extend the analysis to digital activities and related technologies, emphasizing valuation, operating performance, and stock returns (Babina et al., 2024; Ca’Zorzi et al., 2025; Chen and Wang, 2024; Chen and Srinivasan, 2024; Drechsler et al., 2025; Eisfeldt et al., 2023). Using a high-frequency measure of firm-level digital innovation, we show that the digital innovation premium is not priced on technological capability alone: it is in fact concentrated where the institutional support behind commercialization is credible. Support credibility, in other words, is central to how markets price digital innovation in a policy-driven economy.

Second, we provide evidence that government support is a priced, state-contingent exposure. Prior work shows that government support is often shaped by political connections and institutional frictions, with mixed effects on firm performance (Lim et al., 2018; Guo et al., 2016; Cheng et al., 2019; Fang et al., 2023), and that policy uncertainty affects asset prices, particularly for firms more exposed to government actions (Pastor and Veronesi, 2012; Pástor and Veronesi, 2013; Liu et al., 2017; Hu et al., 2025). Our results tie these strands together: government intervention does not simply raise or lower firm value; it simultaneously

provides resources and demand and exposes firms to the credibility of the state providing them. DPI predicts the allocation of digital subsidies and procurement contracts, and the premium earned by digital innovators depends on the fiscal sustainability of the supporting government rather than merely on whether support is received. The pricing implications of government support thus operate through its credibility, not just its allocation, a mechanism that extends beyond China and beyond digital patents.

2 Data and Measurement

2.1 Data sources

We collect detailed patent information for A-share listed firms from the China National Intellectual Property Administration (CNIPA), including application and grant dates and International Patent Classification (IPC) codes. Stock returns, firm-level accounting data, subsidy details, the Economic Policy Uncertainty (EPU) index, and analyst forecast data come from the China Stock Market and Accounting Research (CSMAR) database. Government digital procurement data and local government work reports are from the Chinese Research Data Services Platform (CNRDS). Local government fiscal data are from the China National Bureau of Statistics.

2.2 Measuring digital patent intensity

A digital patent is a patent that intensely utilizes digital technologies ([Nambisan et al., 2017](#)). We identify digital patents by matching each patent’s IPC with the Reference Relationship Table between Core Industries Classification of Digital Economy and International

Patent Classification issued by CNIPA in April 2023.⁴

At the end of each month, firm-level digital patent intensity is defined as:

$$DPI_{i,t} = \frac{\text{Digital patent applications}_{i,[t-11,t]}}{\text{Market capitalization}_{i,t} \text{ (in billions)}} \quad (1)$$

where the numerator counts invention patent applications filed over the past 12 months.⁵ The 12-month rolling window smooths the seasonality in Chinese patent filings, where applications surge in November-December and drop sharply in January-February due to the government performance evaluation cycles (Sun et al., 2021). Accumulating over 12 months also captures the delayed economic effects of innovation, consistent with models in which technological innovations generate growth options that are gradually exercised (Garleanu et al., 2012; Kung and Schmid, 2015). Finally, scaling by market capitalization offers a forward-looking benchmark that incorporates investor expectations (Hou et al., 2015) and mitigates size heterogeneity in innovation activities (Cohen et al., 2013; Gu, 2016).

2.3 Sample

Our sample contains firms listed on China’s A-share Main Board from January 2009 to December 2024 (192 months), starting after the major revision of China’s Accounting Standards in 2007.⁶ We exclude financial firms, firms designated as ST/ST*/PT, and first-

⁴The table maps IPC codes to four digital economy dimensions: digital product manufacturing, digital product services, digital technology applications, and digital factor-driven industries. See https://www.gov.cn/zhengce/zhengceku/2023-04/11/content_5750914.htm.

⁵Utility-model and design patents are excluded, as they are typically easier to obtain and are regarded as responses to regulatory incentives rather than substantive innovation (Tong et al., 2014).

⁶We exclude firms listed on the SZSE ChiNext Market and SSE STAR Market from the main sample due to their distinct institutional features: the registration-based IPO system (introduced in 2020 and 2019, respectively), the wider $\pm 20\%$ daily price limit, and the short sample coverage of the SSE STAR Market (launched in 2019). However, for robustness, in Appendix C, we replicate all main analyses on the expanded

year post-IPO observations. The final sample comprises 385,958 firm-month observations with non-missing DPI and control variables. All continuous variables are winsorized at the 1st and 99th percentiles by month in regression analysis.

Table 1 reports summary statistics. The average monthly stock return is 1.038%, with a standard deviation of 12.224%, reflecting the A-share market’s high volatility. Mean monthly DPI is 2.506, with a standard deviation of 5.702, indicating substantial cross-sectional heterogeneity in digital innovation activity.

[Insert Table 1 here.]

3 The Digital Innovation Premium

3.1 Portfolio sorts

Does digital innovation predict returns? To assess whether it does, at the end of each month we sort stocks into quintile portfolios by DPI. The bottom quintile consists of firms with zero DPI, while the remaining firms are sorted into the second through fifth quintiles. Portfolios are value-weighted by market capitalization and held for the next month.

Panel A of Table 2 reports portfolio summary statistics. Monthly raw returns are 0.821% in the bottom quintile and 1.476% in the top quintile. The long-short portfolio H–L earns 0.656% per month (7.87% annualized) with a Sharpe ratio of 0.163. Digital innovators thus earn economically large returns; the question is whether standard risk exposures account for them.

Panel B reports a series of significance tests. The t -statistic for the raw return of the long-

sample and find similar results.

short portfolio H-L, computed with Newey-West standard errors of 12 lags, is 3.16, significant at the 1% level. We further estimate factor-adjusted alphas under six benchmark models: the Fama-French three-factor model (FF3), the Carhart four-factor model (Carhart4), the Fama-French five-factor model (FF5), a seven-factor model that augments FF5 with momentum and illiquidity factors (7-Fac), and the China-specific CH-3 and CH-4 models developed by Liu et al. (2019).⁷ Alphas under all six benchmark models remain significant at the 1% level. In particular, the CH-4 alpha of H-L is 0.832% per month ($t = 3.41$), or 9.98% annualized. These results indicate a robust DPI premium that is not accounted for by standard factor models.

Because short selling in the A-share market is restricted to a limited set of eligible stocks and is costly, the long-short spread overstates what an investor could capture in real time. The premium does not depend on the short leg, however: the top-quintile portfolio alone earns a CH-4 alpha of 0.523% per month ($t = 3.01$), so the return predictability is accessible through long positions.

[Insert Table 2 here.]

3.2 Fama-MacBeth regressions

Does the premium survive the standard cross-sectional determinants of returns? To control simultaneously for multiple stock characteristics, we estimate monthly Fama-MacBeth

⁷Liu et al. (2019) construct size and value factors tailored to China by excluding the smallest 30% firms, whose valuations are distorted by “shell value” from reverse mergers, and by replacing the traditional Book-to-Market ratio with the Earnings-Price ratio. They further extend the model with a turnover-based sentiment factor to capture the influence of retail-driven trading activity. The factor data are provided on Robert Stambaugh’s homepage, see <https://finance.wharton.upenn.edu/~stambaug/>.

regressions (Fama and MacBeth, 1973):

$$Return_{i,t} = \alpha + \beta DPI_{i,t-1} + \gamma Controls_{i,t-1} + IndustryFE + \epsilon_{i,t} \quad (2)$$

where controls include the natural logarithm of market capitalization (LnME), the natural logarithm of Book-to-Market ratio (LogBM), the cumulative return for the previous 12 months (Mom), return on assets (ROA), the growth rate of total assets (Invest), Amihud’s illiquidity measure (Illiq), Earnings-to-Price ratio (EP), average daily turnover (Turnover). Industry fixed effects are based on the 2012 China Securities Regulatory Commission (CSRC) classification. t -statistics are computed using standard errors with Newey-West correction of 12 lags.

Table 3 reports the results. Across ten specifications that add the controls individually and then jointly, the coefficients on DPI remain significant at 1% level. In the full specification (Column 10), the coefficient is 0.033 ($t = 4.97$), confirming that DPI predicts returns after controlling for the standard cross-sectional determinants.

[Insert Table 3 here.]

3.3 Digital versus non-digital patents

Is the premium about digital innovation specifically, or about patenting activity in general? To answer this question, we construct a non-digital patent intensity measure (NonDPI) following the same procedure as DPI, replacing digital patent applications with non-digital patent applications scaled by market capitalization, and compare the two measures within specification (2). Table 4 reports the results.

NonDPI does predict returns on its own: without controls, its coefficient is 0.047 ($t =$

5.36) in Column (3), if anything larger in magnitude than DPI’s. But adding the standard characteristics drives the NonDPI coefficient to 0.004 ($t = 0.63$) in Column (4), so that the non-digital patent premium is entirely absorbed. The DPI coefficient, by contrast, is essentially unaffected by the same controls (Column 2). When both measures compete directly in Column (6), DPI remains significant at the 1% level (0.035, $t = 4.96$) while NonDPI turns insignificantly negative (-0.010 , $t = -1.45$). The economic magnitudes point in the same direction: the NonDPI long-short portfolio earns a monthly Sharpe ratio of 0.066, against 0.163 for the DPI portfolio (roughly 0.23, versus 0.56, annualized). The digital innovation premium is thus neither a generic patenting effect nor a repackaging of standard characteristics. Section 7 and Appendix A report the full battery of NonDPI results, including portfolio sorts and credibility-state subsamples.

[Insert [Table 4](#) here.]

3.4 Validating the DPI measure

Although scaling by market capitalization offers advantages, a natural concern is that DPI may mechanically predict returns through a valuation-ratio channel rather than through innovation content. We address this concern with four tests, all reported in [Table 5](#). First, we replace market capitalization with total assets as the scaling variable (DPI_A). The long-short portfolio alpha remains highly significant (CH-4 alpha = 1.071%, $t = 3.53$). Second, we replace patent applications with patent grants (DPI_G), which addresses the concern that unfulfilled applications may not represent genuine innovation. The alpha is 0.871% ($t = 3.35$). Third, we orthogonalize DPI with respect to the natural logarithm of market capitalization using firm-level time-series regressions and sort on the residual (ODPI). The long-short portfolio alpha is 0.544% ($t = 3.87$) under the seven-factor model and 0.319%

($t = 2.03$) under CH-4, and the Fama-MacBeth coefficient is 0.034 ($t = 4.17$) with the full set of controls. Fourth, we perform a double sort on DPI and market capitalization. The DPI premium is significant in both the small-cap group (CH-4 alpha = 0.939%, $t = 4.97$) and the large-cap group (0.793%, $t = 3.30$). Across all specifications, the return predictability of DPI survives. These results make it unlikely that the return predictability is mechanically generated by the choice of scaling variable in the denominator or the construction of the innovation measure in the numerator.⁸

A separate timing concern is that DPI counts patent applications by filing date, and filings are not observable to investors on the filing day, raising the possibility of look-ahead bias in the baseline sorts. The institutional disclosure rules bound this concern: under Article 34 of China’s Patent Law, CNIPA publishes an invention patent application 18 months after the filing date once it passes preliminary examination, and earlier at the applicant’s request, so 18 months is a hard upper bound on the disclosure delay.⁹ We impose the worst case: we re-form the portfolios using DPI lagged 19 months, so that at formation month t , the measure counts only applications filed between months $t - 31$ and $t - 19$, every one of which is guaranteed to have been published before t . The long-short portfolio remains significant under this genuinely real-time measure, earning a raw return of 0.448% per month ($t = 2.02$) and alphas of 0.733% ($t = 2.81$) under CH-3 and 0.830% ($t = 3.08$) under CH-4. As a second check, we construct (DPI_P) directly from patent publication dates rather than filing dates; the long-short portfolio earns 0.640% per month ($t = 3.14$) and is significant under all six

⁸Further detailed results are reported in Appendix B.

⁹See <https://english.cnipa.gov.cn/col/col3068/index.html>. Using patent application dates to predict returns follows Hsu (2009), who documents that aggregate innovation shocks measured by application dates forecast market risk premiums. Firms in fast-iterating digital technologies also have incentives to request early publication to establish priority, so actual disclosure is likely to run ahead of the statutory bound.

factor models (CH-4 $\alpha = 0.802\%$, $t = 3.35$). Both sets of results are reported in [Table B5](#) and [Table B6](#) in Appendix B. The DPI premium is therefore not an artifact of information that investors could not have observed at portfolio formation.

[Insert [Table 5](#) here.]

4 Government Support as the Mechanism

Having established the DPI premium, we next investigate how governments support digital innovation and how that support shapes the premium. China has adopted digital transformation as a national strategic priority, with digital technologies positioned at the core of industrial upgrading and economic growth. Unlike market-driven innovation ecosystems, China typically pursues strategic objectives through a broad set of industrial policies designed to support firms' innovation activities and help realize policy goals. As a result, the return predictability associated with digital innovation may vary with the intensity and sustainability of government support.

In this section, we first study government support from both the supply and demand sides - digital subsidies and government digital procurement projects - to examine whether DPI systematically increases firms' exposure to government-supported digital activities. We then ask whether the premium varies with the two components of support credibility defined in the introduction: the government's *willingness* to support digital development, measured by provincial digital focus, and its *capacity* to sustain that support, measured by provincial fiscal pressure.

4.1 DPI predicts government support allocation

Does DPI predict access to government support? Government support for digital innovation in China operates through two complementary channels. On the supply side, digital subsidy programs impose strict eligibility requirements, including technological criteria and sectoral orientation toward high-tech industries (Guo et al., 2016). Firms with higher DPI, given their strong R&D capabilities and alignment with China’s strategic goal of developing the digital economy, are well positioned to satisfy these requirements and attract digital-related subsidies. On the demand side, government digital procurement programs use fiscal funds to purchase digital products and services, providing firms with government-backed demand for their digital outputs. Firms with stronger digital innovation capabilities are more likely to participate in and win such procurement contracts. If DPI captures firms’ ability to generate digital intangible capital aligned with government priorities, firms with higher DPI should be more likely to access government-supported digital projects and receive greater policy-related resources.

We define a government subsidy program as digital-related if the program title contains at least one keyword associated with digital technologies. The keyword dictionary for digital technologies is constructed following Wu et al. (2021) and Chen and Srinivasan (2024). Specifically, titles that contain keywords such as artificial intelligence, blockchain, cloud computing, and big data are classified as digital-related. Similarly, we identify a government digital procurement project if its contract title, main subject matter, or technical specification contains at least one keyword associated with digital technologies.

Given that the innovation-related subsidies and government procurement projects typically generate persistent incentives rather than one-time shocks, we test whether DPI predicts

access to these programs using firm-year panel regressions:

$$\begin{aligned} DigitalSubsidy_{i,y} (DigitalProcurement_{i,y}) = & \alpha + \beta DPI_{i,y-1} + \gamma Controls_{i,y-1} \\ & + IndustryFE + YearFE + \epsilon_{i,y} \end{aligned} \quad (3)$$

where $DigitalSubsidy_{i,y}$ ($DigitalProcurement_{i,y}$) represents three alternative measures of digital-related subsidies (digital-related government procurements) in year y : (i) DigSub (DigPro), the dummy variable equals 1 if firm i receives (wins) any digital-related subsidy (government procurement) and 0 otherwise; (ii) DigSubNum (DigProNum), the number of digital-related subsidy programs (government procurement projects); (iii) DigSubAmo (DigProAmo), the amount of digital-related subsidies (government procurement projects). $DPI_{i,y-1}$ represents the digital patent intensity of firm i in year $y-1$, $Controls_{i,y-1}$ represents a set of control variables, and $IndustryFE$ and $YearFE$ represent industry and year fixed effects, respectively.¹⁰ Depending on the characteristics of each measure, we use the Logit model for the DigSub (DigPro), and the Poisson model for DigSubNum (DigProNum) and DigSubAmo (DigProAmo). t -statistics are computed based on standard errors two-way clustered at firm and year level.

Table 6 reports the results. The answer is yes: in every specification, higher DPI predicts a significantly greater likelihood, number, and amount of both digital subsidies and digital procurement contracts, with all coefficients significant at the 1% level. For digital subsidies, the Logit coefficient is 0.042 ($t = 7.43$, Column 1) and the Poisson coefficients are 0.036 ($t = 7.77$, Column 2) and 0.043 ($t = 8.97$, Column 3), respectively. A one-standard-deviation

¹⁰We include industry rather than firm fixed effects in these regressions because a large proportion of firms report zero digital subsidies or procurement projects throughout the sample period. Controlling for firm fixed effects would eliminate approximately 60% of the sample and introduce severe selection bias.

increase in DPI raises the probability of receiving any digital subsidy by approximately 1.503 percentage points and increases the expected number of digital subsidy programs by 0.024, and lifts the subsidy amount by 0.022 million. For government digital procurement, the Logit coefficient is 0.066 ($t = 9.11$, Column 4) and the Poisson coefficient is 0.040 ($t = 7.24$, Column 5) and 0.045 ($t = 7.48$, Column 6), respectively. A one-standard-deviation increase in DPI raises the probability of winning any government digital procurement project by approximately 1.546 percentage points and increases the expected number of digital procurement projects by 0.055, and raises the contract value by 0.397 million.¹¹

The economic content of these results goes beyond the observation that innovative firms attract support. What matters for pricing is that the same characteristic that gives firms privileged access to government resources also loads them more heavily on the credibility of the government providing those resources. This exposure is the bridge between innovation and policy risk: when support is credible, this exposure enhances value; when support falters, it becomes a liability.

[Insert [Table 6](#) here.]

4.2 The premium depends on government digital focus

We turn first to the willingness component of support credibility. While firms with higher DPI are more exposed to government-supported digital activities, the pricing impli-

¹¹Government digital procurement data are available only from 2015 onward; the economic magnitude calculations use the corresponding subsample statistics, with a standard deviation of DPI of 5.81 in the subsidy sample and 5.60 in the procurement sample ([Table 1](#)). Probability effects are average marginal effects from the Logit models, computed post-estimation and scaled by the standard deviation of DPI; because the Logit coefficients in [Table 6](#) are on the log-odds scale, these effects cannot be recovered directly from the reported coefficients. Count and amount effects use the exact Poisson semi-elasticity, $(\exp(\beta \sigma_{DPI}) - 1) \times E[y]$, evaluated at the subsample mean of the outcome.

cations of such exposure may depend on the strength of local governments' policy focus on digital development. In China's decentralized policy environment, provincial governments play a central role in translating national digital strategies into concrete implementation priorities, yet the degree of emphasis on digital transformation varies substantially across regions and over time. A stronger government focus reflects not only policy attention but also a sustained commitment to allocating administrative and fiscal resources toward digital industries, making government-supported projects more likely to be prioritized and implemented consistently. As a result, the return predictability associated with DPI may differ systematically across regions with varying levels of government digital focus.

To capture this variation, we define provincial-level digital focus as the share of digital-related sentences in each province's annual Report on the Work of the Government, identified using the same keyword-based approach used to construct digital subsidy measures.¹² Provinces are then classified into low- and high-focus groups based on government digital focus at the end of each year, aligned with the following twelve months. In each group, we construct DPI-sorted portfolios following the same procedure as in the univariate analysis.

