Firm Political Alignment: Measurement and Effects*

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ABSTRACT

We develop time-varying firm-level measures of firm political alignment (FPA), an important yet understudied political strategy for managing political risks. In the context of China, we compile two dictionaries of policy phrases reflecting annual government priorities and employ a generative large language model to measure FPA as the frequency of policy-aligned mentions in firms' annual reports, distinguishing between action-based and rhetorical alignment. We validate our measure by demonstrating that: (1) FPA correlates with country-level political risks, firm-level indicators of political risk and resource dependence on the government; (2) FPA has increased while political connection has declined since China's 2012 Anti-Corruption Campaign, supporting FPA's role as a distinct risk management strategy; (3) higher FPA is associated with favorable firm outcomes. Notably, action-based alignment, unlike rhetorical alignment, is consistently linked to fewer regulatory penalties and smaller stock price declines during political shocks, indicating it is more effective in mitigating political risk.

Keywords: political alignment; political cost hypothesis; policy risk; Common Prosperity Policy; Anti-Corruption Campaign
JEL Classification: G12, G14, G18, D72

1. Introduction

Governments worldwide increasingly use policy tools to exert influence on businesses in pursuit of economic, social, and geopolitical goals (The Economist 2021). This trend is evident in initiatives such as the Inflation Reduction Act in the U.S., the Net Zero Industry Act in the EU, and Made in China 2025, all designed to align business activities with government priorities in economic development, climate policy, and global competition. This trend also includes a growing use of coercive measures, even in market-oriented economies like the U.S., where the ongoing tariff shocks reflect a break from the tradition of limited government intervention. As government influence expands, so do political risks[1] for firms, especially those misaligned with government objectives. These firms may face regulatory actions or policy shifts that could adversely impact their performance.[2]

The literature in accounting and economics identifies several channels through which firms address political risks, including building connections with politicians (Faccio 2006, Tahoun 2014), making political donations (Wellman 2017), lobbying (Hassan et al., 2019), employing downward earnings management (Boland and Godsell 2020), and strategic advertising (Cuny et al., 2022). These strategies are typically aimed at *influencing* legislative outcomes, assuming firms hold some leverage over governments. However, an important yet understudied approach is firm political alignment (FPA), defined as the extent to which firms *align* their actions and rhetoric with government agendas. As government influence over businesses grows, FPA becomes an increasingly critical strategy to manage political risks. Accurately assessing the antecedents and consequences of FPA, however, requires a robust measure for FPA. This study aims to develop and validate such a measure.

[1] Political risk is the likelihood that a firm's performance is negatively affected by government policies (Pástor and Veronesi 2012). It stems from changes in economic policy, government interference, or regulatory actions.
[2] For example, in China, sudden crackdowns on Ant Financial, Didi, and tutoring firms hit their stock prices and growth prospects (Yang and Wei 2020). In the U.S., Ford's licensing of EV battery technologies from a Chinese company contradicts federal efforts to reduce reliance on China, triggering regulatory scrutiny and potentially disqualifying Ford from the $7,500 tax credit under the Inflation Reduction Act (Eckert and Duehren, 2023).

We construct a firm-year measure of FPA in the context of China because it offers a high-powered, compelling setting. First, firms in China face significant political risks due to the country's authoritarian political system and weak legal framework, allowing the government to make abrupt policy changes without being challenged. This provides strong incentives for firms to adopt FPA as a strategy to mitigate political risks. Furthermore, these regulatory shocks in China present a unique opportunity to validate our measure in relation to political risks (Lennox and Wu 2022). Second, the Chinese government routinely sets explicit economic and sociopolitical goals using standardized language in official government documents, which enables us to empirically measure the extent to which firms align with government goals through textual analysis.

To construct our FPA measure, we first compile a master list of 444 policy phrases drawn from three authoritative government documents covering the Hu and Xi administrations from 2003 to 2020 (Piotroski et al., 2017; Wong et al., 2020). From this master list, we develop two time-varying dictionaries by selecting the top 40 most frequently referenced policies each year from *People's Daily* and *Government Work Report*. Using GPT-4, we quantify FPA by the frequency of *policy-aligned* references in firms' annual reports and distinguish between action-based alignment (concrete actions and commitments) and rhetorical alignment (verbal support without specific actions or commitments).

Our FPA measure offers two key advantages. First, it comprehensively captures alignment with a broad spectrum of government agendas across economic and sociopolitical domains. This comprehensive approach allows us to assess a firm's overall capacity to leverage political alignment to mitigate risks and secure government-related benefits—an insight that narrow measures focused on compliance with individual policies cannot provide. Second, it differentiates between action-based and rhetorical alignment, enabling a deeper understanding of firms' different political alignment strategies and their association with risk

conditions and firm outcomes. To validate our GPT-based approach, we conduct human coding verification, a crucial step in AI-assisted research (De Kok 2025).

Having constructed our measures, we provide extensive evidence that they effectively capture political alignment. First, our FPA measures vary intuitively over time and across industries. Peaks in FPA align closely with periods of heightened economic policy uncertainty in China. FPA is also higher in industries subject to greater government oversight. Moreover, our policy-specific FPA measures—such as those related to Made in China 2025 and the Belt and Road Initiative—correlate with broader industry and investment trends that reflect firm alignment with these national policies.

Second, we show that our action-based alignment measure strongly correlates with direct indicators of firm compliance with government policies. Specifically, we find positive associations between action alignment and observable firm behaviors implementing three flagship policies: Indigenous Innovation, Poverty Alleviation, and Environmental Protection. In contrast, rhetorical alignment shows no systematic correlation with actual firm actions. Moreover, firm actions explain a significantly larger share of variation in action-based alignment than in rhetorical alignment, reinforcing the distinction between the two dimensions. These findings bolster our confidence in our measure's ability to differentiate between alignment through tangible actions versus political rhetoric.

Third, our FPA measures correlate with both country-level political uncertainty and firm-specific conditions in ways consistent with theoretical predictions. Specifically, firms facing greater country-level political risks show increased alignment with government agendas, as evidenced by strong correlations between our measures and established metrics like the Economic Policy Uncertainty (EPU) index (Baker, Bloom, and Davis, 2016) and conference call-based country risk measures (Hassan et al., 2024). Larger and more profitable firms demonstrate higher FPA, consistent with positive accounting theory's "political cost"

hypothesis (Watts and Zimmerman, 1983). Similarly, firms with greater leverage—suggesting greater resource dependence on the government—exhibit stronger alignment, confirming political economy predictions (Faccio, 2006; Claessens et al., 2008). These findings validate our measure and indicate the role of FPA as a potential strategic response to political risk and economic dependence on the government.

Fourth, we assess discriminant validity by showing that our FPA measure captures a construct distinct from political connections. Conceptually, FPA captures alignment with government policies, while political connection reflects government ties of top executives. We leverage Xi's unprecedented Anti-Corruption Campaign, launched in 2012 and still ongoing, which investigated and punished nearly five million officials across all levels by 2022 (Wang and Dickson, 2022). As the campaign directly targets politicians and substantially weakens the effectiveness of political connections for firms—long used in China to manage government relations (Lennox and Wu, 2022), it offers a natural setting to examine whether firms turn to FPA as an alternative political strategy. Using an established political connection measure—based on whether executives hold or previously held roles in policymaking bodies or government agencies—we find that while political connection declines post-2012, FPA increases. This divergence indicates that firms have shifted toward FPA as an alternative risk management strategy in the wake of the Anti-Corruption Campaign, confirming that FPA is different from political connections.

Furthermore, the Anti-Corruption Campaign doesn't uniformly diminish the value of political connection; rather, it may shift influence toward those within the inner circle of the central leadership. If so, firms with connections to central leadership should have less need for FPA compared to those without such ties. Following Francois, Trebbi, and Xiao (2023) and Liu, Shu, and Wei (2017), we measure central connections through: 1) executives and board members affiliated with Xi-aligned factions, and 2) headquarters in provinces where Xi

previously served. As predicted, firms without central leadership connections demonstrate higher FPA post-2012 than peers with such connections, suggesting FPA and central connections function as alternatives in firms' political risk management. Together, these findings confirm FPA as a distinct political strategy; while political connections have lost appeal since 2012, FPA has become increasingly prevalent, particularly among firms lacking central leadership connections.

Fifth, we validate the predictive validity of our measure by demonstrating its strong association with three key outcomes indicative of benefits from FPA: regulatory leniency, access to government resources, and resilience during periods of heightened political risk. Prior studies suggest that strong government relationships can lead to greater regulatory leniency (Haveman et al., 2017; Ang and Jia, 2014) and better access to government-controlled resources (Faccio, 2006; Li et al., 2008; Claessens et al., 2008). Our findings confirm these predictions: firms with higher FPA experience a lower likelihood of adverse regulatory actions, receive larger bank loans, and obtain more government subsidies, though we find no association with interest rates.

We also examine whether FPA mitigates stock price declines following adverse policy shocks. Prior research suggests that political uncertainty increases risk premiums and triggers negative market reactions (Pástor and Veronesi, 2013; Liu, Shu and Wei, 2017). We expect that investors perceive firms with higher FPA as better able to navigate policy shocks due to reduced risks of intervention, leading to smaller stock price declines. To test this, we analyze market reactions to China's Common Prosperity Policy announced on August 17, 2021—a major political shock that heightens policy uncertainty for firms. Given the increasing adoption of FPA since 2012, the 2021 event offers a strong setting to test its predictive validity, as firms had time to adopt the FPA strategy. We find that while firms experienced an average three-day price decline of 1.79% (approximately 42 million USD),

the negative reaction was significantly attenuated for firms with higher FPA. Economically, a one-standard-deviation increase in FPA is associated with a 16.7% to 18.9% reduction in negative returns. These results further validate FPA's predictive validity by confirming its role in buffering firms against adverse policy shocks.

While we cannot establish causal relationships between FPA and the three sets of firm outcomes, our findings provide strong evidence that FPA is associated with fewer adverse regulatory actions, greater access to government-controlled resources, and smaller stock price declines during political shocks. These correlations suggest that FPA captures meaningful firm-government relationships that translate into specific economic advantages, reinforcing its utility as a predictive tool for understanding political alignment outcomes. Importantly, these associations persist after controlling for state ownership, political connections, and central leadership ties, confirming FPA as distinct from other political relationships.

Our validation tests also reveal both commonalities and distinctions between action-based and rhetorical alignment. Both forms correlate with political risk indicators and have increased since the 2012 Anti-Corruption Campaign, suggesting that firms employ both strategies to mitigate political risks. Regarding benefits, both are associated with greater access to bank loans and government subsidies. However, only action-based alignment correlates with reduced regulatory penalties and weaker negative market reactions during political shocks. This pattern suggests that while both forms may yield financial benefits, action alignment may be more effective in mitigating the adverse impacts of political risks.

In our additional analyses, we first show that the associations between FPA and its economic determinants, political favor, and risk buffering effects remain robust across alternative FPA measures. We then conduct preliminary analyses to demonstrate the relevance of FPA in the U.S. Lacking a comprehensive list of government policies, we assess action-based alignment through case studies and partisan language alignment through

analysis of 10-K filings. Recent reshoring initiatives by Apple and Eli Lilly exemplify action-based alignment with the Trump administration's economic priorities on expanding domestic production. Beyond case studies, we apply Gentzkow, Shapiro, and Taddy's (2019) methodology to measure partisan language in 10-K filings. The Democratic-minus-Republican language differential peaks under Obama in 2014, declines after Trump's 2016 election, and rises again following Biden's victory in 2021. These patterns suggest that U.S. firms adjust their language to align with the sitting administration's preferences. However, such linguistic alignment may not necessarily reflect policy alignment, as the partisan dictionary captures party language preferences rather than specific policy agendas.

We acknowledge three main caveats to our analyses. First, like most text-based measures, our FPA measures may contain significant measurement error and should be interpreted with caution. Second, while the Chinese context allows us to examine the relationship between FPA and political strategies such as political connections and central government ties, it limits our ability to explore FPA's relationship with other forms of political engagement common in democratic systems, such as corporate lobbying and political donations, which are prohibited in China. Third, although we find significant associations between FPA and favorable firm outcomes, we do not claim that FPA is inherently more important than other forms of political engagement.

Our study contributes to several strands of literature. First, we extend research on corporate strategies for reducing political costs by introducing a new strategy—FPA—and developing and validating a measure of FPA. Prior work has examined two approaches: (1) accounting techniques to lower reported profits (Ramanna and Roychowdhury, 2010; Boland and Godsell, 2020) and (2) political engagement, including political connections, political contributions, lobbying, and strategic advertising (Hung et al., 2012; Tahoun 2014; Mehta et al., 2020; Christensen et al., 2022; Cuny et al., 2022). While existing literature emphasizes

firm efforts to influence policymakers, our study shifts the focus to how firms align with prevailing government agendas. We show that FPA is a distinct political strategy, separate from political connections and central leadership ties. As political risks intensify and power centralizes, political connections may lose value, while FPA serves as an effective alternative, especially for firms lacking connections to central leadership.