Panel A of Table 7 reports the results. The DPI premium is significant only in provinces with high digital focus. The CH-4 alpha of the long-short portfolio for the high-focus group is 0.969% ($t = 4.10$), significant at the 1% level. In contrast, the corresponding alpha for the low-focus group is 0.540% ($t = 1.60$), which remains positive but is not statistically significant. The CH-3 and seven-factor alphas tell the same story: 0.920% ($t = 4.04$) and 0.785% ($t = 3.69$) for the high-focus group versus 0.479% ($t = 1.54$) and 0.298% ($t = 1.10$) for the low-focus group. The premium accrues where governments credibly commit to digital

¹²The annual Report on the Work of the Government outlines key policy objectives and development priorities for the upcoming year while reviewing past achievements, serving as an authoritative summary of local government policy attention.

development.

The capacity component matters as well: policy commitment alone is insufficient if governments lack the fiscal resources to honor it. In China’s decentralized fiscal system, local governments bear substantial expenditure responsibilities while facing heterogeneous revenue conditions, causing fiscal capacity to vary markedly across regions and over time. High fiscal pressure constrains governments’ ability to provide financial support and honor procurement commitments. Even when digital transformation is emphasized as a policy priority, limited fiscal resources may weaken the continuity and intensity of government-supported digital activities, leading the return predictability associated with DPI to differ systematically across regions with varying levels of fiscal pressure.

To examine how fiscal pressure conditions the DPI premium, we measure province-level fiscal pressure as the fiscal deficit-to-GDP ratio, following [Chen et al. \(2020\)](#). We also classify provinces into high- and low-pressure groups at the end of each year and construct DPI-sorted quintile portfolios in each group. Panel B of [Table 7](#) reports the results. The DPI premium is stronger in provinces with low fiscal pressure. The seven-factor alpha of the long-short portfolio for the low-pressure group is 0.621% ($t = 2.79$), significant at the 1% level. In contrast, the corresponding alpha for the high-pressure group is 0.469% ($t = 1.64$), which remains positive but is not statistically significant. The China-model alphas are ordered the same way, although they remain significant in the high-pressure state: under CH-4, 0.853% ($t = 3.41$) for the low-pressure group versus a marginally significant 0.567% ($t = 1.96$) for the high-pressure group; under CH-3, 0.758% ($t = 3.09$) versus 0.620% ($t = 2.21$), the latter significant at the 5% level. Fiscal pressure dampens the premium rather than eliminating it, consistent with support credibility deteriorating gradually as fiscal capacity tightens.

[Insert [Table 7](#) here.]

Taken together, these results suggest a consistent pattern: digital innovators command a higher expected-return premium when government support is both a clear political priority and backed by sufficient fiscal capacity. Thus, the DPI premium does not represent a broad reward for innovation itself, but rather a conditional premium tied to the credibility and sustainability of the institutional support surrounding digital innovation.

5 When Support Credibility is Tested

The preceding section establishes that the DPI premium depends on cross-sectional variation in support credibility. We now examine what happens to the premium in the time series when support credibility is tested. We first condition on aggregate policy uncertainty to assess whether the premium is state-dependent in the time series, and then exploit a specific event that generated a sudden shift in market expectations about government payment reliability.

5.1 Policy uncertainty and state dependence

Government support reshapes the risk structure of digital innovation rather than eliminating risk altogether. Through subsidies, the government enhances firms' internal financing capacity, alleviates liquidity constraints, and lowers the marginal cost of innovation investment, thereby mitigating technological and financing risks inherent in digital innovation. Similarly, government digital procurement reduces commercialization risk by providing stable demand backed by state credit. Procurement contracts guarantee a minimum market for digital products, shorten the payback period of digital investments, and improve firms'

access to external financing through government-backed credit channels.¹³

However, these arrangements reallocate risk toward government support credibility: once innovation outcomes become contingent on government-related payment flows, firms are exposed to the sustainability of that support. Aggregate policy uncertainty identifies states in which investors' confidence in that support is lower, so the DPI premium should weaken when policy uncertainty is elevated.

We first test whether the premium simply proxies for policy uncertainty. Following Xu (2020), we construct a residual EPU measure ($ResEPU_t$) by regressing the Economic Policy Uncertainty index (Baker et al., 2016) on industrial production growth, social consumption growth, M2 monetary growth, CPI inflation, and stock market returns using a rolling 60-month window. We then augment the seven-factor model with $ResEPU$.

Panel A of Table 8 reports the factor loadings. The H-L portfolio has an alpha of 0.678% ($t = 3.24$) under the seven-factor model augmented with $ResEPU$, which is significant at the 1% level. The loading on $ResEPU$ is -0.372 ($t = -1.35$) and not statistically significant. The DPI premium is not subsumed by aggregate policy uncertainty exposure.

Panel B of Table 8 examines whether the premium is state-dependent by splitting the sample into low- and high- $ResEPU$ periods at the median. In low- $ResEPU$ months, the seven-factor alpha is 0.966% ($t = 3.98$), which is significant at the 1% level and is both economically larger and statistically stronger than the baseline estimate. In contrast, the corresponding alpha in the high- $ResEPU$ months is 0.236% ($t = 1.08$), which remains posi-

¹³For example, the Notice from the Shenzhen Municipal Finance Commission on Launching Pilot Projects for Government Procurement Order Financing Reform issued in November 2016 stipulates that financial institutions should establish green channels for procurement-based financing, shorten loan approval time, offer lending rates below prevailing market levels, and reduce collateral and guarantee requirements—especially for innovative and small enterprises. See https://www.ccgp.gov.cn/zcfg/dffg/shenzhen/201612/t20161209_7714270.htm.

tive but is not statistically significant. The alphas under the seven-factor model augmented with *ResEPU* are consistent: 0.861% ($t = 2.30$) for low-*ResEPU* months versus 0.119% ($t = 0.39$) for high-*ResEPU* months. The China factor models sharpen the contrast further: the CH-4 alpha is 1.189% ($t = 5.02$) in low-uncertainty months versus 0.313% ($t = 1.37$) in high-uncertainty months, with CH-3 similar (1.135%, $t = 4.99$, versus 0.213%, $t = 0.97$). The DPI premium is earned in tranquil times and is statistically indistinguishable from zero when policy uncertainty rises, consistent with a conditional risk premium for policy-related risk (Pastor and Veronesi, 2012; Liu et al., 2017).

At first glance, the absence of a significant loading on *ResEPU* in Panel A may appear at odds with a risk-based interpretation. It is not: the risk we identify is the credibility of local government support, which is distinct from aggregate policy uncertainty. Credibility shocks are infrequent and discrete—support flows steadily until a fiscal event disrupts it—so exposure to this risk is poorly captured by monthly covariation with an aggregate uncertainty index. Instead, it manifests exactly as the data show: a premium earned in tranquil states that contracts when uncertainty rises and turns into losses when a credibility shock materializes, as in the LGFV default we examine next. This is the structure of a peso-problem premium (Rietz, 1988; Barro, 2006), but with a defined “disaster” mechanism (the government credibility), as in Tiu and Yoeli (2013): compensation for a rare adverse state that is underrepresented in any finite sample.

[Insert Table 8 here.]

5.2 The LGFV default: A credibility shock

To move beyond time-series conditioning, we exploit a discrete event that shifted expectations about government payment reliability. Our setting coincides with China’s 2017

deleveraging campaign, which sought to curb excessive local government borrowing.¹⁴ On December 15, 2017, Yunnan State-Owned Capital Operation Co., Ltd., which is a local government financing vehicle (LGFV), failed to repay principal and interest on the Zhongrong Jiarun No. 30 and No. 31 Assembled Funds Trust products, totaling RMB 1.5 billion. This was the first publicly disclosed default of LGFV shadow debt in China.¹⁵ Before this event, LGFV-related financing arrangements had operated without publicly disclosed repayment failures, and government-related payment flows were generally viewed as stable. The repayment delay associated with this LGFV incident represents the first widely reported disruption to this pattern, and investor expectations of government payment reliability shifted downward. The event thus provides a sharp setting in which to examine how firms with different ex ante DPI exposures respond to a deterioration in perceived government payment reliability. Because the default occurred during the broader deleveraging campaign, we do not treat it as a controlled experiment; the identifying variation is cross-sectional, comparing firms with different predetermined DPI exposures around the same event.

If the DPI premium compensates for exposure to government payment credibility, high-DPI firms should react more negatively to this shock. We employ an event-study approach to examine how firms with different levels of DPI react to this shift in expectations. To isolate the effect of new information on stock prices, we compute cumulative abnormal returns (CARs) relative to the Fama-French five-factor model. Since the repayment delay first occurred in December 2017 and the formal default announcement was made in January 2018, we define the event window as $[-20, +20]$ trading days around the default event, roughly

¹⁴See <https://features.csis.org/timeline-of-chinas-deleveraging-campaign/>.

¹⁵Reuters reported the event on January 16, 2018. See <https://www.reuters.com/article/world/exclusive-china-s-yunnan-to-inject-capital-in-firm-that-missed-shadow-loan-payment-idUSKBN1F41V3/>.

covering two months. Following standard practice in the event-study literature, we estimate factor loadings using an estimation window of $[-130, -21]$ trading days (110 trading days). We compute daily abnormal returns (ARs) for each stock and then obtain equal-weighted and value-weighted average abnormal returns (AARs) for each quintile portfolio sorted by DPI at the end of November 2017. Finally, we calculate cumulative average abnormal returns (CAARs) for each portfolio by aggregating AARs over the event window.

Figure 2 plots the CAAR of the H–L portfolio. Before the event, the CAAR is positive and stable, consistent with the baseline premium. Following the first repayment negotiation on December 27, 2017 (day -10), the CAAR begins to decline. After the formal default announcement on January 11, 2018 (day 0), it declines further and remains well below its pre-event level through the end of the event window.

[Insert Figure 2 here.]

Table 9 reports formal significance tests across event windows, where the long-short column H–L is the difference between the CAARs of the H and L portfolios. For the equal-weighted H–L portfolio, the CAAR is -1.388% ($t = -3.69$) over $[0, 5]$ and -2.166% ($t = -3.72$) over $[-10, 5]$, both significant at the 1% level, and remains significantly negative at -1.924% ($t = -2.06$) over $[-10, 20]$. Value-weighted CAARs are larger: -4.375% ($t = -3.71$) over $[-10, 5]$ and -5.213% ($t = -2.58$) over $[-10, 20]$, indicating that the results are not driven by small firms. The underperformance of high-DPI firms thus emerges around the first repayment negotiation and cumulates over roughly one month of trading days, the horizon over which the market absorbs the shock to expected government payment reliability. Consistent with Figure 2, the differential drift bottoms out around day 15, and the H–L CAAR has not returned to its pre-event level by day 20: prices settle at a lower level for exposed firms once the news is absorbed, a repricing of support credibility rather than a

transitory overreaction. This one-month repricing of the event is also distinct from the long-horizon behavior of the premium itself, which shows no reversal over horizons of up to 36 months (Table 13). The quintile-level CAARs further indicate that investors rotated out of exposed firms and into unexposed ones around the announcement: the H portfolio’s own equal-weighted CAAR is significantly negative over $[0, 5]$ (-1.330% , $t = -4.44$), while the zero-DPI L portfolio earns positive abnormal returns over $[-10, 5]$ (1.313% , $t = 3.99$). Pre-event H–L returns over $[-20, -11]$ are statistically indistinguishable from zero under both weighting schemes, providing no evidence of differential pre-event performance between high- and low-DPI firms (0.331% , $t = 0.79$ equal-weighted; 1.057% , $t = 1.43$ value-weighted).

[Insert Table 9 here.]

5.3 Real effects after the LGFV shock

If the stock market reaction reflects a genuine reassessment of government support credibility, we should observe real deterioration in the financial condition of high-DPI firms. Table 10 reports changes in firm-level outcomes from 2017 to 2018 for the DPI quintiles, sorted at the end of November 2017. The reported outcomes include (1) Accounts receivable: Net amount of accounts receivable; (2) Cost of debt: Interest expenses; (3) Investment: Net investment in fixed assets, intangible assets, and other long-term assets. All outcome variables are constructed as percentage changes scaled by average total assets, following the formula:

$$100 * \frac{Y_{i,2018} - Y_{i,2017}}{0.5 * (TotalAsset_{i,2018} + TotalAsset_{i,2017})} \quad (4)$$

These variables capture firms’ exposure to government payment delays, financing conditions, and real investment activity, respectively.

Accounts receivable increase by 1.598% for high-DPI firms ($t = 6.98$), compared with 0.640% for low-DPI firms ($t = 5.05$), yielding a significant spread of 0.957% ($t = 3.66$) at the 1% level; the larger increase is consistent with greater exposure of high-DPI firms to delayed government-related payments. The cost of debt rises by 0.239% for high-DPI firms ($t = 10.23$) versus 0.174% for low-DPI firms ($t = 8.76$), with a spread of 0.065% ($t = 2.12$), significant at the 5% level, consistent with tighter financing conditions for high-DPI firms following the credibility shock.¹⁶ Investment changes are small: investment rises by an insignificant 0.093% for high-DPI firms ($t = 0.34$) versus 0.453% for low-DPI firms ($t = 1.96$), and the cross-portfolio difference (-0.360% , $t = -1.00$) is not statistically significant.

[Insert [Table 10](#) here.]

Taken together, these patterns are consistent with a fundamentals channel involving slower cash-flow realization and tighter external financing conditions, rather than with purely transitory price adjustments. The combination of stock market underperformance and real financial deterioration is consistent with the interpretation that the DPI premium reflects compensation for exposure to government support credibility.

6 Possible Mispricing Explanations

Prior studies document that technological innovation is inherently difficult to value due to its high uncertainty, information asymmetry, and delayed realization of economic benefits ([Cohen et al., 2013](#); [Hirshleifer et al., 2018](#)). Compared with conventional innovation, digital innovation is characterized by reprogrammability, generativity, and combinatorial expansion,

¹⁶Scaling interest expense by the average of 2017 and 2018 total liabilities instead of average total assets yields a consistent H–L spread of 0.147% ($t = 2.27$), significant at the 5% level.

implying that the boundaries of innovation outcomes are not ex ante fixed (Yoo et al., 2012). This raises the question of whether information frictions contribute to the DPI premium. We test this question from three mispricing perspectives: analyst forecast errors, earnings announcement effects, and longer horizon return performance.

6.1 Analyst forecast errors

Do investors systematically misjudge the earnings prospects of high-DPI firms? We begin by examining analyst forecast errors to assess whether the difficulty of processing digital innovation-related information leads to predictable expectation errors. Following Bouchaud et al. (2019) and Ma (2025), we define analyst forecast errors as:

$$ForecastError_{i,y}^{\tau} = \frac{EPS_{i,y+\tau} - FEPS_{i,y+\tau}}{Price_{i,y-1}}, \quad (5)$$

where $\tau \in \{1, 2\}$. $EPS_{i,y+\tau}$ represents the realized EPS of firm i in fiscal year $y + \tau$, and $FEPS_{i,y+\tau}$ represents the corresponding analyst consensus EPS forecast. The forecast error is scaled by the stock price at the end of the previous fiscal year, $Price_{i,y-1}$, to ensure comparability across firms. The corresponding analyst consensus forecasts are defined as the median EPS forecasts separately for fiscal years $y + 1$ or $y + 2$ based on analyst reports issued within 90 days after the release of firms' annual reports in year y .

We then regress analyst forecast errors on DPI:

$$ForecastError_{i,y}^{\tau} = \alpha + \beta DPI_{i,y-1} + \gamma Controls_{i,y-1} + FirmFE + YearFE + \epsilon_{i,y} \quad (6)$$

If market expectations fully incorporate DPI information, the conditional expectation of analyst forecast errors should be zero. In this case, β would be zero. Table 11 reports the

results. The coefficients on DPI are 0.016 ($t = 0.91$) and 0.014 ($t = 0.57$) for one- and two-year-ahead analyst forecast errors, both positive but not statistically significant, indicating that high-DPI firms do not tend to realize earnings that exceed prior expectations.

[Insert [Table 11](#) here.]

6.2 Earnings announcement effects

If a return premium reflects investors' biased expectations about future cash flows, new information released at earnings announcements should partially correct these biases, causing the premium to be concentrated in announcement windows ([Engelberg et al., 2018](#)). We next test whether this pattern holds for the DPI premium by interacting DPI with an earnings announcement dummy in daily Fama-MacBeth regressions:

$$\begin{aligned} Return_{i,d} = & \alpha + \beta DPI_{i,t-1} + \theta Announce_{i,d} + \phi DPI_{i,t-1} \times Announce_{i,d} \\ & + \gamma Controls_{i,t-1} + IndustryFE + \epsilon_{i,d} \end{aligned} \quad (7)$$

where $Announce_{i,d}$ is a dummy variable equal to one if day d falls within the earnings announcement window of firm i , defined as days around the release of quarterly or annual reports, and zero otherwise. We consider four window definitions: $[0, 3]$, $[0, 5]$, $[-3, 3]$, and $[-5, 5]$. [Table 12](#) reports the results. The coefficient on DPI remains positive and significant at the 1% level across all specifications. The interaction coefficients $DPI \times Announce$ are statistically insignificant across all four window definitions, indicating that the DPI premium does not concentrate around earnings announcement days.

[Insert [Table 12](#) here.]

6.3 Longer horizon return performance

A third implication of the mispricing hypothesis is that the DPI premium should eventually reverse over longer horizons as investor expectations are gradually corrected and prices converge toward fundamentals. We re-estimate the baseline Fama-MacBeth regression replacing the dependent variable with cumulative returns over the next 3, 6, 12, 24, and 36 months. [Table 13](#) reports the results. The coefficient on DPI remains positive and significant at the 1% level across all horizons, indicating that there is no evidence of reversal for the DPI premium over longer horizons.

Taken together, these results provide evidence against the most prominent mispricing explanations: expectation errors that analysts would embed, corrections concentrated at information events, and eventual reversal. They cannot rule out every behavioral account, but the patterns are more consistent with compensation for exposure to policy-related risk than with the systematic correction of investor errors.

[Insert [Table 13](#) here.]

7 Robustness

We have already addressed the most important robustness concern—the price-in-denominator issue—in [Section 3.4](#). Here we report additional tests.

Non-digital patent intensity. [Section 3.3](#) shows that the return predictability of non-digital patent intensity (NonDPI), unlike that of DPI, is entirely absorbed by standard characteristics. [Appendix A](#) reports the complete battery of NonDPI tests and supports this conclusion with portfolio methods. In univariate sorts ([Table A1](#)), the NonDPI long-short portfolio earns significant alphas under the Fama-French family of models (0.562%–

0.606% per month), but under the China-specific factor models of [Liu et al. \(2019\)](#) (the appropriate benchmark for A-shares), the spread falls to 0.216% ($t = 1.33$) under CH-3 and a marginally significant 0.305% ($t = 1.66$) under CH-4, compared with 0.832% ($t = 3.41$) for DPI. The credibility-split sorts (Tables [A2–A4](#)) show no consistent credibility pattern under the China-specific models. The CH-model spreads that attain significance appear in the high-digital-focus state (CH-3: 0.408%, $t = 1.91$; CH-4: 0.500%, $t = 2.03$) but also in the *high*-fiscal-pressure state (CH-3: 0.452%, $t = 1.97$; CH-4: 0.437%, $t = 1.91$), the opposite of what a credibility-based premium would imply. In the policy-uncertainty split they are at best marginal (low-uncertainty CH-4: 0.463%, $t = 1.78$), and augmenting the factor models with *ResEPU* eliminates all spreads. The DPI premium, by contrast, lines up with support credibility in all three dimensions (Tables [7](#) and [8](#)), with fiscal pressure damping rather than eliminating it, and survives characteristics throughout. The premium we document is therefore specific to digital innovation rather than a generic exposure of innovative firms to local economic conditions.

Equal-weighted portfolios. To ensure that the DPI premium is not driven by a few large firms, we form equal-weighted portfolios. The H–L alpha under the seven-factor model is 0.541% ($t = 3.53$); under CH-4 it is 0.859% ($t = 4.69$). Results are reported in [Table 14](#), Panel A.

Excluding IT firms. Firms in the Information Transmission, Software, and Information Technology Services industry naturally hold more digital patents. Excluding them from the sample, the seven-factor H–L alpha is 0.621% ($t = 3.17$) and the CH-4 alpha is 0.755% ($t = 3.29$). See [Table 14](#), Panel B.

STAR and ChiNext markets. Our main sample is restricted to the Main Board. In Appendix C, we replicate all main analyses using the expanded sample that includes the

SZSE ChiNext Market and SSE STAR Market. Results are qualitatively similar.

In sum, the DPI premium is specific to digital innovation rather than reflecting a general patent activity effect, and remains robust across portfolio weighting schemes, industry composition, market segments, DPI construction methods, and scaling variables.

[Insert [Table 14](#) here.]

8 Conclusion

This paper provides evidence that the pricing of digital innovation in China’s stock market depends on the credibility of government support. Digital patent intensity predicts future returns, but the premium is strongest where support is politically emphasized and fiscally sustainable. When credibility deteriorates, whether through elevated policy uncertainty or a discrete fiscal shock, the premium weakens or turns into losses, and affected firms experience real financial deterioration. In short, government support does not eliminate the risk of digital innovation; it changes its source, from technological and commercialization risk to the credibility of the government providing the support.

The findings carry implications for managers and policymakers alike. For corporate managers, the payoff to digital innovation cannot be assessed in isolation from the policy environment: firms that depend heavily on government subsidies and procurement face the risk that the very support enhancing their competitive position may be withdrawn or weakened, and managing this exposure, through diversification of revenue sources or active monitoring of local fiscal conditions, is a strategic consideration. For policymakers, subsidies and procurement contracts can accelerate digital transformation by alleviating capital constraints and reducing commercialization risk, but these benefits are undermined when fiscal capacity

cannot sustain them; the underperformance of high-DPI firms around the 2017 LGFV default illustrates how inconsistent support can destabilize the firms it targets. Our evidence suggests that the durability of innovation policy depends critically on the credibility and fiscal capacity of the government providing support.

Our identification of the support-credibility mechanism relies on cross-sectional heterogeneity and a single salient event; future work could exploit additional policy shocks or quasi-experimental variation in subsidy allocation to strengthen causal claims. And while we focus on China, the tension between government support and policy risk is relevant in any economy where the state plays an active role in innovation policy, including through tax credits, DARPA-style funding, or green technology subsidies. Extending this framework to other settings is a natural next step.

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Figure 1: The Average Government Digital Focus

This figure reports the average government digital focus from 2009 to 2024. The provincial-level digital focus is defined as the ratio of digital-related sentences in each province's annual Report on the Work of the Government, and the figure presents the simple average across provinces. The solid dark blue line depicts the average digital focus across provinces, while the dashed red line represents the smooth trend obtained using a local polynomial (lpoly) fit with a bandwidth of 2.

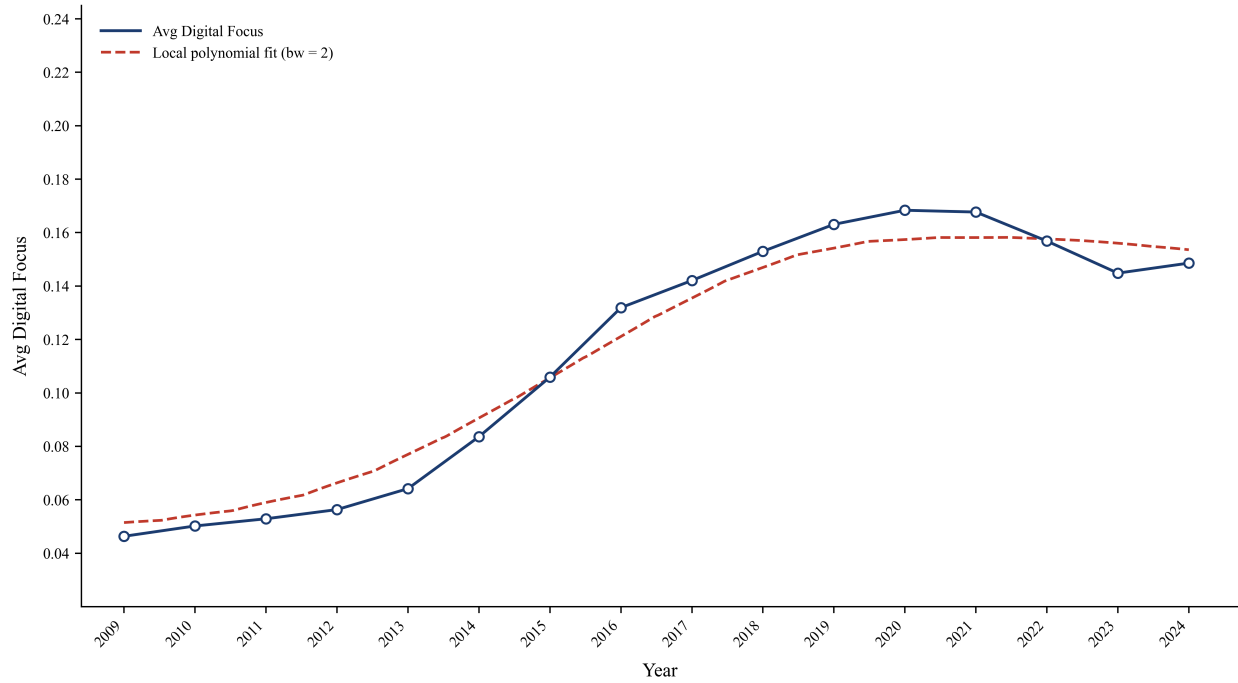


Figure 2: Portfolio CAARs During LGFV Event

This figure reports the cumulative average abnormal return of value-weighted long-short portfolio H-L sorted by *Digital Patent Intensity* (DPI) during Zhongrong Jiarun No. 30 and No. 31 Assembled Funds Trust event. Trading-day windows are defined relative to the formal default announcement on January 11, 2018 (day 0). At the end of November 2017, stocks are sorted into quintiles by DPI. The bottom quintile portfolio consists of stocks with zero DPI, while the remaining stocks are sorted into the second through fifth quintiles. The cumulative abnormal return of each stock is estimated using the Fama-French five-factor model over a 110-day window preceding the event. We mark two key event dates: the first negotiation to postpone payment on December 27, 2017, and the official pronouncement of default on January 11, 2018.

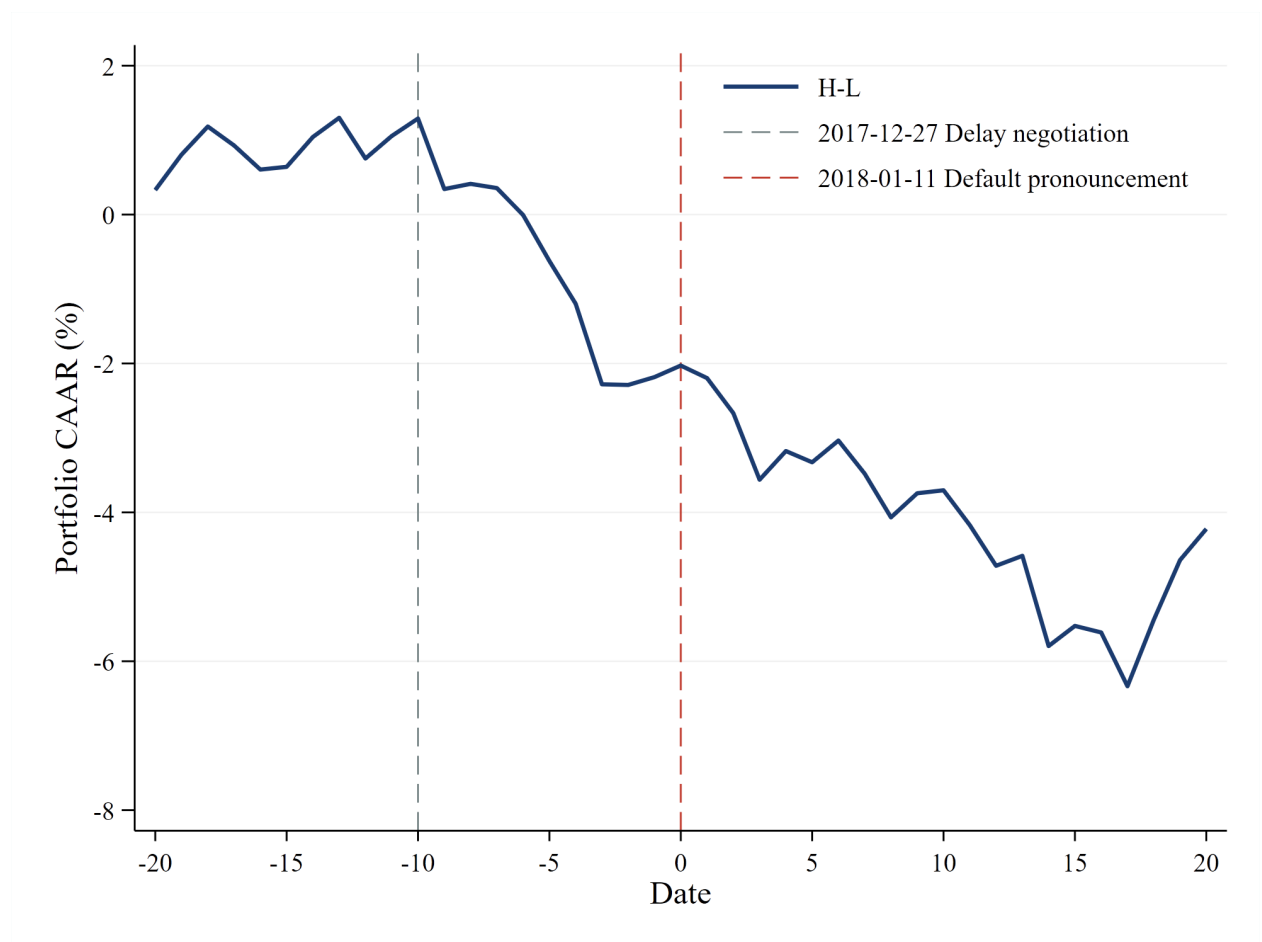


Table 1: Summary Statistics

This table reports the summary statistics for each variable, containing the number of observations, mean, standard deviation, minimum, median, and maximum. All variables are winsorized at 1% and 99% levels by month (year).

Variable	Obs	Mean	Std.Dev	Min	Median	Max
<i>Panel A: Firm-month Panel Summary Statistics</i>						
Return (%)	385,958	1.038	12.224	-46.501	-0.038	92.752
DPI	385,958	2.506	5.702	0.000	0.413	66.514
LnME	385,958	22.376	1.088	19.261	22.242	26.167
LnBM	385,958	-0.164	0.857	-3.070	-0.205	2.709
Mom	385,958	0.094	0.492	-0.832	-0.017	5.632
ROA	385,958	0.023	0.041	-0.505	0.017	0.238
Invest	385,958	0.026	0.079	-0.343	0.015	1.188
Illiq	385,958	0.041	0.050	0.001	0.026	1.382
EP	385,958	0.018	0.042	-0.541	0.014	0.275
Turnover	385,958	2.235	2.239	0.069	1.469	18.605
<i>Panel B: Firm-year Panel Summary Statistics</i>						
DigSub	31,154	0.072	0.259	0.000	0.000	1.000
DigSubNum	31,154	0.102	0.411	0.000	0.000	3.000
DigSubAmo	31,154	77656.965	440360.274	0.000	0.000	6023333.500
DigPro	22,143	0.058	0.234	0.000	0.000	1.000
DigProNum	22,143	0.221	1.383	0.000	0.000	25.000
DigProAmo	22,143	1386330.674	9584574.979	0.000	0.000	137400000.000
ForecastError ¹	16,359	-2.585	6.124	-52.633	-2.016	43.319
ForecastError ²	13,998	-3.935	7.581	-59.433	-3.296	54.608
DPI	31,154	2.501	5.808	0.000	0.389	57.584
DPI (After 2015)	22,143	2.618	5.595	0.000	0.521	53.100
LnME	31,154	22.348	1.112	19.274	22.234	26.053
LnBM	31,154	-0.181	0.853	-2.862	-0.217	2.551
Mom	31,154	0.106	0.543	-0.831	-0.012	4.263
ROA	31,154	0.037	0.056	-0.258	0.034	0.238
AnnualInvest	31,154	0.139	0.291	-0.354	0.081	3.366
AnnualIlliq	31,154	0.051	0.067	0.001	0.032	0.935
EP	31,154	0.029	0.058	-0.335	0.027	0.275
AnnualTurnover	31,154	2.326	1.886	0.145	1.774	13.784

Table 2: Univariate Sorting

This table reports the performance of value-weighted portfolios sorted by *Digital Patent Intensity* (DPI) over the holding period from Jan 2009 to Dec 2024. At the end of each month, stocks are sorted into quintiles by DPI. The bottom quintile portfolio consists of stocks with zero DPI, while the remaining stocks are sorted into the second through fifth quintiles. The quintile portfolios are held over the next month. Panel A reports the summary statistics of each portfolio. Panel B reports the average monthly portfolio raw returns (RawRet) and portfolio alphas under the Fama-French three-factor model (FF3), the Carhart four-factor model (Carhart4), the Fama-French five-factor model (FF5), and the Fama-French five-factor model augmented with momentum factor and illiquidity factor (7-Fac). The portfolio alphas under the China-specific CH-3 and CH-4 factor model constructed by [Liu et al. \(2019\)](#) (CH3, CH4) are also reported. *t*-statistics in parentheses are computed using standard errors with Newey-West correction of 12 lags. *, **, *** indicate significance at the 10%, 5% and 1% level, respectively.

Panel A: Portfolio Summary Statistics									
Portfolio	Obs	Mean	Std	Min	25%	50%	75%	Max	SR
L	192	0.821	7.370	-27.585	-3.368	0.600	4.531	21.139	0.088
2	192	0.624	6.902	-25.933	-3.415	0.746	3.884	21.719	0.066
3	192	1.018	6.829	-21.413	-2.745	0.461	4.590	27.596	0.124
4	192	1.024	6.834	-24.013	-2.443	1.217	4.372	19.090	0.125
H	192	1.476	7.444	-26.833	-2.407	1.518	4.838	23.662	0.176
H-L	192	0.656	2.986	-9.654	-1.433	0.609	2.769	8.787	0.163
Panel B: Significance Test									
Portfolio	Raw Ret	FF3	Carhart4	FF5	7-Fac	CH3	CH4		
L	0.821 (1.50)	-0.334*** (-3.53)	-0.334*** (-3.72)	-0.283*** (-2.95)	-0.290*** (-3.21)	-0.232** (-2.00)	-0.308** (-2.51)		
2	0.624 (1.26)	-0.059 (-0.38)	-0.057 (-0.39)	-0.077 (-0.53)	-0.040 (-0.30)	-0.203 (-1.31)	-0.222 (-1.44)		
3	1.018* (1.85)	0.082 (0.55)	0.005 (0.03)	0.142 (0.93)	0.056 (0.36)	0.169 (1.05)	0.208 (1.21)		
4	1.024* (1.94)	0.075 (0.51)	0.037 (0.27)	0.091 (0.62)	0.077 (0.54)	0.273* (1.82)	0.255 (1.59)		
H	1.476** (2.50)	0.330* (1.83)	0.301* (1.73)	0.355** (2.07)	0.333* (1.94)	0.519*** (3.14)	0.523*** (3.01)		
H-L	0.656*** (3.16)	0.664*** (2.96)	0.635*** (2.98)	0.639*** (2.91)	0.624*** (2.94)	0.751*** (3.18)	0.832*** (3.41)		

Table 3: Fama-MacBeth Regression

This table reports average slope coefficients from Fama-MacBeth regressions, and the sample period is from Jan 2009 to Dec 2024. The dependent variable is the monthly return of month t . The key independent variable is *Digital Patent Intensity* (DPI) in month $t - 1$. Control variables all lag by one month, containing the natural logarithm of market capitalization (LnME), the natural logarithm of Book-to-Market ratio (LogBM), the cumulative return for the previous 12 months (Mom), return on assets (ROA), the growth rate of total assets (Invest), Amihud's illiquidity measure (Illiq), Earnings-to-Price ratio (EP), average daily turnover (Turnover). IndustryFE represents the industry dummy variables based on the 2012 China Securities Regulatory Commission (CSRC) industry classification codes. t -statistics in parentheses are computed based on standard errors with Newey-West correction of 12 lags. *, **, *** indicate significance at the 10%, 5% and 1% level, respectively.

Dep.Var: Return	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
DPI	0.030*** (4.81)	0.028*** (4.34)	0.023*** (3.32)	0.028*** (4.27)	0.036*** (6.13)	0.030*** (4.80)	0.030*** (4.56)	0.032*** (5.37)	0.032*** (4.99)	0.033*** (4.97)
LnME		-0.376** (-2.26)								-0.734*** (-4.80)
LnBM			0.343** (2.57)							0.236** (2.26)
Mom				-1.068** (-2.25)						-0.423 (-1.10)
ROA					23.350*** (5.04)					16.136*** (5.23)
Invest						2.063*** (3.62)				1.531*** (4.46)
Illiq							20.801*** (2.95)			9.231** (2.55)
EP								29.898*** (6.92)		25.320*** (10.17)
Turnover									-0.302*** (-7.94)	-0.340*** (-10.32)
Observations	385,958	385,958	385,958	385,958	385,958	385,958	385,958	385,958	385,958	385,958
Adj. R ²	0.046	0.071	0.062	0.066	0.064	0.049	0.062	0.064	0.064	0.131
IndustryFE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Table 4: Digital versus Non-Digital Patent Intensity

This table compares the return predictability of digital and non-digital patent intensity in Fama-MacBeth regressions. The sample period is from Jan 2009 to Dec 2024. The dependent variable is the monthly return of month t . The key independent variables are *Digital Patent Intensity* (DPI) and *Non-Digital Patent Intensity* (NonDPI) in month $t - 1$, where NonDPI is constructed following the same procedure as DPI with non-digital patent applications in the numerator. Columns (1)–(2) include DPI only, Columns (3)–(4) include NonDPI only, and Columns (5)–(6) include both. Control variables all lag by one month, containing the natural logarithm of market capitalization (LnME), the natural logarithm of Book-to-Market ratio (LogBM), the cumulative return for the previous 12 months (Mom), return on assets (ROA), the growth rate of total assets (Invest), Amihud’s illiquidity measure (Illiq), Earnings-to-Price ratio (EP), average daily turnover (Turnover). IndustryFE represents the industry dummy variables based on the 2012 China Securities Regulatory Commission (CSRC) industry classification codes. t -statistics in parentheses are computed based on standard errors with Newey-West correction of 12 lags. *, **, *** indicate significance at the 10%, 5% and 1% level, respectively.