Second, we contribute to the literature on the value of political relationships by demonstrating that FPA is meaningfully associated with a variety of favorable firm outcomes. Consistent with prior research linking political ties to regulatory leniency (Haveman et al., 2017; Ang and Jia, 2014) and access to government resources (Faccio, 2006; Li et al., 2008; Claessens et al., 2008), we find that firms with higher FPA face fewer regulatory penalties, receive more bank loans and government subsidies, and experience smaller stock price declines during political shocks. Importantly, action-based alignment is more consistently associated with mitigating the adverse effects of political risk than rhetorical alignment, suggesting that political rhetoric alone is insufficient to address political risks.

Third, we make methodological contributions by applying generative AI tools—specifically, GPT-4—to classify policy alignment content from firms' annual reports. By constructing policy dictionaries and leveraging time-specific political shocks in China, we offer a replicable framework for measuring and validating FPA in a systematic way. This approach opens the door for future research to extend FPA measurement to other institutional contexts, including democratic economies such as the U.S.

2. Data

We collect 43,114 annual reports for 4,391 unique firms listed in China A-shares between 2003 and 2020, sourced from the Shanghai Stock Exchange and Shenzhen Stock

Exchange annual filing database.[3] Our measure of FPA is constructed using the full content of annual reports, excluding financial statements.

We manually collect the curriculum vitae of CEOs and chairmen to determine their political connections, including memberships in China's two political councils (Chinese People's Congress, Chinese People's Political Consultative Conference), Party Committee, or Party Congress, as well as prior experience in government agencies. Additionally, we collect the EPU index, based on the South China Morning Post (Baker, Bloom and Davis 2016), and a textual measure for China-specific country risk, derived from earnings conference calls (Hassan et al., 2024). Finally, we collect firm-year data from CSMAR, including balance sheet and income statement information, adverse regulatory actions, innovation activity, stock performance, and investment related to various flagship policies.

For our analyses in the U.S. setting, we collect 69,348 10-K filings for publicly listed U.S. firms from the EDGAR database, covering 2012 to 2023. The phrase-level partisan scores from each congressional session spanning 1873–2017 (43rd–114th U.S. Congress) are obtained from Gentzkow, Shapiro, and Taddy (2019). **Appendix A** provides details on the construction of all variables.

3. Measuring Firm Political Alignment

This section outlines the construction of the time-varying firm-level measure of FPA. We begin by developing policy dictionaries reflecting annual government priorities. Using these dictionaries, we measure FPA as the frequency of policy-aligned mentions in annual reports, distinguishing between action-based and rhetorical alignment. We then validate FPA as a proxy for the extent to which firms align with government policies.

[3] Shanghai Stock Exchange: http://www.sse.com.cn/disclosure/listedinfo/regular/; Shenzhen Stock Exchange: http://www.cninfo.com.cn/new/index.

3.1 Developing annual policy dictionaries

To capture central government policies and goals from 2003 to 2020, spanning the Hu and Xi administrations, we first compile a master list of policy phrases from three authoritative sources. For the Hu era, we draw on (1) *The Dictionary of Scientific Development* (Xi 2007), which catalogs policies from 1978 to the Hu administration and has been used in prior studies to identify political content in analyst reports and media (Piotroski et al., 2017; Wong et al., 2020). To cover the Xi era, we use two documents that capture key policies in government documents from 2012 onward: (2) *The Dictionary of Keywords that Party Members Must Know after the 18th National Congress of the Chinese Community Party*, and (3) *The Outline of Xi Jinping Thought on Socialism with Chinese Characteristics in the New Era*.[4] We combine these three sources, remove duplicates, and exclude generic business terms, resulting in a master list of 444 policy phrases.[5]

Although our master list offers a comprehensive view of central government priorities, it remains static. While government policies are centrally determined and largely stable, their relative emphasis may shift over time. To capture the evolving nature of government policy priorities, we construct two annual dictionaries: one based on *People's Daily*, the official newspaper of the Chinese Communist Party (CCP), and the other on the *Government Work Report,* the Premier's annual policy address. Although both sources reflect the central government's agenda, they differ to some extent. The *Government Work Report* provides a structured annual overview of formalized policies, often with concrete metrics and implementation plans, signaling policies with strong institutional backing. In contrast,

[4] http://theory.people.com.cn/GB/68294/428935/index.html; http://theory.people.com.cn/GB/40557/413700/index.html

[5] We make two adjustments. First, we retain only the shortest version of policies with multiple variations to prevent double counting (e.g., using only "New Era" rather than all variations: "New Era", "New Era Socialism with Chinese Characteristics," "New Era Defense"). Second, we remove general business terms like "Shareholder," once policy-relevant but now standard. The final keyword list is available upon request.

People's Daily offers daily insights into CCP's evolving viewpoints, serving as a leading indicator of emerging priorities before their formal adoption.

To create dictionaries that reflect the evolving importance of policies over time, we track the annual frequency of each policy phrase from the master list in *People's Daily* and *Government Work Report*. Specifically, we create two annual dictionaries by selecting the top 40 most frequently referenced policies each year from each source, resulting in 119 distinct policies across all years from each source, capturing 88% and 94% of policy mentions in the respective source.[6] Of these, 80 policies (67%) overlap between the two dictionaries, suggesting that they are both consistent and complementary: they capture a common core of emphasized policies while also reflecting source-specific nuances. Together, the two dictionaries provide a more complete picture of the government's evolving priorities over time. **Online Appendix A** visualizes the policies selected for each year from 2003 to 2020.

3.2 Applying a generative large language model to annual reports

Next, we apply the two policy dictionaries to firms' annual reports using Python, extracting 344,429 policy-referenced sentences from the *People's Daily*-based dictionary and 251,022 from the *Government Work Report*-based dictionary.[7] We focus on annual reports for several reasons. First, our study focuses on developing a firm-year measure of FPA that captures a firm's overall alignment with key government policies. Annual reports are ideal for this purpose, as they are a key channel through which firms convey their strategic positioning and alignment with government priorities, given the importance of political alignment for corporate success. These reports offer a comprehensive account of firm activities during the reporting year. Second, annual reports are a primary source of information for investors, regulators, and banks to assess firm exposure to political risk,

[6] We evaluate cutoffs ranging from top 10 to top 100 when developing our dictionaries. Our results remain robust across this range, as detailed in Section 6.1.
[7] Firms typically reference policy phrases in either the "Report of the Board of Directors" or the "Material Matters" section of their annual reports.

regulatory compliance, and creditworthiness. Finally, the mandatory and periodic nature of annual reports enables consistent cross-sectional and time-series comparison of how firms adapt to shifting government policy priorities. This makes annual reports well-suited for examining the associations between FPA and regulatory penalties, government subsidies, bank loans, and stock market reactions to political shocks.

To further identify whether these policy-mentioned sentences indicate action or rhetorical alignment, we leverage recent advancements in natural language processing, specifically Generative Large Language Models (GLLM).[8] OpenAI's GPT-4 model allows us to effectively classify sentences within days, significantly faster than traditional machine learning methods. Specifically, we implement a two-stage classification process using GPT. In the first stage, the model identifies sentences reflecting substantive alignment through concrete actions or commitment—235,159 sentences (68.3%) and 184,264 sentences (73.4%), based on the two policy dictionaries. In the second stage, among remaining sentences, GPT detects those indicating rhetorical or verbal alignment—82,828 (24%) and 58,556 (23.3%), respectively. Sentences mentioning policy phrases but lacking any form of alignment—26,442 (7.7%) and 8,202 (3.3%)—are excluded from our FPA measures.[9]

We follow the framework outlined in De Kok (2025) to evaluate the performance of the GPT-4 model. Specifically, we draw a random sample of sentences related to all policies in the two policy dictionaries, selecting five sentences per policy per year whenever possible. We then engage three independent research assistants to manually identify whether each sentence indicates firm actions that align with specific policies. These assessments by human

[8] The Stanford AI Index Report (2024) suggests that AI has surpassed human performance on several benchmarks, including some in image classification, visual reasoning, and language comprehension. https://hai-production.s3.amazonaws.com/files/hai_ai-index-report-2024-smaller2.pdf

[9] **Appendix B** details the GPT processing procedure. **Appendix C** provides illustrative examples of the policy-aligned sentences.

raters serve as a gold-standard benchmark against which we compare our GPT-based results. We find that the GPT-4 model yields a reasonably high accuracy of 90%.[10]

3.3 Constructing firm-level FPA

Based on the policy-aligned sentences in annual reports identified by GPT, we construct three firm-level FPA measures. These include: *FPA_Action,* the frequency count of instances where firms indicate concrete commitments or tangible actions aligned with government policies; *FPA_Rhetoric*, the frequency count of rhetorical references that signal alignment without action or commitment; and *FPA*, the sum of both measures. Formally, the untransformed overall FPA measure for firm *i* in year *t* is defined as:

$$FPA_{i,t} = \sum_{p \in \mathbb{P}_t} \sum_{s \in \mathbb{S}_p} n_{i,t,p,s}$$

where $\mathbb{P}_t$ is the set of policies in year *t* from the dictionary. $\mathbb{S}_p$ represents the set of sentences in firm *i*'s annual report mentioning policy *p* and indicating alignment, and $n_{i,t,p,s}$ denotes the number of policy-aligned mentions of policy *p* in sentence *s*. Similarly, we decompose this measure into action-based and rhetorical components:

$$FPA_Action_{i,t} = \sum_{p \in \mathbb{P}_t} \sum_{s \in \mathbb{S}_p} \mathbb{I}[Action_{i,t,p,s}] \times n_{i,t,p,s}$$

$$FPA_Rhetoric_{i,t} = \sum_{p \in \mathbb{P}_t} \sum_{s \in \mathbb{S}_p} (1 - \mathbb{I}[Action_{i,t,p,s}]) \times n_{i,t,p,s}$$

where $\mathbb{I}[Action_{i,t,p,s}]$ is a sentence-level indicator variable that equals one if sentence *s* for firm *i* in year *t* demonstrates action-based alignment with policy *p*, and zero otherwise.

Finally, we label them as *FPA1*, *FPA1_Action*, and *FPA1_Rhetoric* when derived from the *People's Daily* dictionary, and as *FPA2*, *FPA2_Action*, and *FPA2_Rhetoric* when

[10] Accuracy rate is defined as the sum of True Positive (TP) and True Negative (TF), divided by the sum of True Positive (TP), False Positive (FP), True Negative (TN), False Negative (FN). Furthermore, we obtain 92% precision rate (TP/(TP+FP)), 90% recall rate (TP/(TP+FN)) and 91% F1 score (2TP/(2TP+FN+FP)), reaffirming the validity of our GPT-based measure. The sample used for validation is available upon request.

based on the *Government Work Report* dictionary. To mitigate the impact of extreme values, we apply the inverse hyperbolic sine (IHS) transformation to all six measures.[11]

3.4 Validation

We next describe the statistics of the FPA measure and assess its validity in capturing firms' action-based and rhetorical alignment with government policies. **Panel A** of **Table 1** presents the 25 policy-aligned mentions most frequently cited in annual reports based on the two policy dictionaries. Notable commonalities include Sustainable Development, Poverty Alleviation, Indigenous Innovation, Belt and Road Initiative, and Ecological Civilization. Despite these shared policies, there are also meaningful differences between these two lists.

To further assess the properties of our FPA measure across ownership types, we compare state-owned enterprises (SOEs) and non-state-owned enterprises (non-SOEs). As shown in **Panel B** of **Table 1**, SOEs consistently outperform non-SOEs in aligning with government goals across nearly all years from 2003 to 2020. This finding is intuitive, as SOEs are majority-owned by the government and generally operate in closer alignment with government goals. This comparison demonstrates that our FPA measures effectively capture meaningful variation across ownership structures.

Figure 1 plots the time series of our FPA measures alongside Baker, Bloom, and Davis's (2016) newspaper-based EPU index. The year-level correlation coefficients between our two FPA measures and the EPU index are 0.867 and 0.899, respectively. Several notable EPU peaks correspond with FPA peaks. The first peak occurs during the 2008-2009 global financial crisis. The second emerges in 2012, when Xi assumed power and initiated the Anti-Corruption Campaign. The third peak appears in 2016, marked by Xi's formal designation as the "core" leader, signaling a more centralized governance approach. The fourth peak,

[11] The inverse hyperbolic sine (IHS) transformation is defined as $IHS(y) = \ln\left(y + \sqrt{y^2 + 1}\right)$, which is particularly useful for handling skewed data and zeros, as it approximates a logarithmic transformation for larger values and remains linear for smaller values (Aihounton and Henningsen, 2021).

spanning 2018 to 2020, aligns with several major events: the constitutional removal of presidential term limits, escalating U.S.–China trade tensions, and zero-COVID policy implementation. These events marked significant shifts in political governance and economic policies, creating substantial uncertainty for firms. Overall, the plot suggests economic policy uncertainty is likely an important driver of FPA.

Further probing the variation of our FPA measure across industries in **Figure 2**, we find that it aligns intuitively with the extent of government oversight and incentives. Industries such as construction, mining, water and environmental management, transportation, and electricity, where government oversight is typically high, exhibit higher levels of FPA. Sectors like scientific research and technical services show elevated FPA due to strong policy incentives to promote innovation. In contrast, firms in service-oriented sectors such as education, wholesale and retail, and accommodation are generally less subject to direct government intervention and may display lower FPA.

We further examine whether alignment with government policies can substantially shape firm production functions and investment strategies. We focus on two major policies with the potential to drive such shifts: Made in China 2025 (MIC 2025), an ambitious plan to position China as a global technology leader[12] and the Belt and Road Initiative (BRI), a flagship initiative to enhance global infrastructure and connectivity.[13] **Table 2 Panels A** and **B** provide summary statistics on investment trends and FPA associated with MIC 2025 and BRI, respectively. **Panel A** illustrates two key insights about MIC 2025: 1) Both the percentage of firms operating in the ten key MIC 2025 target industries and their share of

[12] Launched in 2015, MIC 2025 aims to transform China from a low-tech manufacturing hub to a global leader in ten strategic high-tech industries such as robotics, aerospace, new materials, and electric vehicles, supported by substantial government incentives to encourage firm participation and leadership (Zhang and Peng 2024).
[13] The Belt and Road Initiative represents China's most ambitious international economic strategy in decades. Launched in 2013, the BRI had engaged over 120 countries across Asia, Africa, and Europe by late 2021. This global development strategy enhances trade connectivity through infrastructure investments, creating international expansion opportunities for Chinese firms (Sacks, 2021).

total market value show a steady increase after 2014.[14] 2) The average frequency of MIC 2025-aligned references in annual reports across all firms closely tracks this industry distribution trend. Specifically, the correlations between *FPA_MIC2025* and the percentage of firms in MIC 2025 industries and the corresponding share of the total market value are 61.5% and 47.9%, respectively. **Panel B** provides statistics associated with BRI. We observe a similar increasing trend in FPA as well as Chinese firm investments in BRI countries. The correlation between *FPA_BRI* and these investments is 25.9%.[15] Overall, these findings not only validate our FPA measure for the two policies but also suggest that aligning with government policies is not merely superficial; it can substantially shape firms' fundamental business decisions, such as their industry choice or geographic investment focus.

Next, we verify that *FPA_Action* captures the degree of firm actions aligning with a given policy, while *FPA_Rhetoric* reflects references to government policies without substantive actions. To substantiate this, we examine the correlation between our textual FPA measures and actual firm actions for three flagship policies: Indigenous Innovation, Poverty Alleviation, and Environmental Protection, for which we can directly measure firm-level specific actions and commitments. For Indigenous Innovation, we employ two measures: 1) R&D spending scaled by average sales revenue (*RDSpend*); 2) the number of patents applied and granted (*NumPatent*). For Poverty Alleviation, we assess corporate action and commitment via two metrics: 1) the amount spent on poverty alleviation scaled by average sales revenue (*PovAmt*); 2) the presence of future poverty alleviation plans in annual reports (*TPAPlan*). For Environmental Protection, we utilize two indicators: 1) investment in

[14] Bloomberg Intelligence Research finds China's "Made in China 2025" initiative largely successful. Of 13 critical technologies assessed, China now leads in five sectors—high-speed rail, graphene, drones, solar panels, and EV/batteries—while rapidly advancing in seven others (Bloomberg, 2024).
[15] *FPA_MIC2025* captures the IHS on "Made in China 2025" references, while *FPA_BRI* measures the IHS on references to policy phrases related to Belt and Road initiatives.

environmental protection measured in billions of RMB (*EPInves*t); 2) the number of environmental protection projects undertaken (*NumEP*).[16]

Panels A, B, and C of Table 3 report regression results examining the relationship between FPA for Indigenous Innovation (*FPA_Innov*), Poverty Alleviation (*FPA_Poverty*), and Environmental Protection (*FPA_Envr*), and corresponding firm actions in years t-1, t, and t+1, while controlling for firm and year fixed effects, respectively.[17] For each panel, the first two columns present results for the overall *FPA*, and the subsequent four columns report findings for the corresponding action and rhetoric *FPA* measures. If our textual measures of *FPA* and *FPA_Action* effectively capture firm actions aligning with corresponding policies, we expect these firm actions to be positively associated with the *FPA* and *FPA_Action* measures, but not with *FPA_Rhetoric*.

Consistent with our expectation, we find that firm actions in each of the three years have incremental explanatory power for both our *FPA* and *FPA_Action* measures, but not for the *FPA_Rhetoric* measure. For instance, R&D spending (*RDSpend*) and number of patents (*NumPatent*) in the past, current, and next years are positively associated with *FPA_Innov* and *FPA_Innov_Action*, suggesting that when firms increase their R&D investment, they are more likely to discuss their action aligning with the Indigenous Innovation policy in their annual reports. In contrast, such actions are not significantly associated with *FPA_Innov_Rhetoric*. Additionally, the adjusted R-squared values range from 55.2% to 56.5% for *FPA_Innov* and *FPA_Innov_Action*, but only 26.5% for *FPA_Innov_Rhetoric,* indicating that firms' past, current, and future actions explain a substantial proportion of variation in our *FPA_Action* measure, while being less effective in explaining the measure capturing merely rhetorical references.

[16] Summary statistics for these variables are presented in **Online Appendix Table OA1.**
[17] *FPA_Innov* captures firm alignment with policies promoting Indigenous Innovation. *FPA_Poverty* reflects alignment with Poverty Alleviation policies. *FPA_Envr* measures alignment with policies regarding Environmental Protection. Detailed definitions appear in **Appendix A**.

Taken together, across three policies, our results demonstrate that *FPA_Action* measures are highly correlated with actual firm actions, while *FPA_Rhetoric* measures show no systematic correlation with firm actions. Moreover, the actions explain a substantially greater proportion of variation in the *FPA_Action* measure compared to the *FPA_Rhetoric* measure. These results validate our measurement approach that differentiates between action-based and rhetorical alignment.[18]

4. Firm Political Alignment: Determinants and Comparisons

In this section, we evaluate the validity of our FPA measure by examining how it correlates with country-level political risks, firm-level indicators of political risks and resource dependence on the government within a multivariate regression framework. We then demonstrate the discriminant validity of our FPA measure by comparing it with political connection, a conceptually different but related strategy for managing political risks. We leverage the Anti-Corruption Campaign initiated in 2012, which substantially increased political risks and arguably diminished the value of political connection, especially ties with politicians outside of Xi's circle. We theorize that, after 2012, firms are more likely to resort to FPA as an alternative mechanism for managing political risks.

4.1 Determinants of FPA

We examine the correlation between FPA and a set of factors, including country-level policy risk, various firm-level characteristics that indicate political risks and resource dependence on the state. The literature suggests three broad predictions. First, recent global trends and our central argument propose that firms facing greater country-level political risks are more likely to engage in FPA to manage political risk. We use two measures: the

[18] To mitigate potential type II errors where firms engage in policy-aligned actions without disclosure, we examine whether increased reporting reflects heightened disclosure rather than action. If this were the case, we would expect correlations between firm actions and our textual measures of the three policies to increase over time. However, annual correlations for these policies with observable firm actions (untabulated) show no clear trend, suggesting firms are not systematically altering their emphasis on policy alignment in reporting over time.

newspaper-based EPU index by Baker, Bloom, and Davis (2016) and the conference call-based country risk measure developed by Hassan et al., (2024). Due to the potential high correlation between these measures, we estimate our models using each measure in alternate specifications.

Second, positive accounting theory posits that larger, more profitable firms face heightened "political costs" through potential government regulation, taxation, or political actions that could reduce firm value (Watts and Zimmerman, 1983). As such, these firms have stronger incentives to engage in FPA as a strategic mechanism to proactively mitigate political risks. Third, a large literature in political economy predicts that firms have incentives to cultivate government relationships in exchange for preferential treatment (Faccio, 2006; Claessens et al., 2008). We measure firms' need for preferential treatment through leverage ratio and sales growth. Highly leveraged firms face financial constraints, while rapidly growing firms require additional resources, potentially motivating them to align more closely with government policies.

We focus on a sample of publicly listed A-share firms from 2008 to 2018 and exclude observations with missing information on CEOs, board chairs, or key determinants, as detailed in **Table 4, Panel A**. **Table 5** reports the summary statistics of regression variables. Our main specification takes the following form:

$$FPA_{it} = \alpha_0 + \alpha_1 PolicyRisk_{it-1} + \alpha_2 Size_{it-1} + \alpha_3 ROA_{it-1} + \alpha_4 Leverage_{it-1} + \alpha_5 Growth_{it-1} + Controls + FEs + \varepsilon_{it} \quad (1)$$

The dependent variable, *FPA*, is one of the two previously defined measures, *FPA1* or *FPA2*. *PolicyRisk* can be *EPU* or *CountryRisk*, with other variables being self-explanatory (detailed definitions in **Appendix A**). We include two additional control variables: 1) an indicator variable for *SOEs*; and 2) annual report length (*Length*). We also include firm fixed effects to

control for time-invariant firm characteristics and year fixed effects to account for macroeconomic factors common to all firms in a year. We cluster standard errors by industry.

Table 6 presents the results. The first three columns report the results for *FPA1*, while the last three columns report the results for *FPA2*. For each dependent variable, the first column includes *EPU*, the second column includes *CountryRisk*, and the third column includes year fixed effects. Since both *EPU* and *CountryRisk* are measured annually with no within-year variation, they are perfectly collinear with year fixed effects. Therefore, specifications including these policy risk measures necessarily exclude year fixed effects.

We highlight three key findings. First, periods of greater country-level political risk or economic policy uncertainties correlate positively with FPA. Second, SOEs, firms exposed to elevated political risks (large firms) and financially constrained firms (highly leveraged firms) tend to demonstrate stronger alignment with government goals. Third, contrary to our prediction, the coefficient on growth is negative, suggesting that rapidly growing firms may lack sufficient resources or strategic bandwidth to prioritize pro-government alignment. Collectively, these associations largely align with theoretical predictions and provide additional construct validation for our textual measures of FPA. While these correlations do not establish causality, they suggest that our FPA measure theoretically aligns with established incentives known to drive political alignment.

4.2 Political connection versus FPA

We assess our measure's discriminant validity by demonstrating that FPA captures a construct distinct from political connection. We leverage the Anti-Corruption Campaign initiated by Xi in 2012 as a significant policy shift that has altered the political landscape for firms. This campaign substantially increases political risks and weakens the efficacy of political connections as a risk management strategy (Piotroski, Wong, and Zhang 2022), likely prompting firms to adopt alternative strategies. This setting provides a valuable

opportunity to investigate whether firms shift toward more visible, legitimate forms of political engagement through alignment with government priorities. If FPA represents a construct distinct from political connection, we would expect differential responses to this exogenous shock, with FPA potentially serving as a complementary or substitutive strategy for firms navigating the changed political environment.

We modify our previous regression by adding an indicator for the post-Anti-Corruption Campaign period (*POST*). To facilitate comparison, we simultaneously examine changes in firms' use of political connections during the same time period. We measure political connection using an indicator variable (*PoliticalConnection*) that equals one if the CEO or board chair is or was a member in Chinese People's Congress, Chinese People's Political Consultative Conference, Party Committee, Party Congress, or has worked in government agencies, and zero otherwise (Fan, Wong and Zhang, 2007). We estimate parallel regressions for both *FPA* and *PoliticalConnection* to compare how firms' use of these two distinct political strategies responds to heightened political risks surrounding the Anti-Corruption Campaign:

$$FPA_{it} \text{ or } PoliticalConnection_{it} = \alpha_0 + \alpha_1 POST + Controls + FEs + \varepsilon_{it} \quad (2)$$

POST is an indicator variable for years after 2012, and zero otherwise. For either *FPA* or *PoliticalConnection*, a positive coefficient on *POST* suggests that firms become more likely to engage in that particular political strategy following the Anti-Corruption Campaign, while a negative or insignificant coefficient would indicate diminished use of the respective strategy in the post-campaign period. We include firm fixed effects but exclude year fixed effects, as the latter would be perfectly collinear with *POST*. Standard errors are clustered at the industry level to account for within-industry correlation.

Panel A of **Table 7** reports the results. The first two columns present findings for the two *FPA* measures, and the last column examines *PoliticalConnection*. The coefficient on

POST is significantly positive across both *FPA* columns, while significantly negative for *PoliticalConnection*. These results suggest a substitution effect, with firms shifting away from political connections and increasingly relying on FPA to manage heightened political risks. This analysis bolsters our confidence that FPA represents an alternative, distinct strategy to managing political risk, different from political connections.

To more precisely examine the nuanced impact of the Anti-Corruption Campaign, we investigate whether its effects shift the value of political connection towards those within Xi's inner circle, rather than universally diminishing their importance. We measure a firm's connection to the central leadership using two approaches. First, we construct a variable indicating whether a firm has a Xi-affiliated politician serving as a top executive or board member (*CC_Exec*). We begin with the curriculum vitae of Chinese politicians compiled by Francois, Trebbi and Xiao (2023), which identifies ties to key factions within the CCP. We classify a politician as Xi-affiliated if they belong to factions closely associated with him, including the Shanghai Gang, Princeling Faction, Tsinghua Clique, and Shaanxi Gang.[19] Next, we merge this dataset with board directors and top managers from the CSMAR Corporate Governance database. To ensure accurate matching, we require that names, birth year, and gender of directors and managers align with those of the politicians. For unsuccessful matches, we manually verify identities by reviewing director and manager biographies on Sina Finance. Through this process, we identify 37 directors and managers who are also politicians within Xi's inner circle. These individuals serve on 53 firms, where *CC_ Exec* is assigned a value of one.