Dep.Var: Return	(1)	(2)	(3)	(4)	(5)	(6)
DPI	0.030*** (4.81)	0.033*** (4.97)			0.022*** (3.26)	0.035*** (4.96)
NonDPI			0.047*** (5.36)	0.004 (0.63)	0.038*** (4.08)	-0.010 (-1.45)
LnME		-0.734*** (-4.80)		-0.730*** (-4.79)		-0.738*** (-4.85)
LnBM		0.236** (2.26)		0.254** (2.47)		0.246** (2.38)
Mom		-0.423 (-1.10)		-0.419 (-1.09)		-0.421 (-1.09)
ROA		16.136*** (5.23)		15.398*** (4.96)		16.144*** (5.25)
Invest		1.531*** (4.46)		1.545*** (4.54)		1.536*** (4.50)
Illiq		9.231** (2.55)		9.088** (2.46)		9.251** (2.53)
EP		25.320*** (10.17)		25.034*** (10.01)		25.421*** (10.19)
Turnover		-0.340*** (-10.32)		-0.338*** (-10.08)		-0.341*** (-10.30)
Observations	385,958	385,958	385,958	385,958	385,958	385,958
Adj. R ²	0.046	0.131	0.045	0.129	0.047	0.132
IndustryFE	YES	YES	YES	YES	YES	YES

Table 5: DPI Measure Validation

This table summarizes the robustness of the DPI premium across alternative measure constructions and portfolio sorts. Panel A reports long-short portfolio alphas (H–L) from univariate sorts on each DPI variant. The baseline DPI scales digital patent applications by market capitalization. DPI_A scales by total assets. DPI_G uses patent grants scaled by market capitalization. ODPI is the residual from a firm-level time-series regression of DPI on the natural log of market capitalization. Small ME and Large ME report H–L alphas from double sorts on DPI and market capitalization. Panel B reports Fama-MacBeth regression coefficients on each DPI variant with the full set of controls (LnME, LnBM, Mom, ROA, Invest, Illiq, EP, Turnover, and industry fixed effects). *t*-statistics in parentheses use Newey-West standard errors with 12 lags. *, **, *** indicate significance at 10%, 5%, and 1%, respectively.

<i>Panel A: Long-Short Portfolio Alphas (H–L), Monthly %</i>				
DPI Variant	Raw Ret	7-Fac	CH4	Obs (months)
Baseline DPI (patents/ME)	0.656*** (3.16)	0.624*** (2.94)	0.832*** (3.41)	192
DPI_A (patents/assets)	0.535** (2.20)	0.510** (2.14)	1.071*** (3.53)	192
DPI_G (grants/ME)	0.634*** (2.88)	0.568*** (2.64)	0.871*** (3.35)	192
ODPI (orthogonalized)	0.511*** (3.34)	0.544*** (3.87)	0.319** (2.03)	192
Small ME (double sort)	0.725*** (4.76)	0.556*** (3.65)	0.939*** (4.97)	192
Large ME (double sort)	0.648*** (3.25)	0.584*** (2.75)	0.793*** (3.30)	192
DPI_L19	0.448** (2.02)	0.407** (2.01)	0.830*** (3.08)	192
DPI_P	0.640*** (3.14)	0.610*** (2.93)	0.802*** (3.35)	192
<i>Panel B: Fama-MacBeth Regression Coefficients (Full Controls)</i>				
DPI Variant	Coefficient	<i>t</i> -stat	Obs	
Baseline DPI	0.033***	(4.97)	385,958	
DPI_A	0.036***	(5.56)	385,958	
DPI_G	0.166***	(3.81)	385,958	
ODPI	0.034***	(4.17)	385,953	
DPI_L19	0.031***	(4.25)	375,886	
DPI_P	0.037***	(4.25)	385,958	

Table 6: Government Support Allocation

This table reports Logit (Columns 1 & 4) and Poisson (Columns 2, 3, 5 & 6) regressions using firm-year data. Columns 1-3 use data from 2009 to 2024; Columns 4-6 use data from 2015 to 2024. The dependent variables are the dummy variable indicating whether a firm receives any digital subsidy (DigSub) or any government digital procurement project (DigPro), the number of digital subsidies (DigSubNum) or government digital procurement projects (DigProNum), and the amount of digital subsidies (DigSubAmo) or government digital procurement projects (DigProAmo) in year y . The key independent variable is *Digital Patent Intensity* (DPI) in year $y - 1$. Control variables all lag by one year, containing the natural logarithm of market capitalization (LnME), the natural logarithm of Book-to-Market ratio (LnBM), the cumulative return for the previous 12 months (Mom), return on assets (ROA), the growth rate of annual total assets (AnnualInvest), annual Amihud's illiquidity measure (AnnualIlliq), Earnings-to-Price ratio (EP), and annual average daily turnover (AnnualTurnover). IndustryFE and YearFE represent industry and year fixed-effects. t -statistics in parentheses are computed based on standard errors, two-way clustered at firm and year level. *, **, *** indicate significance at the 10%, 5% and 1% level, respectively.

Dep.Var	(1) DigSub	(2) DigSubNum	(3) DigSubAmo	(4) DigPro	(5) DigProNum	(6) DigProAmo
DPI	0.042*** (7.43)	0.036*** (7.77)	0.043*** (8.97)	0.066*** (9.11)	0.040*** (7.24)	0.045*** (7.48)
LnME	0.061 (1.20)	0.082* (1.85)	0.232*** (3.39)	0.501*** (6.53)	0.383*** (6.91)	0.366*** (4.51)
LnBM	-0.062 (-0.94)	-0.007 (-0.12)	-0.074 (-0.83)	0.220*** (2.69)	0.140* (1.86)	0.214** (2.38)
Mom	0.145 (1.48)	0.153* (1.70)	0.108 (1.03)	-0.169 (-1.15)	-0.009 (-0.08)	0.002 (0.01)
ROA	0.583 (0.80)	0.465 (0.74)	-0.806 (-0.98)	-3.155*** (-3.03)	-3.271** (-2.42)	-2.984** (-2.41)
AnnualInvest	0.140* (1.81)	0.179** (2.30)	0.239* (1.96)	-0.038 (-0.44)	0.068 (0.65)	0.083 (0.43)
AnnualIlliq	-4.343** (-2.10)	-5.492*** (-3.48)	-7.347*** (-3.03)	-4.423 (-1.61)	-9.243** (-2.18)	-10.476*** (-2.90)
EP	-0.651 (-0.93)	-0.666 (-1.09)	-0.550 (-0.83)	2.544*** (2.76)	2.641*** (2.63)	3.466*** (2.90)
AnnualTurnover	-0.022 (-1.16)	-0.016 (-0.86)	-0.025 (-1.00)	0.007 (0.14)	0.011 (0.31)	-0.032 (-0.79)
Constant	-4.547*** (-3.21)	-3.679*** (-3.46)	6.676*** (4.13)	-14.118*** (-7.17)	-9.020*** (-6.87)	6.976*** (3.65)
Observations	31,051	29,844	29,844	22,082	22,082	22,082
Pseudo R ²	0.109	0.132	0.229	0.289	0.423	0.429
IndFE	YES	YES	YES	YES	YES	YES
YearFE	YES	YES	YES	YES	YES	YES

Table 7: Government Support Credibility and the DPI Premium

This table reports the performance of value-weighted portfolios double-sorted by *Digital Patent Intensity* (DPI) and measures of government support credibility. Panel A sorts provinces into high and low groups based on local government digital focus at the end of each year, aligned with the next twelve months. Panel B sorts provinces into high and low groups based on local government fiscal pressure. In each group, stocks are further sorted into quintile portfolios by DPI at the end of each month. The bottom quintile portfolio consists of stocks with zero DPI, while the remaining stocks are sorted into the second through fifth quintiles. The quintile portfolios are held over the next month. The average monthly portfolio raw returns (RawRet), portfolio alpha under the Fama-French five-factor model augmented with momentum factor and illiquidity factor (7-Fac), and portfolio alpha under the CH-3 and CH-4 factor model (CH3, CH4) are reported. *t*-statistics in parentheses are computed using standard errors with Newey-West correction of 12 lags. *, **, *** indicate significance at the 10%, 5% and 1% level, respectively.

<i>Panel A: Local Government Digital Focus</i>								
Portfolio	Raw Ret	7-Fac	CH3	CH4	Raw Ret	7-Fac	CH3	CH4
Low Focus					High Focus			
L	0.870 (1.48)	-0.233 (-1.61)	-0.168 (-0.86)	-0.240 (-1.15)	0.776 (1.45)	-0.342*** (-3.34)	-0.298*** (-2.64)	-0.376*** (-3.00)
2	0.557 (1.02)	-0.108 (-0.56)	-0.267 (-1.19)	-0.332 (-1.36)	0.671 (1.38)	0.006 (0.04)	-0.151 (-0.84)	-0.143 (-0.85)
3	0.785 (1.62)	-0.255 (-1.42)	-0.041 (-0.20)	-0.055 (-0.26)	1.162* (1.92)	0.172 (0.84)	0.292 (1.39)	0.366* (1.65)
4	0.942* (1.85)	-0.046 (-0.23)	0.273 (1.06)	0.261 (1.02)	1.054* (1.93)	0.119 (0.85)	0.219 (1.51)	0.209 (1.34)
H	1.238** (1.97)	0.064 (0.30)	0.310 (1.58)	0.300 (1.45)	1.596*** (2.73)	0.443** (2.54)	0.622*** (3.51)	0.592*** (3.15)
H-L	0.367 (1.38)	0.298 (1.10)	0.479 (1.54)	0.540 (1.60)	0.820*** (4.04)	0.785*** (3.69)	0.920*** (4.04)	0.969*** (4.10)
<i>Panel B: Local Government Fiscal Pressure</i>								
Portfolio	Raw Ret	7-Fac	CH3	CH4	Raw Ret	7-Fac	CH3	CH4
Low Pressure					High Pressure			
L	0.818 (1.47)	-0.270*** (-2.74)	-0.213* (-1.91)	-0.298** (-2.49)	0.817 (1.50)	-0.383** (-2.40)	-0.329 (-1.64)	-0.367* (-1.71)
2	0.445 (0.96)	-0.259** (-2.37)	-0.399*** (-3.60)	-0.387*** (-3.80)	1.232* (1.93)	0.698** (2.26)	0.493 (1.33)	0.419 (1.06)
3	1.061* (1.84)	0.052 (0.31)	0.200 (1.20)	0.207 (1.26)	1.026* (1.65)	-0.042 (-0.16)	0.094 (0.31)	0.084 (0.27)
4	1.067** (2.02)	0.135 (0.91)	0.297* (1.94)	0.272* (1.68)	0.777 (1.46)	-0.328 (-1.23)	-0.074 (-0.23)	0.025 (0.08)
H	1.490** (2.55)	0.352* (1.92)	0.544*** (2.96)	0.556*** (2.88)	1.222* (1.76)	0.086 (0.34)	0.291 (1.32)	0.200 (0.87)
H-L	0.672*** (3.10)	0.621*** (2.79)	0.758*** (3.09)	0.853*** (3.41)	0.405 (1.39)	0.469 (1.64)	0.620** (2.21)	0.567* (1.96)

Table 8: Explanations by EPU

This table reports the performance of value-weighted portfolios sorted by *Digital Patent Intensity* (DPI) over the holding period from Jan 2009 to Dec 2024. At the end of each month, stocks are sorted into quintiles by DPI. The bottom quintile portfolio consists of stocks with zero DPI, while the remaining stocks are sorted into the second through fifth quintiles. The quintile portfolios are held over the next month. Panel A reports factor loadings of 7-Factor model augmented with ResEPU. ResEPU is defined as the residual component of the Economic Policy Uncertainty (EPU) index after removing the effects of industrial production growth, social consumption growth, M2 monetary growth, CPI inflation, and stock market returns using a rolling 60-month window. Panel B reports the average monthly portfolio raw returns (RawRet), portfolio alphas under 7-Fac model, 7-Fac model augmented with ResEPU, and CH-3 and CH-4 factor model. *t*-statistics in parentheses are computed using standard errors with Newey-West correction of 12 lags. *, **, *** indicate significance at the 10%, 5% and 1% level, respectively.

Panel A: Factor Loadings of 7-Fac Model With ResEPU

	Alpha	MKT	SMB	HML	UMD	RMW	CMA	IML	ResEPU
L	-0.322*** (-3.37)	1.009*** (42.66)	0.264*** (3.23)	-0.202*** (-3.79)	0.005 (0.24)	-0.045 (-0.48)	0.227*** (2.71)	0.004 (0.14)	0.216* (1.85)
2	-0.062 (-0.48)	1.013*** (43.00)	-0.131** (-2.25)	-0.256*** (-4.70)	-0.004 (-0.13)	0.184*** (2.23)	0.138 (1.34)	-0.044* (-1.69)	0.147 (0.85)
3	0.095 (0.57)	1.013*** (24.94)	-0.021 (-0.31)	-0.066 (-1.06)	0.098*** (2.82)	-0.022 (-0.30)	0.327*** (3.13)	0.013 (0.45)	-0.264* (-1.95)
4	0.098 (0.71)	0.969*** (27.19)	0.149* (1.84)	-0.208*** (-3.16)	0.049 (1.52)	-0.025 (-0.30)	0.065 (0.54)	-0.031 (-0.61)	-0.142 (-1.00)
H	0.356** (2.05)	0.998*** (31.79)	0.322*** (3.11)	-0.151* (-1.74)	0.039 (0.99)	-0.128 (-1.08)	-0.018 (-0.14)	-0.010 (-0.32)	-0.156 (-0.67)
H-L	0.678*** (3.24)	-0.011 (-0.36)	0.057 (0.42)	0.051 (0.52)	0.035 (0.74)	-0.083 (-0.50)	-0.245* (-1.84)	-0.015 (-0.29)	-0.372 (-1.35)

Panel B: Time Series Analysis

Portfolio	Raw Ret	7-Fac	Low ResEPU period		CH3	CH4	Raw Ret	High ResEPU period		CH3	CH4
			7-Fac + ResEPU	7-Fac + ResEPU				7-Fac	7-Fac + ResEPU		
L	0.905 (1.28)	-0.352** (-2.25)	-0.021 (-0.13)	-0.402** (-2.39)	-0.461*** (-2.62)	0.736 (1.10)	-0.177* (-1.92)	-0.070 (-0.45)	0.024 (0.24)	-0.046 (-0.42)	
2	0.359 (0.53)	-0.000 (-0.00)	0.103 (0.41)	-0.258* (-1.66)	-0.288* (-1.88)	0.890 (1.33)	0.013 (0.05)	-0.115 (-0.37)	0.074 (0.23)	0.065 (0.21)	
3	1.089 (1.56)	0.101 (0.45)	0.179 (0.58)	0.208 (0.87)	0.251 (1.08)	0.948 (1.52)	0.031 (0.17)	0.265 (1.26)	0.156 (0.64)	0.147 (0.74)	
4	1.160* (1.80)	0.060 (0.28)	0.081 (0.25)	0.289 (1.48)	0.273 (1.33)	0.888 (1.21)	0.090 (0.49)	0.202 (1.02)	0.182 (0.91)	0.180 (0.85)	
H	1.982*** (2.89)	0.614*** (3.02)	0.840** (2.35)	0.733*** (5.09)	0.728*** (4.77)	0.970 (1.43)	0.060 (0.31)	0.049 (0.20)	0.237 (1.53)	0.266* (1.68)	
H-L	1.078*** (5.07)	0.966*** (3.98)	0.861** (2.30)	1.135*** (4.99)	1.189*** (5.02)	0.234 (1.19)	0.236 (1.08)	0.119 (0.39)	0.213 (0.97)	0.313 (1.37)	

Table 9: Portfolio CAARs During LGFV Event

This table reports t-test on cumulative average abnormal returns of quintile portfolios and the long-short portfolio H-L (equal-weighted in Panel A and value-weighted by first-day market capitalization in Panel B) sorted by *Digital Patent Intensity* (DPI) during the Zhongrong Jiarun No. 30 and No. 31 Assembled Funds Trust event. Trading-day windows are defined relative to the formal default announcement on January 11, 2018 (day 0). At the end of November 2017, stocks are sorted into quintiles by DPI. The bottom quintile portfolio consists of stocks with zero DPI, while the remaining stocks are sorted into the second through fifth quintiles. The long-short column H-L reports the difference between the CAARs of the H and L portfolios. The cumulative abnormal return of each stock is estimated using the Fama-French five-factor model over a 110-day window preceding the event. *t*-statistics in parentheses are computed based on standard errors clustering at firm level. *, **, *** indicate significance at the 10%, 5% and 1% level, respectively.

<i>Panel A: Portfolio CAARs (Equal-Weighted)</i>						
Period	L	2	3	4	H	H-L
[0,5]	0.059 (0.26)	-0.339 (-0.94)	-0.483* (-1.67)	-1.151*** (-3.64)	-1.330*** (-4.44)	-1.388*** (-3.69)
[-10,5]	1.313*** (3.99)	0.785 (1.46)	0.652 (1.45)	-0.640 (-1.29)	-0.853* (-1.77)	-2.166*** (-3.72)
[-10,20]	3.846*** (6.70)	3.547*** (4.66)	3.181*** (4.37)	1.999** (2.36)	1.922*** (2.61)	-1.924** (-2.06)
[-20,-11]	0.291 (1.30)	1.052** (2.45)	0.347 (1.06)	-0.153 (-0.38)	0.622* (1.74)	0.331 (0.78)
<i>Panel B: Portfolio CAARs (First Day Value-Weighted)</i>						
Period	L	2	3	4	H	H-L
[0,5]	-0.101 (-0.25)	-0.050 (-0.08)	-1.076* (-1.89)	-2.630*** (-3.85)	-1.268** (-2.07)	-1.167 (-1.58)
[-10,5]	1.956*** (3.44)	1.496 (1.01)	0.843** (2.24)	-0.810 (-0.48)	-2.419** (-2.34)	-4.375*** (-3.71)
[-10,20]	4.453*** (5.04)	2.779* (1.79)	2.222* (1.85)	2.853* (1.75)	-0.761 (-0.42)	-5.213** (-2.58)
[-20,-11]	-0.060 (-0.17)	1.945*** (2.87)	-0.436 (-1.20)	-0.355 (-0.85)	0.997 (1.53)	1.057 (1.42)

Table 10: Portfolio Financial Performance After LGFV Event

This table reports cross-sectional t-test of post-event portfolio-average changes in financial performance. Portfolios are sorted by *Digital Patent Intensity* (DPI) at the end of November 2017. The reported outcomes include (1) Accounts receivable: Net amount of accounts receivable; (2) Cost of debt: Interest expenses; (3) Investment: Net investment in fixed assets, intangible assets, and other long-term assets. All outcome variables are constructed as percentage changes scaled by average total assets, following the formula:

$$100 * \frac{Y_{i,2018} - Y_{i,2017}}{0.5 * (TotalAsset_{i,2018} + TotalAsset_{i,2017})}$$

t-statistics in parentheses are computed based on standard errors clustering at firm level. *, **, *** indicate significance at the 10%, 5% and 1% level, respectively.