Second, we identify firms headquartered in regions where Xi has had significant personal or career exposure: Shaanxi, Fujian, Zhejiang, Shanghai, Hebei, and Beijing. This approach follows Liu, Shu, and Wei (2017) who use geographic overlap as a proxy for

[19] We exclude Bo Xilai from the Princeling Faction when constructing Xi's inner circle.

political connection. We create an indicator variable, *CC_HQ*, that equals one for firms headquartered in any of these six regions, and zero otherwise. If the Anti-Corruption Campaign indeed shifted the value of political connection toward Xi's inner circle, we would expect firms with such connections to rely less on FPA. We estimate the following modified specification:

$$FPA_{it} = \alpha_0 + \alpha_1 POST + \alpha_2 POST \times CC + Controls + FEs + \varepsilon_{it} \quad (3)$$

CC can be either *CC_Exec* or *CC_HQ*, both capturing central leadership connection. All other variables have been previously defined. We expect α_1 >0, consistent with increased reliance on *FPA* for firms lacking connection to the central leadership. Our primary focus is on α_2, which we expect to be negative, suggesting a substitution effect between connection to Xi's inner circle and *FPA* in mitigating heightened political risks surrounding the Anti-Corruption Campaign. Since both central connection variables are measured at the firm-level, we suppress the *CC* main effects because they are perfectly collinear with firm fixed effects. Standard errors are clustered at the industry level.

Panel B of **Table 7** reports the results. The first and last four columns report the results for *FPA1* and *FPA2*, respectively, using different combinations of central connection measures and fixed effects.[20] Across all specifications, the coefficient on *POST* is positive and statistically significant, suggesting that firms outside Xi's circle increasingly resort to FPA to manage heightened political risks following the Anti-Corruption Campaign. Moreover, we observe a significant negative coefficient on the interaction term across all eight specifications. This pattern supports the discriminant validity of our FPA measure, demonstrating that FPA and central leadership connections function as distinct and substitutable strategies for political risk management. Firms with connections to Xi's inner

[20] Since *CountryRisk* is measured annually, it cannot be included with year fixed effects due to multicollinearity. For parsimony, we report results using only *CountryRisk*. Our inferences remain substantively similar when using the EPU measure instead.

circle exhibited significantly smaller increases in FPA compared to those without such connections, confirming that our FPA measure captures a unique political strategy dimension separate from central leadership ties.

In terms of economic significance, estimated coefficients from column (1) suggest that, on average, firms without central connection increased their FPA by approximately 22% (0.608/2.766) after the Anti-Corruption Campaign, while firms with central connections increased by only 8.9% ((0.608-0.361)/2.766), less than half that amount.[21] This divergence provides supportive evidence for the discriminant validity of our FPA measures. Additionally, we decompose FPA into *FPA_Action* and *FPA_Rhetoric*. **Online Appendix Table OA2** shows both forms of FPA are positively associated with political risk indicators and have increased since the 2012 Anti-Corruption Campaign, suggesting that firms employ both strategies to mitigate political risks.

5. The Benefits of FPA

5.1 FPA and government preferential treatments

In this section, we examine the association between FPA and its potential benefits to establish the predictive validity of our measure. The political economy literature suggests that firms derive significant private benefits through maintaining favorable relationships with the government. These benefits include relaxed regulatory oversight (Haveman et al., 2017; Ang and Jia, 2014), government subsidies (Faccio, 2006), and privileged access to restricted resources and investment opportunities (Li et al., 2008; Claessens et al., 2008, Khwaja and Mian 2005; Agrawal and Knoeber 2001).

We expect FPA to be associated with government preferential treatment in China's state-dominated economy for two reasons. First, China's regulatory environment is

[21] **Panel A** of **Table 4** shows *FPA1* has a sample mean of 7.915 (2.766 after inverse hyperbolic sine transformation).

characterized by substantial discretionary enforcement (Ang and Jia 2014), allowing authorities considerable latitude in implementing rules and sanctions. Within this institutional context, politically aligned firms can reasonably expect reduced regulatory scrutiny and fewer adverse enforcement actions, as regulators may exercise their discretion to support firms that demonstrate commitment to government priorities and policy objectives.

Second, the Chinese government exercises extensive control over critical resources such as land, energy, and capital. With major banks being state-owned, these institutions likely provide favorable treatment (e.g., increased loan accessibility and preferential interest rates) to firms demonstrating strong alignment with government objectives. Similarly, the government may offer enhanced subsidies to firms with high FPA scores.

If our FPA measure effectively captures meaningful political alignment, we should observe associations between higher FPA scores and these tangible benefits. We examine whether FPA is associated with subsequent political favors by employing the following regression model:

$$Political\ Favor_{i,t+1} = \alpha_0 + \alpha_1 \times FPA_{it} + Controls + \varepsilon_{it} \quad (4)$$

We focus on four forms of *Political Favor* in year t+1 subsequent to firms' FPA measured at year *t*: regulatory actions, bank loans, interest rates, and government subsidies. If the Chinese government indeed grants political favors to firms with greater *FPA*, we expect the coefficient α_1 to be positive when political favors are measured as bank loans and government subsidies, and negative when measured as adverse regulatory actions and interest rates. In addition to the control variables specified in equation (1), we also control for three aforementioned measures of political connection: *PoliticalConnection*, *CC_ Exec,* and *CC_HQ*. Essentially, we conduct a "horse race" to demonstrate that FPA can generate political favors above and beyond political connection. Since political connections are measured at the firm level, we include industry and year fixed effects to control for time-

invariant industry characteristics and broader macroeconomic conditions, and cluster standard errors at the industry level.

Table 8 reports the regression results on the association between *FPA* and political favors. **Panels A** through **D** correspond to adverse regulatory action, bank loan, government subsidies, and interest rates, respectively. In Panel A, where we examine the likelihood of adverse regulatory action (*Reg_Action*), the coefficients on *FPA1* and *FPA2* are both significantly negative. When disaggregating *FPA* into action-based and rhetorical components, we find significant negative coefficients for action measures, but not the rhetoric measures. These results support the predictive validity of our FPA measure, especially its action-based components, by demonstrating that regulatory agencies exercise greater leniency toward firms with higher FPA. The differential significance patterns between action-based and rhetorical measures underscore that substantive political alignment, rather than mere rhetorical mentions, is particularly effective in mitigating regulatory punishment.

We observe theoretically consistent patterns among the control variables. The coefficient on *ROA* is negative while that on leverage is positive, suggesting that financially constrained firms exhibit higher propensity for regulatory violations and subsequent penalties. Conversely, *SOE* and *CC_HQ* have significant negative coefficients, suggesting that SOEs and firms with central leadership connections benefit from more relaxed regulatory oversight. The latter aligns with prior literature documenting preferential treatment of politically connected entities within state-dominated economies (Haveman et al., 2017). More importantly, these results underscore that FPA represents a distinct strategy for generating political favors that operates beyond political connections.

For parsimony, we report the results for the remaining three political favors while suppressing the control variables. We highlight two key findings. First, *FPA* is associated with increased bank loan amounts and government subsidies, though not with lower interest

rates. Second, both action-based and rhetorical components of FPA appear to facilitate access to bank loans and government subsidies, suggesting that Chinese authorities respond to both substantive and symbolic forms of political alignment when allocating these resources.

Taken together, these findings demonstrate that our FPA measure successfully identifies firms that receive tangible benefits from government entities. While we cannot make causal claims, these correlations provide evidence that our FPA measures capture meaningful firm-government relationships that translate into specific economic advantages.

5.2 Event study: FPA and market reaction to policy shocks

As a final test of FPA's predictive validity, we examine whether firms with higher political alignment demonstrate greater resilience to adverse policy shocks. If our FPA measures effectively capture meaningful government relationships, then firms with stronger alignment should experience less negative market impacts when facing policy uncertainty. We exploit China's announcement of the Common Prosperity Policy on August 17, 2021, as an exogenous shock that significantly increased regulatory uncertainty. This policy, which emphasized wealth redistribution and tighter regulatory oversight, triggered substantial market volatility and negative returns for many Chinese firms. Baidu search intensity index related to Common Prosperity Policy surged from 722 to over 7,908 per day in late August 2021, reflecting the heightened policy uncertainty. This setting provides a natural experiment to test whether investors recognize the protective value of political alignment during periods of heightened policy risk. If FPA indeed serves as an effective buffer against adverse policy changes, we would expect firms with higher FPA to experience less negative abnormal returns around the Common Prosperity Policy announcement compared to their less-aligned counterparts.

Table 4 Panel B tabulates the sample selection process. We start with a sample of 3,477 non-financial A-share firms listed on the Shanghai or Shenzhen stock exchange for

more than a year by the end of 2020. We exclude 59 firms that were not traded during the three-day window around the Common Prosperity Policy, and 3 firms with insufficient pre-event trading windows. We further remove 200 firms due to contemporaneous earnings announcements and 132 observations due to missing control variables. Our final sample consists of 3,083 firms. As shown in **Table 5**, the average three-day cumulative raw return (*CRR*) around the announcement of the Common Prosperity Policy is significantly negative, with a mean of -1.79% (median = -1.51%), supporting our conjecture that this political event caused heightened political uncertainty in China. The economic significance of this result is substantial, as an average firm lost 304 million Yuan (i.e., U.S. $42 million) in market value over the three-day window. We estimate the following regression model:

$$CAR[-1,1]_{it} = \alpha_0 + \alpha_1 \times FPA_{it-1} + Controls + \varepsilon_{it} \qquad (5)$$

$CAR[-1,1]$ is the three-day market-adjusted cumulative abnormal return.[22] We include control variables specified in equation (1) and standard errors are clustered by industry. We expect α_1 to be positive, suggesting that FPA mitigates the negative impact of political uncertainty associated with the Common Prosperity Policy.

Table 9 presents the regression results. The first two columns report the results for *FPA1* while the last two columns report the results for *FPA2*. The first column reports the effect of the aggregate FPA measure, and the second column reports the corresponding action and rhetoric components. Overall, the coefficients across all four columns show significantly positive associations between market returns and both *FPA1* and *FPA2*, as well as their corresponding action components, while coefficients for the rhetoric components are insignificant. In terms of economic significance, a one-standard-deviation increase in *FPA1* and *FPA2* is associated with a 0.21% increase (0.318×0.665%) and 0.19% (0.202×0.924%)

[22] Our results are robust to using cumulative abnormal return derived from market models.

increase in the three-day CAR, respectively. These effects correspond to a 18.9% and 16.7% increase relative to the sample mean of CAR.

These results further validate our FPA measures, identifying firms that experience less negative market reactions during heightened policy uncertainty. Investors appear to recognize the value of political alignment during the Common Prosperity Policy announcement, suggesting our measure captures meaningful firm-government relationships. Notably, action-based components show consistently positive and significant coefficients, while rhetoric-based components yield insignificant results. This pattern reinforces that substantive political alignment, rather than mere rhetoric, provides tangible benefits and is more reliably valued by market participants during regulatory upheaval.

Collectively, our analyses in Section 5 reveal associations between FPA and various outcomes that support the predictive validity of our FPA measure. We find that FPA correlates with reduced regulatory actions and mitigated negative market reactions to policy shocks, particularly for action-based components. Both action and rhetoric-based alignment show associations with increased access to government-controlled resources including bank loans and subsidies. These correlation patterns align with theoretical expectations about political alignment benefits in China's institutional context. These consistent associations across multiple outcome variables bolster our confidence that our FPA measure effectively captures meaningful dimensions of firm-government relationships.

6. Additional Analyses

6.1 Alternative measures for FPA

We assess the robustness of our results using alternative definitions of FPA. First, instead of relying on dictionaries based on the top 40 most frequently referenced policies, we reconstruct dictionaries using varying thresholds—from the top 10 to the top 100—and generate corresponding FPA measures. Our findings remain robust across all FPA measures,

and we report results based on the top 30 and top 50 as representative examples in **Online Appendix Table OA3**.

Second, we explore two additional alternative measures: 1) FPA scope, capturing the scope of FPA by counting the occurrences of *unique* policies in annual reports (*FPA1_Scope* and *FPA2_Scope*). On average, firms reference three unique policies per annual report. 2) scaled FPA, defined as the number of policy-aligned mentions scaled by annual report page count (*FPA1_Scaled* and *FPA2_Scaled*). **Online Appendix Table OA4** and **OA5** confirm that results using both alternative measures remain consistent with our main findings on FPA determinants, political favors, and market reactions to policy shocks.

Lastly, we examine whether firms express dissent when discussing policies in annual reports using linguistic tone analysis. We expect dissent to be rare as it could elevate political risk without meaningfully influencing government policy. Using GPT-4, we assess the tone of all policy-mentioned sentences. We find that negative tone appears in only 1.3%-1.4% of the sentences (i.e., 3,289 and 4,934, using two dictionaries respectively), with most occurring in the nonalignment category (which is excluded from the construction of our FPA measures). Manual checks reveal that these cases typically discuss implementation challenges rather than expressing dissent towards the policy itself. Nonetheless, treating negative tones as *subtle* dissent indicators, we show in **Online Appendix Table OA6** that only nonnegative policy mentions significantly associate with political favors and weaker negative market reactions during political shocks.

6.2 Political alignment in the United States

Having established and validated our FPA measures in the Chinese context, we explore FPA's significance in the U.S.—a major developed economy characterized by democratic institutions and strong rule of law. In China, national policy priorities are articulated through highly uniform language in centrally issued documents, which enables the

construction of a consistent policy phrase dictionary. In contrast, U.S. policy language is more fragmented and ideologically diverse, varying across political parties, federal agencies, and state governments. This diversity makes it more challenging to compile a set of policy terms that reflect evolving national priorities in a consistent way. We therefore conduct this extension through case studies and systematic analysis of Democratic and Republican linguistic patterns in corporate 10-K filings, providing preliminary evidence of how political alignment manifests in the U.S.

6.2.1 Two case studies

Recent expansion plans by Apple and Eli Lilly demonstrate strategic alignment with the Trump administration's economic priorities on reshoring manufacturing and expanding domestic production. On February 25, 2025, Apple announced over $500 billion in U.S. investments over the next four years, with expansions in nine states, including a new factory in Texas, a doubling of the U.S. Advanced Manufacturing Fund, a manufacturing academy, and accelerated investments in AI and silicon engineering. The company's alignment is evident in CEO Tim Cook's statement: "We are bullish on the future of American innovation… we're thrilled to expand our support for American manufacturing. And we'll keep working with people and companies across this country to help write an extraordinary new chapter in the history of American innovation."[23]

Similarly, on February 26, 2025, Eli Lilly announced plans to bolster domestic medicine production by building four new manufacturing sites in the U.S. The company's alignment is reflected in CEO David A. Ricks' remarks: "Lilly's optimism about the potential of our pipeline across therapeutic areas… drives our unprecedented commitment to our domestic manufacturing build-out. Our confidence positions us to help reinvigorate domestic

[23] https://www.apple.com/newsroom/2025/02/apple-will-spend-more-than-500-billion-usd-in-the-us-over-the-next-four-years/

manufacturing, which will benefit hard-working American families and increase exports of medicines made in the U.S.A."[24] These cases demonstrate that FPA is not limited to China but is also strategically deployed in the U.S., where firms align with government priorities to secure political and economic advantages, even within an environment characterized by strong legal constraints on government intervention. This reveals a nuanced form of corporate-government engagement that extends beyond political connections.

6.2.2 Measuring FPA: partisan leaning in 10-K filings

We leverage Gentzkow, Shapiro, and Taddy's (2019) machine learning-based approach to identify partisan language patterns in text, enabling us to systematically measure FPA in the U.S. context through firms' use of partisan language. The U.S. two-party political system offers a unique methodological advantage: changes in presidential administration can serve as an exogenous shock to political alignment strategies. By analyzing firms' annual reports through linguistic choices that mirror Republican or Democratic congressional discourse, we can detect subtle political alignment.

Gentzkow, Shapiro, and Taddy's (2019) advanced computational approach offers detailed analysis of political language, quantifying partisan differences in congressional speech over a 140-year period with robust statistical precision. Following their approach, we construct a measure of firms' political alignment based on linguistic patterns in corporate disclosures. We begin by utilizing partisanship scores for the 1,000 most partisan bigrams from each congressional session spanning 1873–2017 (43rd–114th U.S. Congress). We then analyze 10-K filings from the EDGAR database for the period 2012 to 2023, focusing specifically on Item 1 (Business Description) and Item 7 (Management's Discussion and Analysis) sections. Each partisan phrase identified in these sections is assigned a partisanship

[24] https://investor.lilly.com/news-releases/news-release-details/lilly-plans-more-double-us-manufacturing-investment-2020.

score based on its corresponding congressional usage. Since the partisanship scores from Gentzkow, Shapiro, and Taddy (2019) are only available through 2017, we apply the most recent available score to all 10-K filings from 2018 to 2023.[25]

To construct a firm-year measure for *Democratic (Republican) Leaning*, we sum up the products of frequency of Democratic (Republican) phrases mentioned in section Item 1 and Item 7 in 10-K filings and their respective partisan scores, scaled by the total frequency of all partisan phrases mentioned. Finally, we measure *Net Partisan Leaning* as the difference between *Democratic Leaning* and *Republican Leaning.*

Figure 3 depicts the time trends of net partisan leaning in 10-K filings from 2012 to 2023, where higher values indicate relatively stronger Democratic leaning. During Obama's administration (2012-2016), corporate disclosures exhibit a strong and increasing Democratic-leaning rhetoric, reaching a remarkable peak of 30 points in 2014. Following the 2016 Republican electoral victory, there was a dramatic decline in relative Democratic-leaning rhetoric, with the partisan advantage plummeting from roughly 30 to merely 6 points. This level remained relatively stable throughout the Trump presidency. This substantial reduction likely reflects firms' strategic adjustments to the changed political environment and regulatory priorities under Republican governance. Following the 2020 Democratic electoral success, we observe a resurgence in relative Democratic-leaning language, with partisan advantage climbing to approximately 11 points by 2021.

This pattern demonstrates that our measure effectively captures firms' political alignment through their language choices in mandatory disclosures. The measure shows notable sensitivity to the political environment, with corporate language clearly responding to election outcomes and shifts in political power. Firms appear to strategically adjust their

[25] **Online Appendix Table OA7** tabulates the top 20 partisan phrases used by Democrats and Republicans in the Item 1 and Item 7 sections of U.S. 10-K filings from 2012 to 2023.

rhetoric to align with the party in power, suggesting that this linguistic measure captures meaningful political signaling by corporations.

While these findings offer valuable insights, important caveats merit consideration. Our linguistic measure captures discursive alignment but cannot definitively determine whether these rhetorical shifts translate into concrete actions or substantive policy engagement. The analysis provides a novel window into corporate political communication, but further research is needed to validate whether linguistic adaptations represent genuine strategic realignment or merely performative rhetoric.

7. Conclusion

Alignment with government goals is an increasingly important political strategy for firms worldwide. While well established in authoritarian regimes like China, it is also gaining traction in liberal market economies. In the U.S., a country historically resistant to industrial policy, recent administrations have used both incentives and coercive tools to steer corporate behavior toward national objectives in technology, climate, and geopolitics. The Biden administration's CHIPS and Science Act and Inflation Reduction Act offer major incentives to firms aligned with strategic goals, while the Trump administration has used tariffs to push for reshoring and expanding manufacturing capacity within the U.S. As state influence expands, firms that fail to align may face regulatory or competitive disadvantages. These trends highlight the need for a robust measure of FPA to study political alignment strategies across institutional contexts.

We construct a firm-year measure of FPA in China that captures the frequency of policy-aligned mentions in firms' annual reports and distinguishes between action alignment and rhetorical alignment. We validate the measure by showing its correlation with alternative indicators of firm behavior aligned with government policies, as well as with macro-level

political risks, and firm-level characteristics such as size, profitability, and leverage—factors that indicate firm-level political risks and dependence on government resources.

We find that FPA has increased while political connection has declined since 2012, following the launch of China's Anti-Corruption Campaign. This suggests that firms may substitute FPA for political connection when the latter becomes less effective. However, firms with ties to the central leadership are less likely to increase FPA, indicating that such ties remain a viable strategy. Overall, our findings suggest that FPA is a distinct political strategy that can serve as an alternative mechanism for managing political risk within a broader portfolio of firm–government engagement.

Finally, we show that higher FPA is associated with favorable outcomes, including fewer regulatory penalties, greater access to bank loans and government subsidies, and smaller stock price declines during political shocks. These results confirm the predictive validity of our measure. Moreover, action alignment—rather than rhetorical alignment—is consistently linked to regulatory leniency and resilience, highlighting it as a particularly effective strategy for managing political risk.

Future research should extend FPA measurement to the U.S. and other economies. Cross-country FPA measures would enable comparative analysis of how firms manage political risks across institutional contexts. Two examples highlight the potential of this agenda. First, the role of FPA likely varies across regimes: in countries with weak rule of law and frequent state intervention, firms may adopt FPA as "insurance" against regulatory risk, whereas in stronger legal systems, FPA may be used to access state benefits like subsidies. Second, in systems that allow lobbying and donations, FPA may act as a substitute—when lobbying is less effective—or as a complement, enhancing a firm's political leverage. These dynamics suggest the need to better understand how FPA interacts with other corporate political strategies across institutional contexts.

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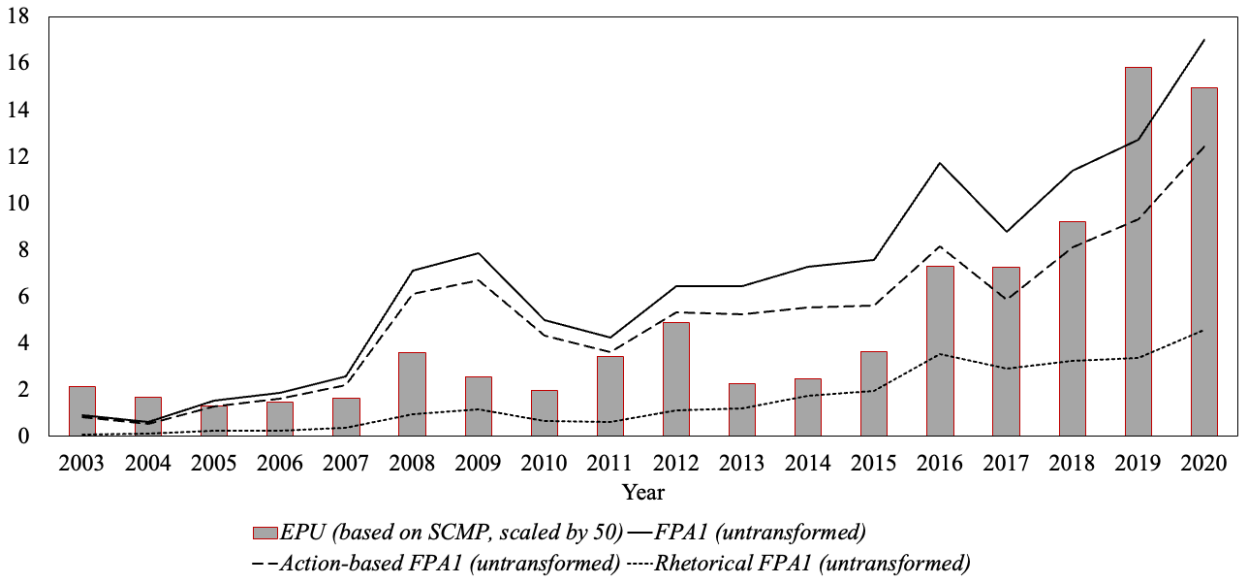
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Figure 1. Annual distribution of FPA

This figure presents the average frequency of FPA, action-based FPA, and rhetorical FPA, all untransformed, in annual reports from 2003 to 2020. FPA1-related measures are constructed using the *People's Daily* dictionary, and FPA2-related measures are based on the *Government Work Report* dictionary. Additionally, it displays the average Economic Policy Uncertainty Index derived from the *South China Morning Post* (*SCMP*) as a bar plot.



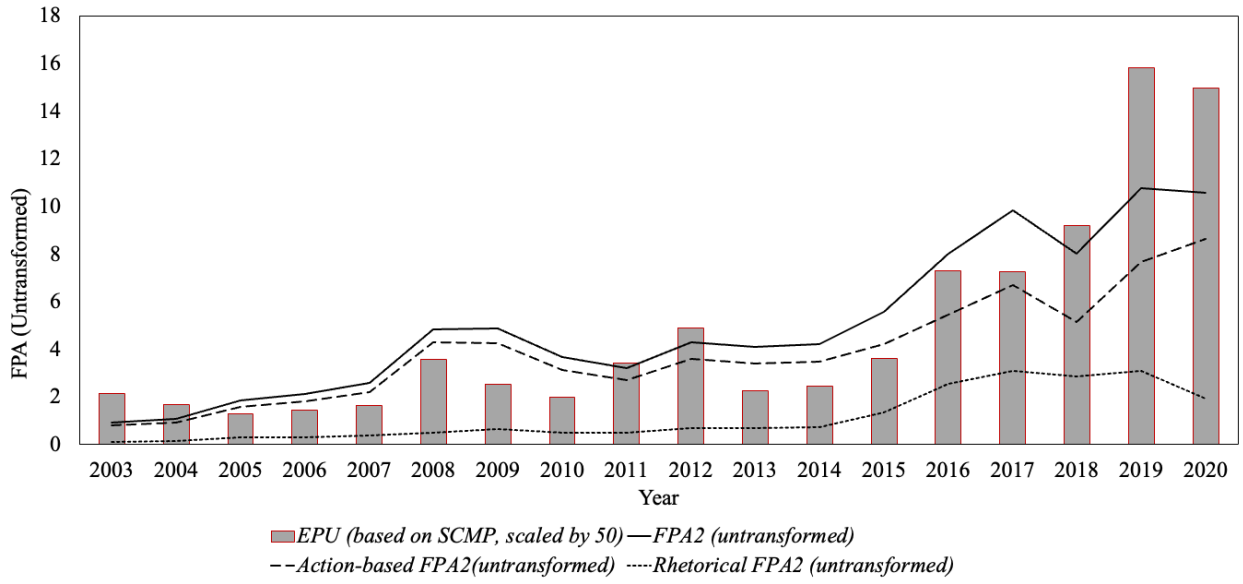


Figure 2. Industry distribution of FPA

This figure presents the average frequency of FPA (untransformed) by industry, based on *People's Daily* and *Government Work Report* dictionary, respectively.