	L	2	3	4	H	H-L
Accounts receivable	0.640*** (5.05)	1.064*** (6.22)	1.255*** (5.70)	1.245*** (6.29)	1.598*** (6.98)	0.957*** (3.66)
Cost of debt	0.174*** (8.76)	0.216*** (8.97)	0.200*** (8.02)	0.179*** (8.38)	0.239*** (10.23)	0.065** (2.12)
Investment	0.453* (1.96)	0.642** (2.16)	0.468 (1.48)	0.269 (1.13)	0.093 (0.34)	-0.360 (-1.00)

Table 11: Analyst Forecast Errors

This table reports fixed-effects regressions using firm-year data from 2009 to 2024. The dependent variables are the analyst forecast errors constructed as the difference between the realized EPS in year $y+1$ or $y+2$ and the corresponding analyst consensus forecasts issued within 90 days after the release of firms' annual reports in year y , scaled by the stock price at the end of year $y-1$ (Ma, 2025). The key independent variable is *Digital Patent Intensity* (DPI) in year $y-1$. Control variables all lag by one year, containing the natural logarithm of market capitalization (LnME), the natural logarithm of Book-to-Market ratio (LogBM), the cumulative return for the previous 12 months (Mom), return on assets (ROA), the growth rate of annual total assets (AnnualInvest), annual Amihud's illiquidity measure (AnnualIlliq), Earnings-to-Price ratio (EP), annual average daily turnover (AnnualTurnover). FirmFE and YearFE represent firm and year fixed-effects. t -statistics in parentheses are computed based on standard errors, two-way clustered at firm and year level. *, **, *** indicate significance at the 10%, 5% and 1% level, respectively.

Dep.Var	(1) ForecastError ¹	(2) ForecastError ²
DPI	0.016 (0.91)	0.014 (0.57)
LnME	-0.999*** (-3.96)	-1.351*** (-3.31)
LnBM	-2.104*** (-4.25)	-1.492** (-2.86)
Mom	0.174 (0.55)	0.218 (0.53)
ROA	-26.868*** (-4.59)	-23.120*** (-4.06)
AnnualInvest	-0.145 (-0.65)	-0.498** (-2.88)
AnnualIlliq	0.626 (0.33)	0.022 (0.01)
EP	3.117 (0.48)	-11.541 (-1.01)
AnnualTurnover	-0.157** (-2.59)	-0.195** (-2.42)
Constant	21.231*** (3.66)	28.603*** (3.11)
Observations	16,015	13,626
Adjusted R ²	0.200	0.224
FirmFE	YES	YES
YearFE	YES	YES

Table 12: Earning Announcement Effect

This table reports average slope coefficients from Fama-MacBeth regressions using firm-day data from Jan 2009 to Dec 2024. The dependent variable is the daily return in month t . The key independent variable is *Digital Patent Intensity* (DPI) in month $t - 1$. Announce is a dummy variable that equals 1 if a given day falls within the earnings announcement window indicated in the column header ([0,3], [0,5], [-3,3], or [-5,5]), and 0 otherwise. Control variables all lag by one month, containing the natural logarithm of market capitalization (LnME), the natural logarithm of Book-to-Market ratio (LogBM), the cumulative return for the previous 12 months (Mom), return on assets (ROA), the growth rate of total assets (Invest), Amihud's illiquidity measure (Illiq), Earnings-to-Price ratio (EP), average daily turnover (Turnover). IndustryFE represents the industry dummy variables based on the 2012 China Securities Regulatory Commission (CSRC) industry classification codes. t -statistics in parentheses are computed based on standard errors with Newey-West correction of 12 lags. *, **, *** indicate significance at the 10%, 5% and 1% level, respectively.

Dep.Var	(1)	(2)	(3)	(4)	(5)
Daily Return	Baseline	[0,3]	[0,5]	[-3,3]	[-5,5]
DPI	0.002*** (4.48)	0.002*** (4.41)	0.002*** (4.21)	0.002*** (4.34)	0.002*** (4.30)
Announce		0.032 (1.05)	0.071* (1.71)	0.109*** (3.30)	0.166*** (3.94)
DPI $\times$ Announce		-0.080 (-1.05)	-0.040 (-0.58)	-0.035 (-0.51)	0.021 (0.29)
LnME	-0.032*** (-5.48)	-0.032*** (-5.50)	-0.032*** (-5.51)	-0.032*** (-5.43)	-0.032*** (-5.43)
LnBM	0.012** (2.27)	0.012** (2.26)	0.012** (2.26)	0.012** (2.31)	0.012** (2.31)
Mom	-0.004 (-0.31)	-0.004 (-0.32)	-0.004 (-0.30)	-0.005 (-0.36)	-0.005 (-0.38)
ROA	0.827*** (4.71)	0.829*** (4.72)	0.833*** (4.74)	0.816*** (4.65)	0.817*** (4.65)
Invest	0.075*** (4.03)	0.075*** (4.04)	0.075*** (4.02)	0.074*** (3.99)	0.074*** (3.95)
Illiq	0.725*** (4.84)	0.728*** (4.87)	0.729*** (4.87)	0.730*** (4.89)	0.730*** (4.88)
EP	1.230*** (8.13)	1.233*** (8.09)	1.230*** (8.09)	1.223*** (8.06)	1.221*** (8.06)
Turnover	-0.013*** (-6.80)	-0.013*** (-6.78)	-0.013*** (-6.79)	-0.013*** (-6.79)	-0.013*** (-6.79)
Observations	7,736,451	7,736,451	7,736,451	7,736,451	7,736,451
Adj. R ²	0.084	0.084	0.084	0.084	0.084
IndustryFE	YES	YES	YES	YES	YES

Table 13: Longer Horizon: Future Cumulative Returns

This table reports average slope coefficients from Fama-MacBeth regressions, and the sample period is from Jan 2009 to Dec 2024. The dependent variable is the cumulative return over the next 3, 6, 12, 24, and 36 months from month t . The key independent variable is *Digital Patent Intensity* (DPI) in month $t - 1$. Control variables all lag by one month, containing the natural logarithm of market capitalization (LnME), the natural logarithm of Book-to-Market ratio (LogBM), the cumulative return for the previous 12 months (Mom), return on assets (ROA), the growth rate of total assets (Invest), Amihud's illiquidity measure (Illiq), Earnings-to-Price ratio (EP), average daily turnover (Turnover). IndustryFE represents the industry dummy variables based on the 2012 China Securities Regulatory Commission (CSRC) industry classification codes. t -statistics in parentheses are computed based on standard errors with Newey-West correction of 12 lags. *, **, *** indicate significance at the 10%, 5% and 1% level, respectively.

Future window	(1) 3-month	(2) 6-month	(3) 12-month	(4) 24-month	(5) 36-month
DPI	0.081*** (4.33)	0.169*** (4.56)	0.380*** (4.62)	0.672*** (5.41)	1.017*** (6.49)
LnME	-1.144*** (-3.19)	-1.858*** (-2.69)	-3.497** (-2.43)	-4.252* (-1.85)	-4.242 (-1.41)
LnBM	-0.171 (-0.46)	-0.384 (-0.42)	-0.623 (-0.32)	1.561 (0.99)	0.735 (0.47)
Mom	0.205 (0.29)	0.288 (0.23)	0.121 (0.09)	-5.144*** (-2.81)	-9.393** (-2.22)
ROA	-14.780 (-1.35)	-40.768 (-1.35)	-39.652 (-0.86)	14.746 (0.27)	82.604 (1.03)
Invest	2.942*** (2.84)	3.911 (1.60)	3.519 (0.97)	11.367 (1.54)	4.981 (0.87)
Illiq	31.318*** (4.06)	47.542*** (3.71)	60.201* (1.67)	147.407*** (3.33)	177.181*** (3.66)
EP	105.374*** (10.12)	152.282*** (6.95)	180.304*** (5.64)	197.666*** (4.85)	186.198*** (3.38)
Turnover	-0.405*** (-6.74)	-0.797*** (-6.80)	-1.425*** (-6.12)	-1.744*** (-6.60)	-2.329*** (-6.64)
Observations	371,584	357,502	330,275	278,528	230,977
Adj. R ²	0.102	0.051	-0.012	0.128	0.138
IndustryFE	YES	YES	YES	YES	YES

Table 14: Robustness: Alternative Portfolio Construction

This table reports the performance of portfolios sorted by *Digital Patent Intensity* (DPI) over the holding period from Jan 2009 to Dec 2024. At the end of each month, stocks are sorted into quintiles by DPI. The bottom quintile portfolio consists of stocks with zero DPI, while the remaining stocks are sorted into the second through fifth quintiles. The quintile portfolios are held over the next month. Panel A reports the performance of equal-weighted portfolios. Panel B reports the performance of value-weighted portfolios excluding Information Transmission, Software and Information Technology Services Industry. The average monthly portfolio raw returns (RawRet) and portfolio alphas under the Fama-French three-factor model (FF3), the Carhart four-factor model (Carhart4), the Fama-French five-factor model (FF5), the Fama-French five-factor model augmented with momentum factor and illiquidity factor (7-Fac), and the China-specific CH-3 and CH-4 factor model are reported. *t*-statistics in parentheses are computed using standard errors with Newey-West correction of 12 lags. *, **, *** indicate significance at the 10%, 5% and 1% level, respectively.

<i>Panel A: Equal-weighted Portfolios</i>							
Portfolio	RawRet	FF3	Carhart4	FF5	7-Fac	CH3	CH4
L	1.259** (2.04)	-0.266*** (-2.99)	-0.222*** (-2.67)	-0.181* (-1.92)	-0.165* (-1.87)	-0.022 (-0.20)	-0.083 (-0.68)
2	0.846 (1.51)	-0.383*** (-4.53)	-0.361*** (-4.03)	-0.325*** (-3.17)	-0.268** (-2.46)	-0.222*** (-2.72)	-0.232** (-2.44)
3	1.365** (2.25)	-0.074 (-0.81)	-0.097 (-1.10)	-0.022 (-0.25)	-0.048 (-0.53)	0.243*** (3.08)	0.212*** (2.76)
4	1.520** (2.38)	0.034 (0.30)	0.038 (0.34)	0.055 (0.51)	0.074 (0.63)	0.408*** (5.11)	0.372*** (4.38)
H	1.861*** (2.85)	0.342** (2.37)	0.348** (2.42)	0.356*** (2.62)	0.376*** (2.70)	0.798*** (7.31)	0.776*** (6.97)
H-L	0.602*** (4.11)	0.608*** (4.03)	0.570*** (3.91)	0.536*** (3.46)	0.541*** (3.53)	0.820*** (4.72)	0.859*** (4.69)
<i>Panel B: Exclude Information-related Industry</i>							
Portfolio	RawRet	FF3	Carhart4	FF5	7-Fac	CH3	CH4
L	0.824 (1.51)	-0.323*** (-3.34)	-0.322*** (-3.53)	-0.272*** (-2.77)	-0.279*** (-3.05)	-0.234** (-1.98)	-0.311** (-2.47)
2	0.651 (1.32)	-0.025 (-0.16)	-0.024 (-0.16)	-0.047 (-0.32)	-0.007 (-0.05)	-0.195 (-1.20)	-0.218 (-1.33)
3	1.002* (1.81)	0.071 (0.45)	0.006 (0.04)	0.126 (0.77)	0.052 (0.31)	0.130 (0.75)	0.183 (0.97)
4	1.014* (1.88)	0.079 (0.49)	0.037 (0.24)	0.102 (0.62)	0.072 (0.45)	0.229 (1.36)	0.214 (1.18)
H	1.452** (2.52)	0.323** (1.98)	0.303* (1.93)	0.351** (2.26)	0.342** (2.24)	0.439*** (2.96)	0.443*** (2.90)
H-L	0.628*** (3.24)	0.646*** (3.05)	0.625*** (3.12)	0.622*** (3.01)	0.621*** (3.17)	0.673*** (2.98)	0.755*** (3.29)

Appendix Table A1: Univariate Sorting by NonDPI

This table reports the performance of value-weighted portfolios sorted by NonDPI over the holding period from Jan 2009 to Dec 2024. At the end of each month, stocks are sorted into quintiles by NonDPI. The bottom quintile portfolio consists of stocks with zero NonDPI, while the remaining stocks are sorted into the second through fifth quintiles. The quintile portfolios are held over the next month. Panel A reports the summary statistics of each portfolio. Panel B reports the average monthly portfolio raw returns (RawRet) and portfolio alphas under the Fama-French three-factor model (FF3), the Carhart four-factor model (Carhart4), the Fama-French five-factor model (FF5), and the Fama-French five-factor model augmented with momentum factor and illiquidity factor (7-Fac). The portfolio alphas under the China-specific CH-3 and CH-4 factor model constructed by [Liu et al. \(2019\)](#) (CH3, CH4) are also reported. *t*-statistics in parentheses are computed using standard errors with Newey-West correction of 12 lags. *, **, *** indicate significance at the 10%, 5% and 1% level, respectively.

<i>Panel A: Portfolio Summary Statistics</i>									
Portfolio	Obs	Mean	Std	Min	25%	50%	75%	Max	SR
L	192	0.777	7.710	-30.279	-3.686	0.408	4.523	23.449	0.079
2	192	0.865	6.893	-25.202	-3.307	0.942	4.170	21.620	0.101
3	192	0.716	6.777	-27.941	-2.635	0.722	4.111	16.962	0.081
4	192	1.117	7.064	-20.542	-2.485	1.166	4.383	24.257	0.134
H	192	1.171	6.694	-24.364	-2.689	0.969	4.373	22.402	0.150
H-L	192	0.394	3.392	-9.986	-1.356	0.207	2.407	16.190	0.066

<i>Panel B: Significance Test</i>							
Portfolio	Raw Ret	FF3	Carhart4	FF5	7-Fac	CH3	CH4
L	0.777 (1.38)	-0.435*** (-4.28)	-0.421*** (-4.03)	-0.367*** (-3.27)	-0.337*** (-3.00)	-0.144 (-1.12)	-0.219 (-1.59)
2	0.865 (1.64)	0.173 (1.50)	0.141 (1.20)	0.138 (1.36)	0.128 (1.11)	0.153 (0.89)	0.167 (0.93)
3	0.716 (1.49)	-0.256* (-1.65)	-0.332*** (-2.66)	-0.233 (-1.47)	-0.294** (-2.48)	-0.227 (-1.55)	-0.233 (-1.46)
4	1.117** (1.99)	0.088 (0.64)	0.056 (0.38)	0.145 (0.99)	0.120 (0.73)	0.196 (1.34)	0.163 (1.20)
H	1.171** (2.22)	0.160 (1.37)	0.185 (1.64)	0.211* (1.88)	0.225** (2.02)	0.072 (0.53)	0.086 (0.56)
H-L	0.394* (1.95)	0.595*** (3.70)	0.606*** (3.71)	0.578*** (3.33)	0.562*** (3.17)	0.216 (1.33)	0.305* (1.66)

Appendix Table A2: Government Digital Focus and the NonDPI Premium

This table reports the performance of value-weighted portfolios double-sorted by NonDPI and government digital focus. Provinces are sorted into high and low groups based on local government digital focus at the end of each year, aligned with the next twelve months. In each group, stocks are further sorted into quintile portfolios by NonDPI at the end of each month. The bottom quintile portfolio consists of stocks with zero NonDPI, while the remaining stocks are sorted into the second through fifth quintiles. The quintile portfolios are held over the next month. The average monthly portfolio raw returns (RawRet) and portfolio alphas under the Fama-French three-factor model (FF3), the Carhart four-factor model (Carhart4), the Fama-French five-factor model (FF5), the Fama-French five-factor model augmented with momentum factor and illiquidity factor (7-Fac), and the China-specific CH-3 and CH-4 factor model constructed by [Liu et al. \(2019\)](#) (CH3, CH4) are reported. t -statistics in parentheses are computed using standard errors with Newey-West correction of 12 lags. *, **, *** indicate significance at the 10%, 5% and 1% level, respectively.

Portfolio	Raw Ret	FF3	Carhart4	FF5	7-Fac	CH3	CH4
Low Focus							
L	0.857 (1.40)	-0.395*** (-2.86)	-0.353** (-2.57)	-0.301** (-2.11)	-0.242* (-1.83)	-0.034 (-0.17)	-0.095 (-0.46)
2	0.602 (1.14)	-0.169 (-0.98)	-0.189 (-1.06)	-0.163 (-0.94)	-0.102 (-0.55)	-0.123 (-0.51)	-0.139 (-0.52)
3	0.667 (1.33)	-0.348 (-1.57)	-0.424** (-2.10)	-0.303 (-1.42)	-0.413** (-2.03)	-0.213 (-0.96)	-0.285 (-1.23)
4	1.420*** (2.58)	0.339* (1.78)	0.251 (1.33)	0.404** (2.14)	0.357* (1.82)	0.602*** (2.60)	0.567** (2.42)
H	1.044* (1.88)	-0.063 (-0.34)	-0.039 (-0.22)	0.008 (0.05)	0.003 (0.02)	-0.094 (-0.49)	-0.101 (-0.50)
H-L	0.187 (0.82)	0.332* (1.72)	0.314* (1.68)	0.310 (1.56)	0.245 (1.35)	-0.061 (-0.28)	-0.006 (-0.03)
High Focus							
L	0.714 (1.27)	-0.496*** (-3.62)	-0.487*** (-3.53)	-0.437*** (-3.01)	-0.424*** (-2.79)	-0.226 (-1.26)	-0.305 (-1.52)
2	1.040* (1.93)	0.393*** (3.05)	0.355*** (2.75)	0.343*** (3.02)	0.301** (2.53)	0.347* (1.87)	0.349* (1.86)
3	0.695 (1.40)	-0.265 (-1.44)	-0.330** (-2.16)	-0.269 (-1.44)	-0.291** (-2.08)	-0.283 (-1.50)	-0.247 (-1.31)
4	1.002* (1.70)	-0.049 (-0.35)	-0.069 (-0.46)	-0.002 (-0.01)	-0.035 (-0.21)	-0.002 (-0.01)	-0.041 (-0.31)
H	1.303** (2.50)	0.329*** (2.76)	0.348*** (2.84)	0.363*** (2.74)	0.383*** (2.92)	0.181 (1.46)	0.194 (1.34)
H-L	0.589** (2.42)	0.825*** (4.27)	0.835*** (4.22)	0.801*** (3.74)	0.806*** (3.60)	0.408* (1.91)	0.500** (2.03)

Appendix Table A3: Government Fiscal Pressure and the NonDPI Premium

This table reports the performance of value-weighted portfolios double-sorted by NonDPI and government fiscal pressure. Provinces are sorted into high and low groups based on local government fiscal pressure at the end of each year, aligned with the next twelve months. In each group, stocks are further sorted into quintile portfolios by NonDPI at the end of each month. The bottom quintile portfolio consists of stocks with zero NonDPI, while the remaining stocks are sorted into the second through fifth quintiles. The quintile portfolios are held over the next month. The average monthly portfolio raw returns (RawRet) and portfolio alphas under the Fama-French three-factor model (FF3), the Carhart four-factor model (Carhart4), the Fama-French five-factor model (FF5), the Fama-French five-factor model augmented with momentum factor and illiquidity factor (7-Fac), and the China-specific CH-3 and CH-4 factor model constructed by [Liu et al. \(2019\)](#) (CH3, CH4) are reported. *t*-statistics in parentheses are computed using standard errors with Newey-West correction of 12 lags. *, **, *** indicate significance at the 10%, 5% and 1% level, respectively.