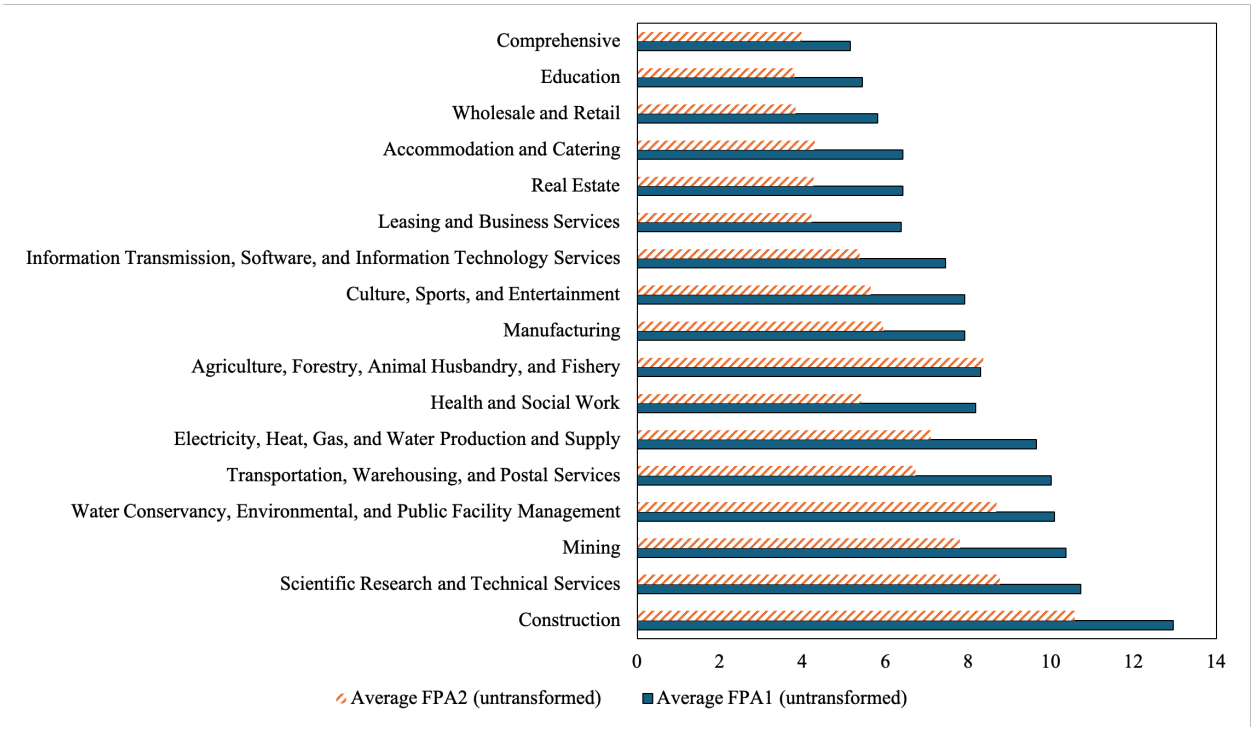


Figure 3. Partisan leaning in U.S. 10-K filings

This figure plots the average net partisan leaning score derived from the Item 1 and Item 7 sections in U.S. 10-K filings from 2012 to 2023. *Net Partisan Leaning* is calculated as *Democratic Leaning* minus *Republican Leaning*. *Democratic (Republican) Leaning* is calculated as the sum of the products of frequency of democratic (republican) phrases mentioned and their respective partisan scores from Gentzkow, Shapiro, and Taddy (2019), scaled by the total frequency of partisan phrases mentioned.

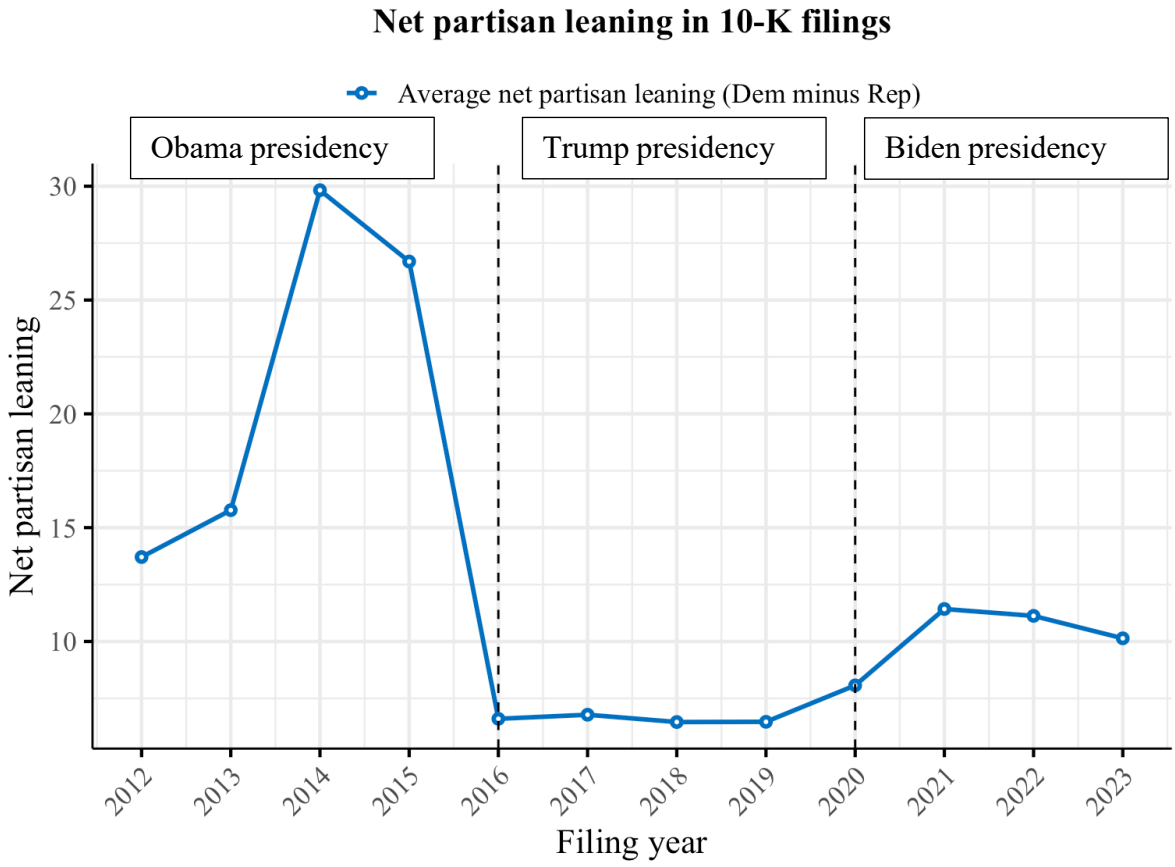


Table 1. Summary statistics of FPA

This table reports the summary statistics of the raw frequency of policy-aligned mentions in annual reports, i.e., FPA1 (untransformed) and FPA2 (untransformed), based on two dictionaries (*People's Daily* and *Government Work Report*). Panel A reports the aggregated frequency across all firms for the 25 most frequently referenced policies in annual reports from 2003 to 2020. Panel B tabulates the average FPA1 and FPA2 for all firms, SOEs, and Non-SOEs from 2003 to 2020 respectively.

Panel A. Aggregated frequency across all firms for the 25 most frequently referenced policies in annual reports

FPA1 (based on *People's Daily*)				**FPA2 (based on *Government Work Report*)**			
In Chinese	**In English**	**#Total freq**	**Action-based**	**In Chinese**	**In English**	**#Total freq**	**Action-based**
社会责任	Social Responsibility	81,720	77%	精准扶贫/脱贫攻坚	Poverty Alleviation	52,553	61%
可持续发展	Sustainable Development	66,232	84%	可持续发展	Sustainable Development	51,139	85%
精准扶贫/脱贫攻坚	Poverty Alleviation	65,542	58%	自主创新	Indigenous Innovation	26,917	90%
自主创新	Indigenous Innovation	23,245	90%	高质量发展	High-quality Development	17,252	75%
高质量发展	High-quality Development	17,252	75%	一带一路	Belt and Road Initiative	14,194	72%
一带一路	Belt and Road Initiative	14,883	71%	循环经济	Circular Economy	12,559	87%
党建	Building of CCP	11,979	94%	公共服务	Public Services	7,683	76%
公共服务	Public Services	7,683	76%	绿色发展	Green Development	6,478	76%
新常态	New Normal	7,286	50%	以人为本	People-Centered Approach	6,469	94%
供给侧结构性改革	Supply-side structural reform	6,468	48%	供给侧结构性改革	Supply-side structural reform	6,468	48%
绿色发展	Green Development	6,324	76%	党建	Building of CCP	6,310	94%
以人为本	People-Centered Approach	5,596	93%	改革创新	Reform and Innovation	4,985	90%
循环经济	Circular Economy	5,550	87%	新常态	New Normal	4,772	52%
改革创新	Reform and Innovation	4,933	90%	中国特色	Chinese Characteristics	4,349	76%
中国特色	Chinese Characteristics	4,490	75%	科学发展观	Scientific Outlook on Development	4,231	96%
生态文明	Ecological Civilization	4,196	54%	生态文明	Ecological Civilization	4,186	54%
科学发展观	Scientific Outlook on Development	3,938	96%	农业产业化	Agricultural Industrialization	3,803	62%
小康社会	Moderately Prosperous Society	3,207	45%	小康社会	Moderately Prosperous Society	3,174	45%
和谐发展	Harmonious Development	2,383	92%	现代企业制度	Modern Enterprise System	2,791	99%
新发展理念	New Development Philosophy	2,016	85%	社会保障体系	Social Security System	2,528	94%
全面深化改革	Comprehensively Deepening Reforms	1,859	56%	和谐发展	Harmonious Development	2,331	92%
生态环境保护	Ecological Environment Protection	1,573	73%	新发展理念	New Development Concept	1,922	86%
国家安全	National Security	1,292	36%	生态环境保护	Ecological Environment Protection	1,921	71%
生态系统	Ecosystem	1,179	78%	海绵城市	Sponge Cities	1,814	79%
和谐社会	Harmonious Society	1,139	85%	自主知识产权	Indigenous Intellectual Property	1,684	91%

Table 1. Summary statistics of FPA (continued)

Panel B. Annual distribution of FPA for full sample, SOEs, and non-SOEs

	Full sample			SOE sample			Non-SOE sample		
Year	**#firm**	**Average FPA1** (untransformed)	**Average FPA2** (untransformed)	**#firm**	**Average FPA1** (untransformed)	**Average FPA2** (untransformed)	**#firm**	**Average FPA1** (untransformed)	**Average FPA2** (untransformed)
2003	1,253	0.92	0.92	906	0.98	0.95	347	0.77	0.84
2004	1,338	0.63	1.08	942	0.69	1.12	396	0.50	0.99
2005	1,335	1.54	1.86	921	1.68	1.98	414	1.22	1.62
2006	1,414	1.89	2.13	916	2.09	2.32	498	1.50	1.77
2007	1,521	2.57	2.61	936	2.92	2.91	585	2.02	2.12
2008	1,552	7.10	4.83	933	8.71	5.77	619	4.67	3.40
2009	1,698	7.86	4.89	900	10.50	6.15	798	4.88	3.48
2010	2,029	5.00	3.66	931	6.14	4.07	1,098	4.04	3.31
2011	2,290	4.24	3.21	953	4.58	3.26	1,337	4.00	3.17
2012	2,427	6.44	4.28	959	6.84	4.33	1,468	6.18	4.25
2013	2,470	6.46	4.11	956	7.14	4.38	1,514	6.03	3.93
2014	2,585	7.27	4.21	960	8.47	4.56	1,625	6.57	4.01
2015	2,771	7.56	5.58	968	8.88	6.47	1,803	6.85	5.10
2016	3,052	11.72	8.01	999	13.86	9.80	2,053	10.68	7.14
2017	3,422	8.79	9.82	1,007	12.17	12.21	2,415	7.38	8.82
2018	3,461	11.38	8.01	997	16.49	12.38	2,464	9.31	6.24
2019	3,802	12.71	10.78	1,153	18.83	17.00	2,649	10.05	8.07
2020	4,263	17.01	10.58	1,212	24.16	16.63	3,051	14.17	8.18

Table 2. FPA and investment trends for MIC 2025 and BRI

This table examines the investment trends for two pivotal Chinese government initiatives. The Made in China 2025 initiative, launched in 2015, aims to transform China from a low-tech manufacturing hub to a global leader in high-tech industries. The Belt and Road Initiative, introduced in 2013, aims to enhance trade and investment connectivity between China and other countries. Panels A and B present the statistics of investments and FPA for these two initiatives, respectively.

Panel A. Made in China 2025 (MIC 2025)

	Sum of FPA (untransformed)			MIC2025 Industry Trends			
Year	*FPA_MIC2025*	Action-based *FPA_MIC2025*	Rhetorical *FPA_MIC2025*	#firms in MIC industries	%firms in MIC industries	Market value of firms in MIC industries (USD billions)	Market value share of firms in MIC industries (%)
2014	31	11	20	995	38.34%	1,266	30.55%
2015	361	143	218	1,099	38.49%	2,110	29.19%
2016	435	187	248	1,206	39.66%	1,904	33.86%
2017	529	231	298	1,425	39.52%	2,264	33.68%
2018	389	156	233	1,467	41.64%	1,564	33.27%
2019	343	139	204	1,564	42.39%	2,334	32.03%
2020	279	131	148	1,748	41.14%	3,988	25.93%

Panel B. Belt and Road Initiative (BRI)

	Sum of FPA (untransformed)			Investment Trends in BRI Countries
Year	*FPA_BRI*	Action-based *FPA_BRI*	Rhetorical *FPA_BRI*	Construction and other investments in BRI countries (USD billions)
2013	32	15	17	91.16
2014	780	439	341	111.47
2015	1,596	1,024	572	122.25
2016	2,222	1,477	745	97.00
2017	3,037	2,097	940	113.70
2018	2,589	1,893	696	117.79

Table 3. FPA and firm actions for three flagship policies

This table reports regression results examining the relationship between FPA and corresponding action across three flagship policies: Indigenous Innovation, Poverty Alleviation, and Environmental Protection (Panels A through C). The firm-year sample periods vary depending on when each policy was first announced. *FPA_Innov*, *FPA_Poverty*, and *FPA_Envr* are measured as inverse hyperbolic sine transformations of policy-aligned mentions for each respective policy in annual reports. All variable definitions are provided in Appendix A. Standard errors are clustered at the industry level and presented in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

Panel A. Indigenous Innovation policy

Dependent variables:	*FPA_Innov*		*FPA_Innov_Action*		*FPA_Innov_Rhetoric*	
	(1)	(2)	(3)	(4)	(5)	(6)
$NumPatent_{t-1}$	0.022***		0.025***		-0.005	
	(0.008)		(0.007)		(0.003)	
$NumPatent_{t}$	0.048***		0.045***		0.007*	
	(0.008)		(0.008)		(0.004)	
$NumPatent_{t+1}$	0.029***		0.026***		0.006*	
	(0.008)		(0.008)		(0.003)	
$RDSpend_{t-1}$		0.002**		0.002**		-0.0001
		(0.001)		(0.001)		(0.0003)
$RDSpend_{t}$		0.002**		0.002**		0.0003
		(0.001)		(0.001)		(0.0003)
$RDSpend_{t+1}$		0.003**		0.003**		0.0002
		(0.001)		(0.001)		(0.0003)
Sample period	2008-2020					
Observations	26,847	26,847	26,847	26,847	26,847	26,847
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R2	0.564	0.565	0.552	0.553	0.265	0.265

Panel B. Poverty Alleviation policy

Dependent variables:	*FPA_Poverty*		*FPA_Poverty_Action*		*FPA_Poverty_Rhetoric*	
	(1)	(2)	(3)	(4)	(5)	(6)
$TPAPlan_{t-1}$	0.113***		0.185***		0.054	
	(0.020)		(0.024)		(0.037)	
$TPAPlan_{t}$	1.713***		1.704***		0.764***	
	(0.027)		(0.030)		(0.044)	
$TPAPlan_{t+1}$	0.115***		0.110***		0.072	
	(0.022)		(0.023)		(0.039)	
$PovAmt_{t-1}$		3.453***		3.209***		0.798
		(1.153)		(1.105)		(0.483)
$PovAmt_{t}$		3.270***		3.054***		0.358
		(1.081)		(0.993)		(0.424)
$PovAmt_{t+1}$		2.331***		1.793***		0.488
		(0.835)		(0.645)		(0.578)
Sample period	2015-2020[26]					
Observations	15,110	15,110	15,110	15,110	15,110	15,110
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R2	0.781	0.364	0.761	0.435	0.616	0.552

[26] The policy of "Poverty Alleviation" was announced in 2015.

Table 3. FPA and firm actions for three flagship policies (continued)

Panel C. Environmental Protection policy

Dependent variables:	*FPA_Envr*		*FPA_Envr_Action*		*FPA_Envr_Rhetoric*	
	(1)	(2)	(3)	(4)	(5)	(6)
$EPInvest_{t-1}$	0.002**		0.002**		-0.00005	
	(0.001)		(0.001)		(0.0002)	
$EPInvest_{t}$	0.001*		0.001*		-0.0001	
	(0.001)		(0.001)		(0.0003)	
$EPInvest_{t+1}$	0.002***		0.003***		0.00004	
	(0.001)		(0.001)		(0.0003)	
$NumEP_{t-1}$		0.013*		0.014*		0.009*
		(0.008)		(0.007)		(0.005)
$NumEP_{t}$		0.023***		0.023***		0.002
		(0.006)		(0.005)		(0.003)
$NumEP_{t+1}$		0.016**		0.015**		0.005
		(0.005)		(0.005)		(0.003)
Sample period	2008-2020					
Observations	28,921	28,921	28,921	28,921	28,921	28,921
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R2	0.561	0.561	0.542	0.543	0.411	0.412

Table 4. Sample selection

This table outlines the sample selection process for the panel analyses and event study related to the Common Prosperity Policy, presented in Panels A and B, respectively.

Panel A: Sample selection for panel analyses

	#firms	#obs
Publicly listed A-share firms from 2008 to 2018	3,534	27,735
Less:		
Observations with missing CEO or Chairman information	3,527	27,514
Observations with missing FPA determinants	3,036	20,213
Final sample:	3,036	21,738

Panel B: Sample selection for the event study for Common Prosperity Policy

	#firms (#obs)
Non-financial A-share firms listed for more than one year as of the end of 2020	3,477
Less:	
Firms with event windows smaller than 3 trading days	3,418
Firms with pre-event trading windows smaller than 100 trading days	3,415
Firms with earnings announcements during the event window	3,215
Firms with missing fundamentals	3,083
Final sample:	3,083

Table 5. Summary statistics of regression sample

This table presents summary statistics for the variables used in the regression analyses. Panel A reports the descriptive statistics, while Panel B presents the Pearson correlation coefficients among the regression variables. All variable definitions are provided in Appendix A. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

Panel A. Descriptive statistics

Statistic	N	Mean	St. Dev.	Min	Median	Max
FPA1 (untransformed)	21,738	7.915	5.883	0	6	21
FPA1_Action (untransformed)	21,738	5.891	4.624	0	5	16
FPA1_Rhetoric (untransformed)	21,738	1.898	1.919	0	1	6
FPA1_Scope (untransformed)	21,738	3.294	1.831	0	3	7
FPA1_Scaled	21,738	0.064	0.093	0	0.044	0.750
FPA2 (untransformed)	21,738	5.745	4.885	0	4	17
FPA2_Action (untransformed)	21,738	4.258	3.799	0	3	13
FPA2_Rhetoric (untransformed)	21,738	1.436	1.821	0	1	6
FPA2_Scope (untransformed)	21,738	2.719	1.717	0	2	6
FPA2_Scaled	21,738	0.046	0.067	0	0.030	0.607
Size	21,738	22.452	0.893	20.5	22.414	24.094
PoliticalConnection	21,738	0.339	0.473	0	0	1
SOE	21,738	0.425	0.494	0	0	1
CC_Exec	21,738	0.021	0.143	0	0	1
CC_HQ	21,738	0.339	0.473	0	0	1
ROA	21,738	0.036	0.046	-0.069	0.033	0.128
Leverage	21,738	0.447	0.204	0.107	0.446	0.806
POST	21,738	0.766	0.424	0	1	1
Growth	21,738	0.172	0.297	-0.301	0.124	0.94
Length	21,738	4.936	0.452	3.332	5.030	5.425
EPU	21,738	205.664	101.278	82.245	179.041	364.833
CountryRisk	21,738	235.317	20.558	182.406	234.244	263.661
Reg_Action	23,688	0.175	0.380	0	0	1
BankLoan	23,688	1,809.741	3,154.631	0	456.228	12,040.420
Subsidy	23,688	28.248	43.070	0	10.450	165.231
InterestRate	16,981	0.069	0.037	0.018	0.061	0.170
CAR[-1,1]	3,083	-1.120	3.977	-9.173	-0.915	7.081
CRR	3,083	-1.790	3.927	-9.686	-1.551	6.193

Table 5. Summary statistics of regression sample (continued)

Panel B. Pearson correlation

	FPA1	*FPA1_Action*	*FPA1_Rhetoric*	*FPA2*	*FPA2_Action*	*FPA2_Rhetoric*	*CC_Exec*	*CC_HQ*
FPA1								
FPA1_Action	0.921***							
FPA1_Rhetoric	0.646***	0.368***						
FPA2	0.804***	0.730***	0.568***					
FPA2_Action	0.730***	0.779***	0.328***	0.909***				
FPA2_Rhetoric	0.536***	0.311***	0.812***	0.644***	0.346***			
CC_Exec	0.008	0.014**	-0.001	-0.009	-0.001	-0.006		
CC_HQ	0.006	0.005	0.006	-0.035***	-0.039***	-0.001	0.089***	
PoliticalConnection	0.038***	0.028***	0.045***	0.038***	0.030***	0.037***	-0.042***	-0.012*
SOE	0.090***	0.149***	-0.062***	0.083***	0.138***	-0.045***	0.065***	-0.009
ROA	0.052***	0.039***	0.045***	0.017**	0.008	0.019***	-0.016**	0.062***
Size	0.308***	0.253***	0.281***	0.262***	0.202***	0.280***	0.054***	0.076***
Leverage	0.045***	0.076***	-0.031***	0.034***	0.065***	-0.021***	0.021***	-0.046***
Growth	0.004	-0.012*	0.020***	0.011	-0.003	0.020***	-0.011	0.010
Length	0.201***	0.111***	0.279***	0.172***	0.086***	0.269***	0.003	-0.014**
EPU	0.162***	0.062***	0.271***	0.223***	0.086***	0.397***	-0.012*	0.012*
CountryRisk	0.165***	0.105***	0.193***	0.121***	0.083***	0.173***	-0.004	0.009

	Political Connection	*SOE*	*ROA*	*Size*	*Leverage*	*Growth*	*Length*	*EPU*
SOE	-0.175***							
ROA	0.076***	-0.125***						
Size	0.009	0.101***	0.313***					
Leverage	-0.067***	0.286***	-0.376***	0.059***				
Growth	0.027***	-0.082***	0.300***	0.146***	0.029***			
Length	0.031***	-0.160***	0.038***	0.252***	-0.078***	0.044***		
EPU	0.006	-0.125***	0.028***	0.197***	-0.093***	0.039***	0.408***	
CountryRisk	0.025***	-0.104***	-0.042***	0.154***	-0.082***	-0.105***	0.294***	0.251***

Table 6. Determinants of FPA

This table reports the regression results of estimating equation (1): the determinants of FPA. The firm-year level sample covers 2008-2018. The dependent variable in columns (1) to (3) is *FPA1*, measured as the inverse hyperbolic sine (HIS) transformation of policy-aligned mentions in annual reports, based on the *People's Daily* dictionary. The dependent variable in columns (4) to (6) is *FPA2*, defined similarly, but based on the *Government Work Report* dictionary. All variable definitions are provided in Appendix A. Standard errors are clustered at the industry level and presented in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

Dependent variables:		*FPA1*			*FPA2*	
	(1)	(2)	(3)	(4)	(5)	(6)
EPU_{t-1}	0.001***			0.002***		
	(0.0002)			(0.0002)		
$CountryRisk_{t-1}$		0.004***			0.002***	
		(0.0003)			(0.001)	
$Size_{t-1}$	0.286***	0.289***	0.121***	0.296***	0.350***	0.043
	(0.018)	(0.025)	(0.022)	(0.020)	(0.031)	(0.028)
ROA_{t-1}	-0.457***	-0.444**	0.881***	-0.782***	-1.168***	0.867***
	(0.133)	(0.158)	(0.163)	(0.157)	(0.206)	(0.191)
$Leverage_{t-1}$	0.258***	0.264***	0.239***	0.122	0.110	0.149**
	(0.087)	(0.081)	(0.070)	(0.076)	(0.071)	(0.068)
$Growth_{t-1}$	-0.116***	-0.075***	-0.002	-0.085**	-0.053**	-0.007
	(0.026)	(0.019)	(0.022)	(0.030)	(0.020)	(0.019)
SOE_{t-1}	-0.006	0.001	0.063**	0.063**	0.043	0.080**
	(0.030)	(0.028)	(0.022)	(0.027)	(0.036)	(0.029)
$Length_t$	0.184***	0.176***	-0.077***	0.018	0.085***	-0.055*
	(0.024)	(0.021)	(0.023)	(0.023)	(0.024)	(0.027)
Observations	21,738	21,738	21,738	21,738	21,738	21,738
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	No	Yes
S.E. cluster	Industry	Industry	Industry	Industry	Industry	Industry
Adjusted R2	0.383	0.386	0.467	0.402	0.379	0.444

Table 7. Political connection versus FPA

This table reports the regression results on examining the discriminant validity of FPA relative to political connection. The firm-year level sample covers 2008-2018. Panel A presents results estimating equation (2): changes in FPA and political connection around the Anti-Corruption Campaign. *PoliticalConnection* is an indicator variable that equals one if the CEO or Chairman is or was a member of Chinese People's Congress, Chinese People's Political Consultative Conference, Party Committee, Party Congress, or has worked in government agencies, and zero otherwise. *POST* is an indicator variable equal to one for years from 2012 onward, and zero otherwise.