Portfolio	Raw Ret	FF3	Carhart4	FF5	7-Fac	CH3	CH4
Low Pressure							
L	0.787 (1.37)	-0.411*** (-3.31)	-0.394*** (-3.10)	-0.355*** (-2.59)	-0.305** (-2.23)	-0.102 (-0.69)	-0.159 (-1.00)
2	0.774 (1.48)	0.042 (0.45)	0.016 (0.15)	0.003 (0.03)	-0.004 (-0.03)	0.066 (0.50)	0.074 (0.54)
3	0.638 (1.34)	-0.322* (-1.82)	-0.410*** (-2.80)	-0.314* (-1.75)	-0.386*** (-2.92)	-0.281* (-1.75)	-0.277 (-1.60)
4	1.117* (1.95)	0.088 (0.58)	0.065 (0.40)	0.127 (0.81)	0.115 (0.66)	0.160 (1.03)	0.134 (0.91)
H	1.192** (2.32)	0.210* (1.95)	0.245** (2.34)	0.254** (2.50)	0.271*** (2.64)	0.104 (0.76)	0.125 (0.81)
H-L	0.405* (1.80)	0.622*** (3.44)	0.639*** (3.51)	0.609*** (3.16)	0.576*** (2.95)	0.206 (1.08)	0.284 (1.31)
High Pressure							
L	0.665 (1.17)	-0.679*** (-4.75)	-0.674*** (-5.06)	-0.560*** (-4.17)	-0.589*** (-4.79)	-0.424** (-2.09)	-0.515** (-2.55)
2	1.160* (1.88)	0.543* (1.72)	0.511* (1.65)	0.536* (1.79)	0.534* (1.80)	0.413 (1.13)	0.395 (1.01)
3	0.807 (1.53)	-0.174 (-0.73)	-0.232 (-1.15)	-0.060 (-0.24)	-0.054 (-0.25)	-0.107 (-0.41)	-0.130 (-0.46)
4	1.337** (2.04)	0.184 (0.75)	0.110 (0.47)	0.345 (1.30)	0.264 (0.97)	0.396 (1.40)	0.408 (1.31)
H	1.118** (2.02)	-0.136 (-0.70)	-0.157 (-0.83)	-0.005 (-0.03)	-0.009 (-0.05)	0.028 (0.15)	-0.078 (-0.41)
H-L	0.453** (2.17)	0.543** (2.52)	0.517** (2.38)	0.555*** (2.72)	0.580*** (2.72)	0.452** (1.97)	0.437* (1.91)

Appendix Table A4: EPU and the NonDPI Premium

This table reports the performance of value-weighted portfolios sorted by NonDPI over the holding period from Jan 2009 to Dec 2024. At the end of each month, stocks are sorted into quintiles by NonDPI. The bottom quintile portfolio consists of stocks with zero NonDPI, while the remaining stocks are sorted into the second through fifth quintiles. The quintile portfolios are held over the next month. ResEPU is defined as the residual component of the Economic Policy Uncertainty (EPU) index after removing the effects of industrial production growth, social consumption growth, M2 monetary growth, CPI inflation, and stock market returns using a rolling 60-month window. We report the average monthly portfolio raw returns (RawRet), portfolio alphas under the same benchmark models as in the baseline results, and alphas under 7-Fac augmented with ResEPU, CH-3 augmented with ResEPU, and CH-4 augmented with ResEPU. *t*-statistics in parentheses are computed using standard errors with Newey-West correction of 12 lags. *, **, *** indicate significance at the 10%, 5% and 1% level, respectively.

Portfolio	Raw Ret	FF3	Carhart4	FF5	7-Fac	CH3	CH4	7-Fac + ResEPU	CH3 + ResEPU	CH4 + ResEPU
Low ResEPU										
L	0.971 (1.30)	-0.515*** (-3.11)	-0.485*** (-3.11)	-0.428** (-2.33)	-0.342* (-1.86)	-0.278 (-1.27)	-0.339 (-1.54)	-0.041 (-0.24)	0.060 (0.29)	0.098 (0.51)
2	0.709 (1.00)	0.256 (1.33)	0.223 (1.15)	0.208 (1.23)	0.190 (1.02)	0.116 (0.55)	0.112 (0.52)	0.398* (1.65)	0.260 (0.85)	0.264 (0.88)
3	0.863 (1.49)	-0.150 (-1.06)	-0.234** (-1.99)	-0.195 (-1.34)	-0.280** (-2.10)	-0.162 (-1.34)	-0.186 (-1.42)	-0.385* (-1.96)	-0.330** (-1.97)	-0.319* (-1.94)
4	1.359** (2.13)	0.309** (2.00)	0.218 (1.26)	0.376** (2.43)	0.284* (1.68)	0.300** (2.32)	0.287** (2.13)	0.300 (1.12)	0.201 (0.92)	0.207 (0.94)
H	1.164* (1.68)	0.250 (1.32)	0.249 (1.37)	0.245 (1.53)	0.195 (1.32)	0.103 (0.53)	0.124 (0.59)	0.421* (1.73)	0.276 (1.02)	0.267 (1.00)
H-L	0.193 (0.75)	0.765*** (3.01)	0.734*** (2.93)	0.673*** (2.72)	0.537** (2.27)	0.380 (1.55)	0.463* (1.78)	0.462 (1.32)	0.216 (0.65)	0.169 (0.52)
High ResEPU										
L	0.584 (0.88)	-0.354*** (-2.67)	-0.362*** (-2.68)	-0.267** (-1.99)	-0.283** (-2.03)	-0.061 (-0.40)	-0.094 (-0.64)	-0.249 (-1.33)	-0.078 (-0.49)	-0.121 (-0.64)
2	1.021 (1.54)	0.171 (1.06)	0.145 (0.98)	0.136 (0.95)	0.135 (0.96)	0.363 (1.55)	0.380 (1.58)	0.169 (0.79)	0.260 (0.89)	0.279 (0.93)
3	0.568 (0.87)	-0.374** (-2.33)	-0.408*** (-2.72)	-0.269* (-1.78)	-0.281** (-2.15)	-0.296* (-1.68)	-0.243 (-1.25)	-0.190 (-1.09)	-0.212 (-0.82)	-0.141 (-0.50)
4	0.875 (1.23)	-0.096 (-0.42)	-0.037 (-0.16)	-0.013 (-0.05)	0.025 (0.10)	0.152 (0.58)	0.075 (0.36)	0.033 (0.12)	0.161 (0.49)	0.062 (0.24)
H	1.178* (1.92)	0.081 (0.81)	0.127 (1.07)	0.157 (1.30)	0.206 (1.60)	0.068 (0.37)	0.044 (0.22)	0.087 (0.70)	0.092 (0.40)	0.061 (0.25)
H-L	0.594** (2.46)	0.435** (2.35)	0.489*** (2.58)	0.424** (2.40)	0.489*** (2.68)	0.129 (0.42)	0.138 (0.46)	0.336 (1.35)	0.169 (0.49)	0.182 (0.51)

Appendix Table B1: Robustness: Univariate Sorting by Alternative DPI

This table reports the performance of value-weighted portfolios sorted by digital patent applications scaled by total asset (DPI_A) and digital patent grants scaled by market capitalization (DPI_G) over the holding period from Jan 2009 to Dec 2024. At the end of each month, stocks are sorted into quintiles by DPI_A (DPI_G). The bottom quintile portfolio consists of stocks with zero DPI_A (DPI_G), while the remaining stocks are sorted into the second through fifth quintiles. The quintile portfolios are held over the next month. The average monthly portfolio raw returns (RawRet) and portfolio alphas under the Fama-French three-factor model (FF3), the Carhart four-factor model (Carhart4), the Fama-French five-factor model (FF5), the Fama-French five-factor model augmented with momentum factor and illiquidity factor (7-Fac), CH-3 and CH-4 factor model are reported. t -statistics in parentheses are computed using standard errors with Newey-West correction of 12 lags. *, **, *** indicate significance at the 10%, 5% and 1% level, respectively.

<i>Panel A: Scaled by Asset</i>							
Portfolio	Raw Ret	FF3	Carhart4	FF5	7-Fac	CH3	CH4
L	0.821 (1.50)	-0.334*** (-3.53)	-0.334*** (-3.72)	-0.283*** (-2.95)	-0.290*** (-3.21)	-0.232** (-2.00)	-0.308** (-2.51)
2	0.727 (1.44)	0.033 (0.25)	0.079 (0.61)	0.040 (0.32)	0.093 (0.71)	-0.194 (-1.56)	-0.204 (-1.60)
3	0.839 (1.61)	-0.165 (-1.22)	-0.212 (-1.63)	-0.092 (-0.69)	-0.129 (-0.98)	-0.128 (-1.00)	-0.128 (-0.95)
4	1.065* (1.92)	0.090 (0.49)	-0.026 (-0.19)	0.101 (0.54)	-0.004 (-0.03)	0.268 (1.08)	0.270 (1.03)
H	1.356** (2.32)	0.302 (1.34)	0.191 (0.93)	0.278 (1.30)	0.220 (1.10)	0.805*** (3.50)	0.763*** (3.07)
H-L	0.535** (2.20)	0.636** (2.35)	0.525** (2.16)	0.561** (2.15)	0.510** (2.14)	1.038*** (3.59)	1.071*** (3.53)
<i>Panel B: Digital Patent Grants</i>							
Portfolio	Raw Ret	FF3	Carhart4	FF5	7-Fac	CH3	CH4
L	0.868 (1.64)	-0.193* (-1.94)	-0.211** (-2.26)	-0.165 (-1.60)	-0.164* (-1.76)	-0.123 (-1.02)	-0.193 (-1.46)
2	0.653 (1.34)	0.030 (0.22)	0.013 (0.10)	0.021 (0.16)	0.036 (0.28)	-0.079 (-0.61)	-0.069 (-0.55)
3	0.813 (1.54)	-0.181 (-1.07)	-0.217 (-1.38)	-0.130 (-0.85)	-0.168 (-1.12)	0.040 (0.22)	-0.004 (-0.02)
4	1.369** (2.17)	0.274* (1.70)	0.215 (1.24)	0.298* (1.82)	0.255 (1.40)	0.413** (2.49)	0.390** (2.19)
H	1.502*** (2.58)	0.372* (1.87)	0.371* (1.84)	0.404** (2.14)	0.404** (2.03)	0.648*** (3.23)	0.677*** (3.21)
H-L	0.634*** (2.88)	0.565** (2.57)	0.582*** (2.66)	0.569*** (2.74)	0.568*** (2.64)	0.772*** (3.13)	0.871*** (3.35)

Appendix Table B2: Univariate Sorting by Orthogonalized DPI

This table reports the performance of value-weighted portfolios sorted by Orthogonalization DPI (ODPI) over the holding period from Jan 2009 to Dec 2024. For each stock, ODPI is estimated as following time-series regression:

$$DPI_{i,t} = \alpha_i + \beta_i \text{LnME}_{i,t} + \text{ODPI}_{i,t},$$

At the end of each month, stocks are directly sorted into quintiles by ODPI. The quintile portfolios are held over the next month. Panel A reports the summary statistics of each portfolio. Panel B reports the average monthly portfolio raw returns (RawRet) and portfolio alphas under the Fama-French three-factor model (FF3), the Carhart four-factor model (Carhart4), the Fama-French five-factor model (FF5), the Fama-French five-factor model augmented with momentum factor and illiquidity factor (7-Fac), and the China-specific CH-3 and CH-4 factor model. *t*-statistics in parentheses are computed using standard errors with Newey-West correction of 12 lags. *, **, *** indicate significance at the 10%, 5% and 1% level, respectively.

Panel A: Portfolio Summary Statistics

Portfolio	Obs	Mean	Std	Min	25%	50%	75%	Max	SR
L	192	0.739	7.260	-26.808	-3.210	1.134	4.287	24.486	0.079
2	192	0.653	6.887	-28.651	-3.065	0.782	3.597	19.252	0.070
3	192	0.852	7.009	-20.687	-3.660	0.792	4.911	20.514	0.098
4	192	1.076	6.638	-23.458	-2.818	0.802	4.168	17.530	0.137
H	192	1.249	7.286	-28.499	-2.649	1.236	4.888	22.293	0.148
H-L	192	0.511	2.484	-9.286	-0.685	0.301	1.976	7.932	0.138

Panel B: Significance Test

Portfolio	Raw Ret	FF3	Carhart4	FF5	7-Fac	CH3	CH4
L	0.739 (1.33)	-0.255** (-2.06)	-0.322*** (-2.89)	-0.248** (-2.01)	-0.303*** (-2.64)	0.018 (0.15)	0.047 (0.40)
2	0.653 (1.23)	-0.277** (-2.40)	-0.344*** (-3.09)	-0.278** (-2.52)	-0.352*** (-3.05)	-0.307** (-2.06)	-0.277* (-1.78)
3	0.852 (1.56)	0.130 (0.77)	0.125 (0.76)	0.141 (0.87)	0.169 (1.09)	0.091 (0.47)	0.011 (0.05)
4	1.076** (2.25)	0.131 (0.99)	0.107 (0.82)	0.152 (1.14)	0.112 (0.80)	0.048 (0.37)	-0.003 (-0.02)
H	1.249** (2.32)	0.160 (1.18)	0.169 (1.25)	0.219* (1.74)	0.241* (1.85)	0.358*** (3.15)	0.366*** (2.96)
H-L	0.511*** (3.34)	0.415*** (2.98)	0.491*** (3.60)	0.467*** (3.34)	0.544*** (3.87)	0.340** (2.35)	0.319** (2.03)

Appendix Table B3: Robustness: Double Sorting by Market Capitalization

This table reports the performance of value-weighted portfolios double-sorted by *Digital Patent Intensity* (DPI) and market capitalization. Stocks are first classified into high and low groups based on market capitalization at the end of each month. In each group, stocks are further sorted into quintile portfolios by DPI at the end of each month. The bottom quintile portfolio consists of stocks with zero DPI, while the remaining stocks are sorted into the second through fifth quintiles. The quintile portfolios are held over the next month. The average monthly portfolio raw returns (RawRet), portfolio alpha under the Fama-French five-factor model augmented with momentum factor and illiquidity factor (7-Fac), and portfolio alpha under the CH-4 factor model (CH4) are reported. *t*-statistics in parentheses are computed using standard errors with Newey-West correction of 12 lags. *, **, *** indicate significance at the 10%, 5% and 1% level, respectively.

Portfolio	Raw Ret	7-Fac	CH4	Raw Ret	7-Fac	CH4
	Small ME			Large ME		
L	1.386** (2.13)	-0.114 (-1.21)	-0.016 (-0.11)	0.640 (1.19)	-0.310*** (-3.09)	-0.408*** (-2.72)
2	1.356** (2.07)	-0.193** (-2.05)	0.010 (0.08)	0.700 (1.42)	0.073 (0.46)	-0.133 (-0.68)
3	1.716** (2.48)	0.081 (0.71)	0.408*** (3.56)	0.657 (1.24)	-0.160 (-1.00)	-0.171 (-0.99)
4	1.748** (2.55)	0.068 (0.52)	0.489*** (5.16)	0.902* (1.72)	0.042 (0.26)	0.268 (1.54)
H	2.111*** (3.01)	0.442*** (3.01)	0.924*** (7.61)	1.289** (2.25)	0.275 (1.61)	0.386** (2.45)
H-L	0.725*** (4.76)	0.556*** (3.65)	0.939*** (4.97)	0.648*** (3.25)	0.584*** (2.75)	0.793*** (3.30)

Appendix Table B4: Robustness: Fama-MacBeth Regression with Alternative DPI

This table reports average slope coefficients from Fama-MacBeth regressions, and the sample period is from Jan 2009 to Dec 2024. The dependent variable is the monthly return of month t . The key independent variable is digital patent applications scaled by total asset (DPI_A), digital patent grants scaled by market capitalization (DPI_G) or orthogonalized DPI (ODPI) in month $t - 1$. Control variables all lag by one month, containing the natural logarithm of market capitalization (LnME), the natural logarithm of Book-to-Market ratio (LogBM), the cumulative return for the previous 12 months (Mom), return on assets (ROA), the growth rate of total assets (Invest), Amihud's illiquidity measure (Illiq), Earnings-to-Price ratio (EP), average daily turnover (Turnover). IndustryFE represents the industry dummy variables based on the 2012 China Securities Regulatory Commission (CSRC) industry classification codes. t -statistics in parentheses are computed based on standard errors with Newey-West correction of 12 lags. *, **, *** indicate significance at the 10%, 5% and 1% level, respectively.

Dep.Var: Return	(1)	(2)	(3)	(4)	(5)	(6)
DPI_A	0.016** (2.12)	0.036*** (5.56)				
DPI_G			0.132*** (3.39)	0.166*** (3.81)		
ODPI					0.049*** (6.72)	0.034*** (4.17)
LnME		-0.744*** (-4.87)		-0.738*** (-4.83)		-0.729*** (-4.77)
LnBM		0.303*** (3.09)		0.238** (2.30)		0.253** (2.47)
Mom		-0.422 (-1.10)		-0.417 (-1.08)		-0.407 (-1.05)
ROA		16.730*** (5.49)		16.099*** (5.25)		15.466*** (4.97)
Invest		1.540*** (4.56)		1.543*** (4.52)		1.538*** (4.47)
Illiq		9.329** (2.56)		9.240** (2.56)		9.185** (2.51)
EP		25.210*** (10.11)		25.419*** (10.32)		25.195*** (10.07)
Turnover		-0.338*** (-10.26)		-0.341*** (-10.33)		-0.336*** (-10.07)
Observations	385,958	385,958	385,958	385,958	385,953	385,953
Adj. R ²	0.047	0.131	0.046	0.131	0.044	0.129
IndustryFE	YES	YES	YES	YES	YES	YES

Appendix Table B5: Real-Time Availability of Patent Information

This table examines whether the DPI premium survives when portfolio formation uses only patent information guaranteed to be publicly available. Under Article 34 of China's Patent Law, CNIPA publishes an invention patent application 18 months after the filing date once it passes preliminary examination, and earlier at the applicant's request. Panel A reports the performance of value-weighted portfolios sorted by DPI lagged 19 months: at formation month t , the measure counts applications filed between months $t - 31$ and $t - 19$, all of which have been published before t under the statutory 18-month upper bound. Panel B reports the performance of value-weighted portfolios sorted by (DPI_P), which is constructed from patent publication dates instead of application filing dates. The holding period is from Jan 2009 to Dec 2024. At the end of each month, stocks are sorted into quintiles by the respective measure; the bottom quintile portfolio consists of stocks with a measure of zero, while the remaining stocks are sorted into the second through fifth quintiles. The quintile portfolios are held over the next month. Each panel reports the average monthly portfolio raw returns (Raw Ret) and portfolio alphas under the Fama-French three-factor model (FF3), the Carhart four-factor model (Carhart4), the Fama-French five-factor model (FF5), and the Fama-French five-factor model augmented with momentum factor and illiquidity factor (7-Fac). The portfolio alphas under the China-specific CH-3 and CH-4 factor model constructed by [Liu et al. \(2019\)](#) (CH3, CH4) are also reported. t -statistics in parentheses are computed using standard errors with Newey-West correction of 12 lags. *, **, *** indicate significance at the 10%, 5% and 1% level, respectively.

Panel A: Portfolios Sorted by DPI Lagged 19 Months

Portfolio	Raw Ret	FF3	Carhart4	FF5	7-Fac	CH3	CH4
L	0.842 (1.57)	-0.289*** (-2.81)	-0.294*** (-3.14)	-0.248** (-2.38)	-0.244*** (-2.62)	-0.196 (-1.47)	-0.257* (-1.84)
2	0.695 (1.38)	0.024 (0.17)	0.085 (0.60)	0.024 (0.17)	0.121 (0.94)	-0.151 (-1.15)	-0.204 (-1.53)
3	0.946* (1.74)	-0.025 (-0.17)	-0.124 (-0.92)	0.020 (0.13)	-0.071 (-0.46)	0.040 (0.25)	0.087 (0.53)
4	1.131** (2.08)	0.146 (1.08)	0.088 (0.63)	0.151 (1.06)	0.105 (0.67)	0.358* (1.94)	0.314* (1.72)
H	1.290** (2.32)	0.266 (1.38)	0.131 (0.79)	0.281 (1.51)	0.162 (1.02)	0.538** (2.56)	0.573*** (2.66)
H-L	0.448** (2.02)	0.556** (2.31)	0.425* (1.95)	0.528** (2.30)	0.407** (2.01)	0.733*** (2.81)	0.830*** (3.08)

Panel B: Portfolios Sorted by Publication-Date (DPI_P)

Portfolio	Raw Ret	FF3	Carhart4	FF5	7-Fac	CH3	CH4
L	0.831 (1.51)	-0.304*** (-3.11)	-0.315*** (-3.72)	-0.252** (-2.46)	-0.261*** (-2.97)	-0.184 (-1.45)	-0.240* (-1.78)
2	0.609 (1.26)	-0.066 (-0.44)	-0.071 (-0.51)	-0.074 (-0.54)	-0.039 (-0.32)	-0.184 (-1.30)	-0.206 (-1.48)
3	1.045* (1.92)	0.061 (0.40)	0.012 (0.08)	0.109 (0.70)	0.084 (0.48)	0.104 (0.64)	0.092 (0.59)
4	0.996* (1.74)	0.007 (0.05)	-0.029 (-0.19)	0.005 (0.03)	-0.023 (-0.14)	0.223 (1.58)	0.231* (1.65)
H	1.471** (2.48)	0.332* (1.83)	0.307* (1.75)	0.371** (2.18)	0.349** (2.08)	0.570*** (3.53)	0.562*** (3.24)
H-L	0.640*** (3.14)	0.636*** (2.81)	0.622*** (2.90)	0.623*** (2.88)	0.610*** (2.93)	0.754*** (3.31)	0.802*** (3.35)

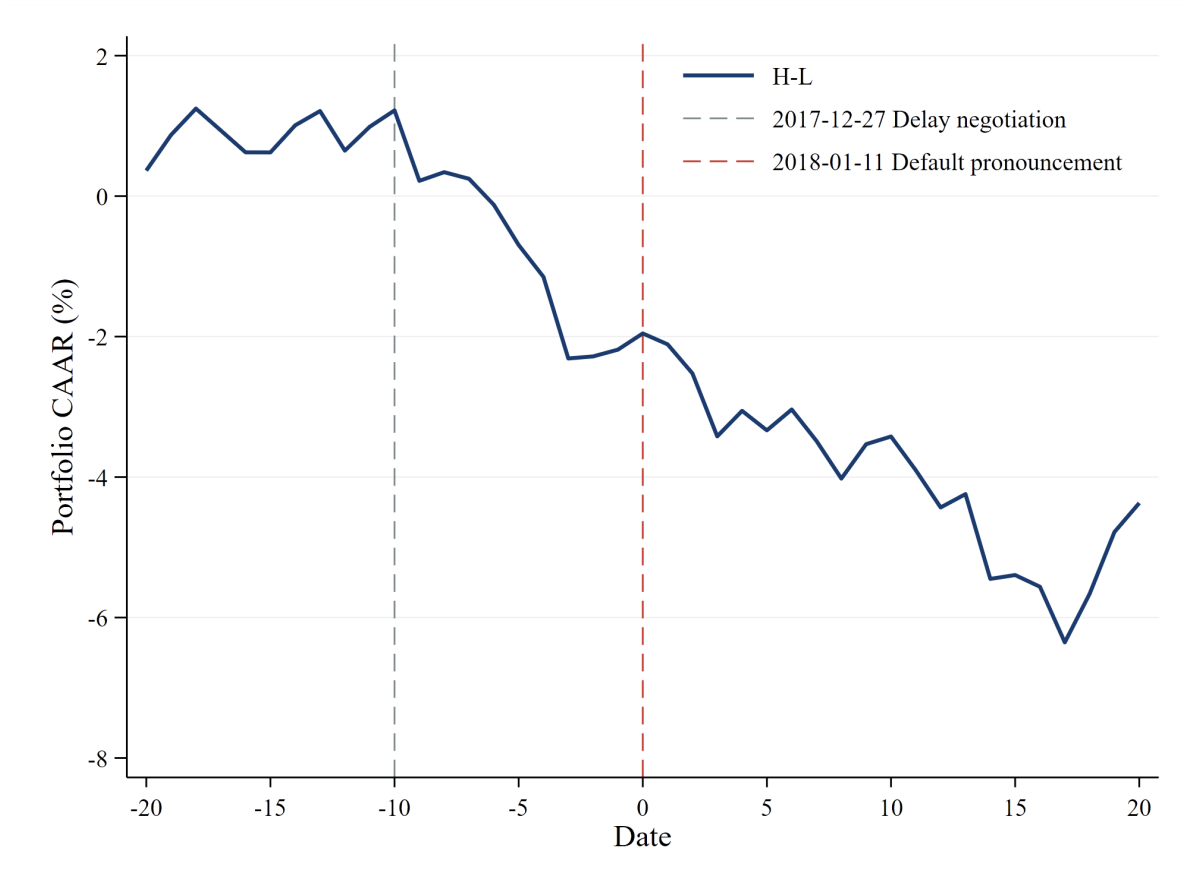
Appendix Table B6: Robustness: Fama-MacBeth Regression with Real-time DPI

This table reports average slope coefficients from Fama-MacBeth regressions, and the sample period is from Jan 2009 to Dec 2024. The dependent variable is the monthly return of month t . The key independent variable is digital patent publications scaled by total asset (DPI_P) in month $t - 1$ or DPI in month $t - 19$ (DPI_L19). Control variables all lag by one month, containing the natural logarithm of market capitalization (LnME), the natural logarithm of Book-to-Market ratio (LogBM), the cumulative return for the previous 12 months (Mom), return on assets (ROA), the growth rate of total assets (Invest), Amihud's illiquidity measure (Illiq), Earnings-to-Price ratio (EP), average daily turnover (Turnover). IndustryFE represents the industry dummy variables based on the 2012 China Securities Regulatory Commission (CSRC) industry classification codes. t -statistics in parentheses are computed based on standard errors with Newey-West correction of 12 lags. *, **, *** indicate significance at the 10%, 5% and 1% level, respectively.

Dep.Var: Return	(1)	(2)
DPI_L19	0.031*** (4.25)	
DPI_P		0.037*** (4.25)
LnME	-0.741*** (-4.88)	-0.735*** (-4.81)
LnBM	0.227** (2.21)	0.236** (2.26)
Mom	-0.506 (-1.29)	-0.418 (-1.09)
ROA	16.105*** (5.28)	16.173*** (5.25)
Invest	1.535*** (4.56)	1.541*** (4.47)
Illiq	9.350** (2.56)	9.256** (2.56)
EP	25.472*** (10.35)	25.376*** (10.19)
Turnover	-0.344*** (-9.87)	-0.341*** (-10.34)
Observations	375,886	385,958
Adj. R ²	0.132	0.131
IndustryFE	YES	YES

Appendix Figure C1: Portfolio CAARs During LGFV Event

This figure reports the cumulative average abnormal return of value-weighted long-short portfolio H-L sorted by *Digital Patent Intensity* (DPI) during Zhongrong Jiarun No. 30 and No. 31 Assembled Funds Trust event. Trading-day windows are defined relative to the formal default announcement on January 11, 2018 (day 0). At the end of November 2017, stocks are sorted into quintiles by DPI. The bottom quintile portfolio consists of stocks with zero DPI, while the remaining stocks are sorted into the second through fifth quintiles. The cumulative abnormal return of each stock is estimated using the Fama-French five-factor model over a 110-day window preceding the event. We mark two key event dates: the first negotiation to postpone payment on December 27, 2017, and the official pronouncement of default on January 11, 2018.



Appendix Table C1: Univariate Sorting

This table reports the performance of value-weighted portfolios sorted by *Digital Patent Intensity* (DPI) over the holding period from Jan 2009 to Dec 2024. At the end of each month, stocks are sorted into quintiles by DPI. The bottom quintile portfolio consists of stocks with zero DPI, while the remaining stocks are sorted into the second through fifth quintiles. The quintile portfolios are held over the next month. Panel A reports the summary statistics of each portfolio. Panel B reports the average monthly portfolio raw returns (RawRet) and portfolio alphas under the Fama-French three-factor model (FF3), the Carhart four-factor model (Carhart4), the Fama-French five-factor model (FF5), and the Fama-French five-factor model augmented with momentum factor and illiquidity factor (7-Fac). The portfolio alphas under the China-specific CH-3 and CH-4 factor model constructed by [Liu et al. \(2019\)](#) (CH3, CH4) are also reported. *t*-statistics in parentheses are computed using standard errors with Newey-West correction of 12 lags. *, **, *** indicate significance at the 10%, 5% and 1% level, respectively.

<i>Panel A: Portfolio Summary Statistics</i>									
Portfolio	Obs	Mean	Std	Min	25%	50%	75%	Max	SR
L	192	0.846	7.413	-27.658	-3.249	0.722	4.474	22.153	0.091
2	192	0.625	6.921	-26.147	-3.204	0.747	3.868	21.719	0.066
3	192	0.967	6.839	-22.119	-2.899	0.675	4.439	21.654	0.117
4	192	1.145	7.128	-24.585	-2.250	1.102	4.449	21.160	0.137
H	192	1.494	7.628	-27.459	-2.633	1.665	5.031	23.662	0.174
H-L	192	0.648	2.996	-9.899	-1.166	0.584	2.633	7.671	0.160

<i>Panel B: Significance Test</i>							
Portfolio	Raw Ret	FF3	Carhart4	FF5	7-Fac	CH3	CH4
L	0.846 (1.55)	-0.320*** (-3.80)	-0.325*** (-4.06)	-0.282*** (-3.32)	-0.280*** (-3.62)	-0.160 (-1.61)	-0.226** (-2.15)
2	0.625 (1.28)	-0.079 (-0.56)	-0.087 (-0.66)	-0.097 (-0.75)	-0.058 (-0.50)	-0.143 (-1.08)	-0.146 (-1.12)
3	0.967* (1.70)	0.016 (0.11)	-0.034 (-0.25)	0.045 (0.31)	-0.006 (-0.04)	0.261* (1.77)	0.261* (1.70)
4	1.145** (2.08)	0.158 (1.09)	0.130 (0.96)	0.152 (1.03)	0.184 (1.34)	0.485*** (3.25)	0.489*** (2.93)
H	1.494** (2.52)	0.306* (1.70)	0.281 (1.61)	0.311* (1.79)	0.312* (1.77)	0.621*** (3.65)	0.635*** (3.53)
H-L	0.648*** (3.20)	0.625*** (2.87)	0.606*** (2.90)	0.593*** (2.76)	0.592*** (2.81)	0.780*** (3.38)	0.861*** (3.59)

Appendix Table C2: Fama-MacBeth Regression

This table reports average slope coefficients from Fama-MacBeth regressions, and the sample period is from Jan 2009 to Dec 2024. The dependent variable is the monthly return of month t . The key independent variable is *Digital Patent Intensity* (DPI) in month $t - 1$. Control variables all lag by one month, containing the natural logarithm of market capitalization (LnME), the natural logarithm of Book-to-Market ratio (LogBM), the cumulative return for the previous 12 months (Mom), return on assets (ROA), the growth rate of total assets (Invest), Amihud's illiquidity measure (Illiq), Earnings-to-Price ratio (EP), average daily turnover (Turnover). IndustryFE represents the industry dummy variables based on the 2012 China Securities Regulatory Commission (CSRC) industry classification codes. t -statistics in parentheses are computed based on standard errors with Newey-West correction of 12 lags. *, **, *** indicate significance at the 10%, 5% and 1% level, respectively.

Dep.Var: Return	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
DPI	0.031*** (5.00)	0.026*** (4.36)	0.025*** (3.70)	0.029*** (4.52)	0.037*** (6.49)	0.031*** (5.05)	0.028*** (4.36)	0.034*** (5.90)	0.034*** (5.38)	0.033*** (4.88)
LnME		-0.400** (-2.38)								-0.804*** (-5.23)
LnBM			0.333** (2.29)							0.248** (2.26)
Mom				-0.987** (-2.11)						-0.337 (-0.89)
ROA					23.513*** (5.15)					16.642*** (5.68)
Invest						2.262*** (3.69)				1.881*** (5.04)
Illiq							20.303*** (3.03)			7.746** (2.19)
EP								32.342*** (7.11)		26.432*** (10.68)
Turnover									-0.273*** (-7.37)	-0.332*** (-11.12)
Observations	495,439	495,439	495,439	495,439	495,439	495,439	495,439	495,439	495,439	495,439
Adj. R ²	0.047	0.071	0.066	0.066	0.064	0.050	0.062	0.064	0.066	0.132
IndustryFE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Appendix Table C3: Government Support Allocation

This table reports Logit (Columns 1 & 4) and Poisson (Columns 2, 3, 5 & 6) regressions using firm-year data. Columns 1-3 use data from 2009 to 2024; Columns 4-6 use data from 2015 to 2024. The dependent variables are the dummy variable indicating whether a firm receives any digital subsidy (DigSub) or any government digital procurement project (DigPro), the number of digital subsidies (DigSubNum) or government digital procurement projects (DigProNum), and the amount of digital subsidies (DigSubAmo) or government digital procurement projects (DigProAmo) in year y . The key independent variable is *Digital Patent Intensity* (DPI) in year $y - 1$. Control variables all lag by one year, containing the natural logarithm of market capitalization (LnME), the natural logarithm of Book-to-Market ratio (LnBM), the cumulative return for the previous 12 months (Mom), return on assets (ROA), the growth rate of annual total assets (AnnualInvest), annual Amihud's illiquidity measure (AnnualIlliq), Earnings-to-Price ratio (EP), and annual average daily turnover (AnnualTurnover). IndustryFE and YearFE represent industry and year fixed-effects. t -statistics in parentheses are computed based on standard errors, two-way clustered at firm and year level. *, **, *** indicate significance at the 10%, 5% and 1% level, respectively.

Dep.Var	(1) DigSub	(2) DigSubNum	(3) DigSubAmo	(4) DigPro	(5) DigProNum	(6) DigProAmo
DPI	0.044*** (9.82)	0.039*** (11.20)	0.045*** (11.16)	0.058*** (11.28)	0.033*** (7.00)	0.037*** (6.87)
LnME	0.087** (2.06)	0.131*** (3.08)	0.279*** (4.85)	0.432*** (5.96)	0.368*** (6.77)	0.384*** (5.27)
LnBM	-0.065 (-1.20)	-0.029 (-0.56)	-0.070 (-0.91)	0.341*** (4.63)	0.263*** (3.99)	0.315*** (4.18)
Mom	0.120 (1.24)	0.113 (1.13)	0.051 (0.46)	-0.027 (-0.19)	0.023 (0.22)	0.002 (0.01)
ROA	0.145 (0.27)	-0.201 (-0.39)	-1.008* (-1.70)	-0.878 (-1.36)	-0.662 (-0.94)	-0.589 (-0.68)
AnnualInvest	0.120* (1.88)	0.121* (1.77)	0.117 (0.99)	-0.080 (-0.62)	-0.026 (-0.31)	-0.041 (-0.31)
AnnualIlliq	-3.438** (-2.08)	-4.687*** (-2.94)	-4.936** (-2.57)	-4.169 (-1.42)	-8.039** (-2.38)	-10.217*** (-2.91)
EP	-0.347 (-0.62)	-0.360 (-0.67)	0.128 (0.21)	1.289** (1.98)	0.810 (1.15)	1.822** (2.12)
AnnualTurnover	-0.017 (-1.26)	-0.011 (-0.81)	-0.003 (-0.18)	0.009 (0.28)	-0.025 (-1.03)	-0.061* (-1.96)
Constant	-5.242*** (-4.27)	-4.635*** (-4.52)	5.712*** (4.18)	-12.656*** (-6.78)	-8.437*** (-6.48)	6.748*** (3.86)
Observations	39,295	38,088	38,088	29,615	29,615	29,615
Pseudo R ²	0.110	0.137	0.234	0.270	0.376	0.385
IndFE	YES	YES	YES	YES	YES	YES
YearFE	YES	YES	YES	YES	YES	YES

Appendix Table C4: Government Support Credibility and the DPI Premium

This table reports the performance of value-weighted portfolios double-sorted by *Digital Patent Intensity* (DPI) and measures of government support credibility. Panel A sorts provinces into high and low groups based on local government digital focus at the end of each year, aligned with the next twelve months. Panel B sorts provinces into high and low groups based on local government fiscal pressure. In each group, stocks are further sorted into quintile portfolios by DPI at the end of each month. The bottom quintile portfolio consists of stocks with zero DPI, while the remaining stocks are sorted into the second through fifth quintiles. The quintile portfolios are held over the next month. The average monthly portfolio raw returns (RawRet), portfolio alpha under the Fama-French five-factor model augmented with momentum factor and illiquidity factor (7-Fac), and portfolio alpha under the CH-3 and CH-4 factor model (CH3, CH4) are reported. *t*-statistics in parentheses are computed using standard errors with Newey-West correction of 12 lags. *, **, *** indicate significance at the 10%, 5% and 1% level, respectively.

<i>Panel A: Local Government Digital Focus</i>								
Portfolio	Raw Ret	7-Fac	CH3	CH4	Raw Ret	7-Fac	CH3	CH4
Low Focus					High Focus			
L	0.859 (1.46)	-0.263* (-1.93)	-0.154 (-0.85)	-0.221 (-1.15)	0.823 (1.54)	-0.307*** (-3.59)	-0.184** (-2.00)	-0.249** (-2.45)
2	0.496 (0.92)	-0.210 (-1.14)	-0.311 (-1.52)	-0.375 (-1.64)	0.653 (1.33)	-0.034 (-0.26)	-0.101 (-0.56)	-0.072 (-0.43)
3	0.869* (1.80)	-0.118 (-0.65)	0.248 (1.02)	0.254 (1.05)	1.118* (1.75)	0.091 (0.50)	0.325* (1.77)	0.359* (1.91)
4	0.961* (1.82)	-0.093 (-0.47)	0.377 (1.57)	0.362 (1.46)	1.225** (2.18)	0.290** (2.00)	0.503*** (3.16)	0.505*** (2.83)
H	1.328** (2.11)	0.153 (0.77)	0.470*** (2.69)	0.486*** (2.59)	1.568*** (2.63)	0.378** (2.03)	0.679*** (3.47)	0.660*** (3.13)
H-L	0.469* (1.80)	0.416 (1.60)	0.624** (2.11)	0.707** (2.22)	0.745*** (3.72)	0.685*** (3.20)	0.863*** (3.79)	0.909*** (3.79)
<i>Panel B: Local Government Fiscal Pressure</i>								
Portfolio	Raw Ret	7-Fac	CH3	CH4	Raw Ret	7-Fac	CH3	CH4
Low Pressure					High Pressure			
L	0.834 (1.50)	-0.278*** (-3.22)	-0.149 (-1.54)	-0.221** (-2.15)	0.883 (1.61)	-0.309* (-1.88)	-0.230 (-1.15)	-0.266 (-1.21)
2	0.464 (0.99)	-0.285*** (-3.03)	-0.322*** (-3.17)	-0.299*** (-3.23)	1.194* (1.87)	0.656** (2.20)	0.481 (1.34)	0.409 (1.06)
3	1.019* (1.84)	0.071 (0.51)	0.322** (2.21)	0.311** (2.07)	0.925 (1.50)	-0.159 (-0.62)	0.000 (0.00)	0.003 (0.01)
4	1.160** (2.05)	0.221 (1.60)	0.515*** (3.34)	0.511*** (3.03)	0.799 (1.49)	-0.316 (-1.18)	-0.022 (-0.07)	0.088 (0.30)
H	1.522** (2.57)	0.334* (1.79)	0.643*** (3.36)	0.664*** (3.31)	1.243* (1.81)	0.074 (0.31)	0.366* (1.85)	0.280 (1.34)
H-L	0.688*** (3.25)	0.612*** (2.78)	0.792*** (3.30)	0.885*** (3.59)	0.360 (1.25)	0.382 (1.37)	0.596** (2.09)	0.545* (1.80)

Appendix Table C5: Explanations by EPU

This table reports the performance of value-weighted portfolios sorted by *Digital Patent Intensity* (DPI) over the holding period from Jan 2009 to Dec 2024. At the end of each month, stocks are sorted into quintiles by DPI. The bottom quintile portfolio consists of stocks with zero DPI, while the remaining stocks are sorted into the second through fifth quintiles. The quintile portfolios are held over the next month. Panel A reports factor loadings of 7-Factor model augmented with ResEPU. ResEPU is defined as the residual component of the Economic Policy Uncertainty (EPU) index after removing the effects of industrial production growth, social consumption growth, M2 monetary growth, CPI inflation, and stock market returns using a rolling 60-month window. Panel B reports the average monthly portfolio raw returns (RawRet), portfolio alphas under 7-Fac model, 7-Fac model augmented with ResEPU, and CH-3 and CH-4 factor model. *t*-statistics in parentheses are computed using standard errors with Newey-West correction of 12 lags. *, **, *** indicate significance at the 10%, 5% and 1% level, respectively.

Panel A: Factor Loadings of 7-Fac Model With ResEPU

	Alpha	MKT	SMB	HML	UMD	RMW	CMA	IML	ResEPU
L	-0.295*** (-3.69)	1.008*** (46.21)	0.322*** (4.44)	-0.217*** (-4.75)	0.010 (0.61)	-0.028 (-0.30)	0.176** (2.38)	-0.013 (-0.51)	0.103 (0.92)
2	-0.067 (-0.62)	1.019*** (45.00)	-0.095* (-1.91)	-0.262*** (-4.89)	0.008 (0.24)	0.199** (2.27)	0.159 (1.62)	-0.058** (-2.10)	0.062 (0.42)
3	0.045 (0.31)	0.992*** (25.77)	0.076 (1.15)	-0.183*** (-3.22)	0.063*** (2.41)	0.002 (0.03)	0.175* (1.86)	0.003 (0.11)	-0.346*** (-2.56)
4	0.200 (1.46)	0.982*** (33.86)	0.275*** (3.22)	-0.263*** (-4.78)	0.035* (1.74)	0.031 (0.46)	0.017 (0.20)	-0.077 (-1.46)	-0.108 (-0.73)
H	0.350** (2.04)	0.991*** (34.75)	0.440*** (4.36)	-0.188** (-2.13)	0.032 (0.75)	-0.090 (-0.80)	-0.083 (-0.71)	-0.033 (-1.08)	-0.265 (-1.21)
H-L	0.646*** (3.15)	-0.017 (-0.62)	0.118 (0.90)	0.029 (0.30)	0.021 (0.44)	-0.062 (-0.38)	-0.259** (-2.07)	-0.020 (-0.42)	-0.368 (-1.36)

Panel B: Time Series Analysis

Portfolio	Raw Ret	7-Fac	Low ResEPU period			Raw Ret	7-Fac	High ResEPU period			CH3	CH4
			7-Fac + ResEPU	CH3	CH4			7-Fac + ResEPU	CH3	CH4		
L	1.010 (1.44)	-0.277** (-2.32)	-0.037 (-0.26)	-0.285** (-2.00)	-0.339** (-2.28)	0.681 (0.99)	-0.210** (-2.42)	-0.072 (-0.49)	0.043 (0.44)	-0.010 (-0.11)		
2	0.429 (0.64)	0.047 (0.28)	0.134 (0.58)	-0.134 (-1.18)	-0.156 (-1.35)	0.821 (1.24)	-0.050 (-0.22)	-0.144 (-0.51)	0.058 (0.20)	0.069 (0.25)		
3	1.141 (1.60)	0.055 (0.26)	-0.071 (-0.28)	0.310 (1.44)	0.316 (1.41)	0.793 (1.21)	-0.084 (-0.47)	0.132 (0.62)	0.186 (0.83)	0.171 (0.92)		
4	1.380** (2.01)	0.242 (1.14)	0.287 (0.98)	0.508*** (2.79)	0.506** (2.55)	0.910 (1.20)	0.129 (0.65)	0.173 (0.87)	0.399** (2.04)	0.427** (2.08)		
H	2.122*** (3.15)	0.644*** (3.43)	0.767** (2.39)	0.850*** (5.34)	0.847*** (4.97)	0.865 (1.24)	-0.000 (-0.00)	0.028 (0.11)	0.305* (1.87)	0.361*** (2.14)		
H-L	1.112*** (5.08)	0.921*** (4.15)	0.804** (2.35)	1.135*** (5.21)	1.186*** (5.17)	0.184 (0.93)	0.210 (0.92)	0.100 (0.32)	0.263 (1.17)	0.371 (1.59)		

Appendix Table C6: Portfolio CAARs During LGFV Event

This table reports t-test on cumulative average abnormal returns of quintile portfolios and the long-short portfolio H-L (equal-weighted in Panel A and value-weighted by first-day market capitalization in Panel B) sorted by *Digital Patent Intensity* (DPI) during the Zhongrong Jiarun No. 30 and No. 31 Assembled Funds Trust event. Trading-day windows are defined relative to the formal default announcement on January 11, 2018 (day 0). At the end of November 2017, stocks are sorted into quintiles by DPI. The bottom quintile portfolio consists of stocks with zero DPI, while the remaining stocks are sorted into the second through fifth quintiles. The long-short column H-L reports the difference between the CAARs of the H and L portfolios. The cumulative abnormal return of each stock is estimated using the Fama-French five-factor model over a 110-day window preceding the event. *t*-statistics in parentheses are computed based on standard errors clustering at firm level. *, **, *** indicate significance at the 10%, 5% and 1% level, respectively.

<i>Panel A: Portfolio CAARs (Equal-Weighted)</i>						
Period	L	2	3	4	H	H-L
[0,5]	0.143 (0.66)	-0.532 (-1.65)	-0.486* (-1.82)	-1.122*** (-4.07)	-0.976*** (-3.43)	-1.118*** (-3.14)
[-10,5]	1.365*** (4.26)	0.593 (1.24)	0.003 (0.01)	-0.590 (-1.39)	-0.466 (-1.04)	-1.831*** (-3.33)
[-10,20]	3.817*** (6.72)	3.588*** (5.15)	2.983*** (4.06)	2.956*** (3.97)	2.383*** (3.65)	-1.433* (-1.66)
[-20,-11]	0.260 (1.19)	0.646* (1.70)	0.332 (1.12)	-0.157 (-0.45)	0.129 (0.42)	-0.131 (-0.35)
<i>Panel B: Portfolio CAARs (First Day Value-Weighted)</i>						
Period	L	2	3	4	H	H-L
[0,5]	-0.090 (-0.23)	-0.292 (-0.50)	-1.004* (-1.87)	-2.522*** (-3.82)	-1.249** (-2.03)	-1.160 (-1.59)
[-10,5]	1.931*** (3.54)	1.366 (1.01)	0.219 (0.31)	-0.771 (-0.54)	-2.347** (-2.26)	-4.277*** (-3.65)
[-10,20]	4.352*** (5.15)	2.821** (2.00)	2.132* (1.85)	3.367** (2.17)	-0.824 (-0.46)	-5.176*** (-2.61)
[-20,-11]	-0.103 (-0.31)	1.710*** (2.71)	-0.563* (-1.66)	-0.203 (-0.52)	0.875 (1.32)	0.978 (1.32)

Appendix Table C7: Portfolio Financial Performance After LGFV Event

This table reports cross-sectional t-test of post-event portfolio-average changes in financial performance. Portfolios are sorted by *Digital Patent Intensity* (DPI) at the end of November 2017. The reported outcomes include (1) Accounts receivable: Net amount of accounts receivable; (2) Cost of debt: Interest expenses; (3) Investment: Net investment in fixed assets, intangible assets, and other long-term assets. All outcome variables are constructed as percentage changes scaled by average total assets, following the formula:

$$100 * \frac{Y_{i,2018} - Y_{i,2017}}{0.5 * (TotalAsset_{i,2018} + TotalAsset_{i,2017})}$$

t-statistics in parentheses are computed based on standard errors clustering at firm level. *, **, *** indicate significance at the 10%, 5% and 1% level, respectively.

	L	2	3	4	H	H-L
Accounts receivable	0.713*** (5.59)	1.205*** (7.09)	1.276*** (6.07)	1.499*** (7.32)	1.956*** (9.11)	1.243*** (4.98)
Cost of debt	0.183*** (9.82)	0.219*** (10.16)	0.221*** (9.53)	0.189*** (10.02)	0.263*** (12.64)	0.080*** (2.86)
Investment	0.350 (1.51)	0.318 (1.16)	0.474 (1.57)	0.202 (0.84)	-0.079 (-0.29)	-0.429 (-1.20)

Appendix Table C8: Analyst Forecast Errors

This table reports fixed-effects regressions using firm-year data from 2009 to 2024. The dependent variables are the analyst forecast errors constructed as the difference between the realized EPS in year $y+1$ or $y+2$ and the corresponding analyst consensus forecasts issued within 90 days after the release of firms' annual reports in year y , scaled by the stock price at the end of year $y-1$ (Ma, 2025). The key independent variable is *Digital Patent Intensity* (DPI) in year $y-1$. Control variables all lag by one year, containing the natural logarithm of market capitalization (LnME), the natural logarithm of Book-to-Market ratio (LogBM), the cumulative return for the previous 12 months (Mom), return on assets (ROA), the growth rate of annual total assets (AnnualInvest), annual Amihud's illiquidity measure (AnnualIlliq), Earnings-to-Price ratio (EP), annual average daily turnover (AnnualTurnover). FirmFE and YearFE represent firm and year fixed-effects. t -statistics in parentheses are computed based on standard errors, two-way clustered at firm and year level. *, **, *** indicate significance at the 10%, 5% and 1% level, respectively.

Dep.Var	(1) ForecastError ¹	(2) ForecastError ²
DPI	0.016 (1.20)	0.012 (0.67)
LnME	-0.977*** (-4.42)	-1.170*** (-3.34)
LnBM	-1.942*** (-4.68)	-1.275** (-2.89)
Mom	0.142 (0.55)	0.203 (0.56)
ROA	-20.429*** (-4.28)	-16.175*** (-3.43)
AnnualInvest	-0.134 (-0.64)	-0.434** (-2.29)
AnnualIlliq	1.205 (0.62)	0.952 (0.54)
EP	1.018 (0.17)	-13.209 (-1.22)
AnnualTurnover	-0.097* (-2.02)	-0.094 (-1.34)
Constant	19.955*** (3.97)	23.598*** (3.02)
Observations	19,267	16,158
Adjusted R ²	0.198	0.224
FirmFE	YES	YES
YearFE	YES	YES

Appendix Table C9: Earning Announcement Effect

This table reports average slope coefficients from Fama-MacBeth regressions using firm-day data from Jan 2009 to Dec 2024. The dependent variable is the daily return in month t . The key independent variable is *Digital Patent Intensity* (DPI) in month $t - 1$. Announce is a dummy variable that equals 1 if a given day falls within the earnings announcement window indicated in the column header ([0,3], [0,5], [-3,3], or [-5,5]), and 0 otherwise. Control variables all lag by one month, containing the natural logarithm of market capitalization (LnME), the natural logarithm of Book-to-Market ratio (LogBM), the cumulative return for the previous 12 months (Mom), return on assets (ROA), the growth rate of total assets (Invest), Amihud's illiquidity measure (Illiq), Earnings-to-Price ratio (EP), average daily turnover (Turnover). IndustryFE represents the industry dummy variables based on the 2012 China Securities Regulatory Commission (CSRC) industry classification codes. t -statistics in parentheses are computed based on standard errors with Newey-West correction of 12 lags. *, **, *** indicate significance at the 10%, 5% and 1% level, respectively.

Dep.Var	(1)	(2)	(3)	(4)	(5)
Daily Return	Baseline	[0,3]	[0,5]	[-3,3]	[-5,5]
DPI	0.002*** (4.23)	0.002*** (4.07)	0.002*** (3.86)	0.002*** (4.13)	0.002*** (4.01)
Announce		0.047 (1.51)	0.087** (2.05)	0.105*** (3.24)	0.182*** (4.29)
DPI $\times$ Announce		-0.017 (-0.52)	0.015 (0.35)	0.011 (0.36)	0.009 (0.24)
LnME	-0.035*** (-5.88)	-0.035*** (-5.91)	-0.035*** (-5.92)	-0.035*** (-5.84)	-0.035*** (-5.83)
LnBM	0.014** (2.45)	0.014** (2.43)	0.014** (2.43)	0.014** (2.50)	0.014** (2.51)
Mom	0.000 (0.03)	0.000 (0.02)	0.000 (0.04)	-0.000 (-0.02)	-0.001 (-0.04)
ROA	0.873*** (5.18)	0.875*** (5.20)	0.878*** (5.20)	0.860*** (5.11)	0.861*** (5.11)
Invest	0.093*** (5.11)	0.093*** (5.12)	0.092*** (5.10)	0.092*** (5.07)	0.091*** (5.05)
Illiq	0.585*** (4.41)	0.585*** (4.43)	0.584*** (4.41)	0.586*** (4.44)	0.586*** (4.44)
EP	1.272*** (8.02)	1.274*** (7.98)	1.272*** (7.99)	1.265*** (7.96)	1.262*** (7.94)
Turnover	-0.014*** (-7.61)	-0.014*** (-7.57)	-0.014*** (-7.59)	-0.014*** (-7.58)	-0.014*** (-7.59)
Observations	9,939,271	9,939,271	9,939,271	9,939,271	9,939,271
Adj. R ²	0.086	0.086	0.086	0.086	0.086
IndustryFE	YES	YES	YES	YES	YES

Appendix Table C10: Longer Horizon: Future Cumulative Returns

This table reports average slope coefficients from Fama-MacBeth regressions, and the sample period is from Jan 2009 to Dec 2024. The dependent variable is the cumulative return over the next 3, 6, 12, 24, and 36 months from month t . The key independent variable is *Digital Patent Intensity* (DPI) in month $t - 1$. Control variables all lag by one month, containing the natural logarithm of market capitalization (LnME), the natural logarithm of Book-to-Market ratio (LogBM), the cumulative return for the previous 12 months (Mom), return on assets (ROA), the growth rate of total assets (Invest), Amihud's illiquidity measure (Illiq), Earnings-to-Price ratio (EP), average daily turnover (Turnover). IndustryFE represents the industry dummy variables based on the 2012 China Securities Regulatory Commission (CSRC) industry classification codes. t -statistics in parentheses are computed based on standard errors with Newey-West correction of 12 lags. *, **, *** indicate significance at the 10%, 5% and 1% level, respectively.

Future window	(1) 3-month	(2) 6-month	(3) 12-month	(4) 24-month	(5) 36-month
DPI	0.075*** (4.49)	0.154*** (4.69)	0.295*** (4.81)	0.598*** (5.05)	0.955*** (6.16)
LnME	-1.338*** (-3.62)	-2.160*** (-3.05)	-3.408** (-2.48)	-4.195* (-1.76)	-4.329 (-1.38)
LnBM	-0.185 (-0.51)	-0.515 (-0.54)	-0.803 (-0.43)	0.662 (0.38)	-0.357 (-0.22)
Mom	0.336 (0.47)	1.314 (0.83)	2.555 (1.11)	-5.543*** (-3.48)	-9.343** (-2.55)
ROA	-14.305 (-1.40)	-34.738 (-1.45)	-79.733 (-1.09)	6.619 (0.14)	84.128 (1.11)
Invest	3.436*** (3.64)	3.953 (1.65)	1.332 (0.27)	7.117 (1.32)	3.342 (0.57)
Illiq	23.641*** (3.01)	39.495*** (3.42)	68.858*** (3.51)	143.387*** (4.16)	168.869*** (4.00)
EP	109.469*** (11.50)	151.056*** (8.64)	186.017*** (6.39)	210.409*** (5.39)	193.165*** (3.70)
Turnover	-0.431*** (-7.93)	-0.800*** (-6.71)	-1.271*** (-6.26)	-1.160*** (-5.28)	-1.431*** (-4.53)
Observations	474,160	453,451	413,934	340,348	275,885
Adj. R ²	0.136	0.133	0.123	0.136	0.145
IndustryFE	YES	YES	YES	YES	YES