Panel B presents results estimating equation (3): changes in FPA and central leadership connections around the Anti-Corruption Campaign. *CC_Exec* is an indicator variable that equals one if the firm ever has a central government-affiliated politician sitting on the board, and zero otherwise. A politician is deemed to have central government affiliation if she has ties to the Shanghai Gang, Princeling faction, Tsinghua clique, and Shaanxi Gang. *CC_HQ* is an indicator variable that equals one if the firm is headquartered in Shaanxi, Fujian, Zhejiang, Shanghai, Hebei or Beijing, and zero otherwise. All variable definitions are provided in Appendix A. Standard errors are clustered at the industry level and presented in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

Panel A. Political connection and FPA around the Anti-Corruption Campaign

Dependent variables:	*FPA1*	*FPA2*	*PoliticalConnection*
	(1)	(2)	(3)
POST	**0.599*** **	**0.311*** **	**-0.020*** **
	(0.018)	**(0.033)**	**(0.004)**
$CountryRisk_{t-1}$	0.0001	0.0002	0.0003***
	(0.0003)	(0.001)	(0.0001)
$Size_{t-1}$	0.251***	0.331***	-0.005
	(0.021)	(0.027)	(0.003)
ROA_{t-1}	0.028	-0.923***	0.212***
	(0.206)	(0.222)	(0.049)
$Leverage_{t-1}$	0.269***	0.112	0.043
	(0.073)	(0.066)	(0.026)
$Growth_{t-1}$	-0.041*	-0.036*	0.001
	(0.022)	(0.020)	(0.006)
SOE_{t-1}	0.053**	0.071*	0.009
	(0.023)	(0.035)	(0.015)
$Length_t$	-0.053**	-0.034	-0.013*
	(0.020)	(0.022)	(0.007)
Firm FE	Yes	Yes	Yes
Year FE	No	No	No
S.E. cluster	Industry	Industry	Industry
Observations	21,738	21,738	21,738
Adjusted R2	0.436	0.390	0.663

Table 7. Political connection versus FPA (continued)

Panel B. Central leadership connection and FPA around the Anti-Corruption Campaign

Dependent variables:	*FPA1*				*FPA2*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
POST	**0.608*** **		**0.659*** **		**0.316*** **		**0.349*** **	
	(0.018)		**(0.018)**		**(0.033)**		**(0.028)**	
POST × CC_Exec	**-0.361*** **	**-0.357*** **			**-0.228** **	**-0.227** **		
	(0.101)	**(0.101)**			**(0.100)**	**(0.099)**		
POST × CC_HQ			**-0.187*** **	**-0.186*** **			**-0.119*** **	**-0.116*** **
			(0.032)	**(0.032)**			**(0.033)**	**(0.032)**
$CountryRisk_{t-1}$	0.0001		0.0001		0.0002		0.0002	
	(0.0003)		(0.0003)		(0.001)		(0.001)	
$Size_{t-1}$	0.251***	0.121***	0.251***	0.121***	0.331***	0.043	0.331***	0.043
	(0.021)	(0.022)	(0.021)	(0.021)	(0.027)	(0.028)	(0.027)	(0.027)
ROA_{t-1}	0.040	0.892***	0.034	0.883***	-0.915***	0.874***	-0.919***	0.868***
	(0.210)	(0.165)	(0.204)	(0.159)	(0.225)	(0.192)	(0.220)	(0.188)
$Leverage_{t-1}$	0.270***	0.240***	0.261***	0.232***	0.113	0.150**	0.107	0.145*
	(0.072)	(0.069)	(0.073)	(0.070)	(0.066)	(0.067)	(0.067)	(0.068)
$Growth_{t-1}$	-0.042*	-0.003	-0.041*	-0.002	-0.036*	-0.007	-0.035	-0.007
	(0.023)	(0.022)	(0.022)	(0.022)	(0.020)	(0.019)	(0.021)	(0.019)
SOE_{t-1}	0.055**	0.065***	0.054**	0.063**	0.072*	0.082**	0.071*	0.080**
	(0.023)	(0.022)	(0.025)	(0.023)	(0.035)	(0.029)	(0.037)	(0.030)
$Length_t$	-0.052**	-0.076***	-0.049**	-0.072***	-0.033	-0.054*	-0.032	-0.052*
	(0.020)	(0.023)	(0.019)	(0.023)	(0.022)	(0.027)	(0.021)	(0.026)
Observations	21,738	21,738	21,738	21,738	21,738	21,738	21,738	21,738
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	No	Yes	No	Yes	No	Yes
S.E. cluster	Industry	Industry	Industry	Industry	Industry	Industry	Industry	Industry
Adjusted R2	0.437	0.468	0.438	0.469	0.391	0.445	0.391	0.445

Table 8. FPA and government preferential treatment

This table presents results of estimating equation (4), examining the association between FPA and government preferential treatment. The firm-year level sample covers 2008-2018. The dependent variables in Panels A through D are adverse regulatory action, bank loans, government subsidies, and interest rates, respectively. *Reg_Action* is an indicator variable that equals one if a firm faces adverse actions from any Chinese government authorities via criticism, warning, condemnation, fine, confiscation of illegal income, revocation of business license, market entry ban, etc., and zero otherwise. *FPA1_Action* and *FPA1_Rhetoric* are measured as inverse hyperbolic sine transformation of action-based and rhetorical alignment, based on *People's Daily*. *FPA2_Action* and *FPA2_Rhetoric* are measured similarly but based on *Government Work Report*. All variable definitions are provided in Appendix A. Standard errors are clustered at the industry level and presented in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

Panel A: Adverse regulatory action

Dependent variable:	Reg_Action_{t+1}			
	(1)	(2)	(3)	(4)
FPA1$_t$	**-0.010*** **			
	(0.003)			
FPA1 Action$_t$		**-0.013*** **		
		(0.002)		
FPA1_Rhetoric$_t$		**0.002**		
		(0.003)		
FPA2$_t$			**-0.010*** **	
			(0.002)	
FPA2_Action$_t$				**-0.013*** **
				(0.002)
FPA2_Rhetoric$_t$				**0.004**
				(0.003)
ROA_t	-1.149***	-1.149***	-1.151***	-1.152***
	(0.077)	(0.076)	(0.077)	(0.077)
$PoliticalConnection_t$	0.008	0.008	0.008	0.008
	(0.006)	(0.006)	(0.006)	(0.006)
CC_Exec	-0.002	-0.002	-0.003	-0.003
	(0.020)	(0.020)	(0.020)	(0.020)
CC_HQ	-0.026***	-0.025***	-0.026***	-0.026***
	(0.003)	(0.003)	(0.003)	(0.003)
$Size_t$	0.002	0.002	0.001	0.002
	(0.005)	(0.005)	(0.005)	(0.005)
$Leverage_t$	0.083***	0.083***	0.082***	0.083***
	(0.020)	(0.020)	(0.020)	(0.020)
$Growth_t$	0.015**	0.014**	0.015**	0.015**
	(0.005)	(0.005)	(0.005)	(0.005)
SOE_t	-0.078***	-0.077***	-0.078***	-0.077***
	(0.004)	(0.004)	(0.004)	(0.004)
$Length_t$	0.055***	0.055***	0.056***	0.056***
	(0.006)	(0.006)	(0.006)	(0.006)
Observations	23,688	23,688	23,688	23,688
Industry, year FE	Yes	Yes	Yes	Yes
S.E. cluster	Industry	Industry	Industry	Industry
Adjusted R2	0.057	0.058	0.058	0.058

Table 8. FPA and government preferential treatment (continued)

Panel B. Bank loan

Dependent variable:	*Log(BankLoan$_{t+1}$)*			
	(1)	(2)	(3)	(4)
FPA1$_t$	**0.236*** **			
	(0.028)			
FPA1_Action$_t$		**0.175*** **		
		(0.041)		
FPA1_Rhetoric$_t$		**0.104*** **		
		(0.027)		
FPA2$_t$			**0.236*** **	
			(0.018)	
FPA2_Action$_t$				**0.186*** **
				(0.025)
FPA2_Rhetoric$_t$				**0.111*** **
				(0.020)
Observations	23,688	23,688	23,688	23,688
Controls	Yes	Yes	Yes	Yes
Industry, year FE	Yes	Yes	Yes	Yes
S.E. cluster	Industry	Industry	Industry	Industry
Adjusted R2	0.501	0.501	0.502	0.502

Panel C. Government subsidy

Dependent variable:	*Log(Subsidy$_{t+1}$)*			
	(1)	(2)	(3)	(4)
FPA1$_t$	**0.107*** **			
	(0.013)			
FPA1_Action$_t$		**0.080*** **		
		(0.014)		
FPA1_Rhetoric$_t$		**0.051*** **		
		(0.013)		
FPA2$_t$			**0.105*** **	
			(0.016)	
FPA2_Action$_t$				**0.071*** **
				(0.018)
FPA2_Rhetoric$_t$				**0.073*** **
				(0.010)
Observations	23,688	23,688	23,688	23,688
Controls	Yes	Yes	Yes	Yes
Industry, year FE	Yes	Yes	Yes	Yes
S.E. cluster	Industry	Industry	Industry	Industry
Adjusted R2	0.306	0.306	0.306	0.307

Table 8. FPA and government preferential treatment (continued)

Panel D. Interest rate

Dependent variable:	*InterestRate*$_{t+1}$			
	(1)	(2)	(3)	(4)
FPA1$_t$	**0.00002**			
	(0.0004)			
FPA1_Action$_t$		**-0.0003**		
		(0.0004)		
FPA1_Rhetoric$_t$		**0.0004**		
		(0.001)		
FPA2$_t$			**0.0001**	
			(0.0003)	
FPA2_Action$_t$				**-0.0004**
				(0.0004)
FPA2_Rhetoric$_t$				**0.001**
				(0.001)
Observations	16,981	16,981	16,981	16,981
Controls	Yes	Yes	Yes	Yes
Industry, year FE	Yes	Yes	Yes	Yes
S.E. cluster	Industry	Industry	Industry	Industry
Adjusted R2	0.037	0.037	0.037	0.037

Table 9. FPA and market reaction to the Common Prosperity Policy

This table presents results of estimating equation (5), examining the market reaction to the announcement of the Common Prosperity Policy on August 17th, 2021. The sample is structured at the firm level. The dependent variable is *CAR[-1,1*], the three-day market-adjusted cumulative abnormal return. The first two columns report results for *FPA1* while the next two columns present results for *FPA2*. All variable definitions are provided in Appendix A. Standard errors are clustered at the industry level and presented in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

Dependent variable:	*CAR[-1,1]*			
	(1)	(2)	(3)	(4)
FPA1$_{t-1}$	**0.318*** **			
	(0.101)			
FPA1_Action$_{t-1}$		**0.210** **		
		(0.084)		
FPA1_Rhetoric$_{t-1}$		**0.041**		
		(0.050)		
FPA2$_{t-1}$			**0.202*** **	
			(0.066)	
FPA2_Action$_{t-1}$				**0.109** **
				(0.048)
FPA2_Rhetoric$_{t-1}$				**0.100**
				(0.061)
PoliticalConnection$_{t-1}$	-0.053	-0.050	-0.042	-0.042
	(0.095)	(0.095)	(0.098)	(0.097)
SOE$_{t-1}$	1.071***	1.077***	1.071***	1.099***
	(0.229)	(0.241)	(0.225)	(0.225)
CC_Exec	0.626**	0.617**	0.641**	0.634**
	(0.317)	(0.314)	(0.318)	(0.320)
CC_HQ	0.270***	0.263***	0.263***	0.257***
	(0.091)	(0.092)	(0.091)	(0.092)
Length$_{t-1}$	-0.056	-0.001	-0.019	-0.005
	(0.457)	(0.452)	(0.490)	(0.491)
ROA$_{t-1}$	3.102	3.091	3.069	3.036
	(2.443)	(2.460)	(2.450)	(2.462)
Size$_{t-1}$	0.074	0.078	0.083	0.088
	(0.117)	(0.116)	(0.117)	(0.117)
Leverage$_{t-1}$	1.319**	1.326**	1.334**	1.322**
	(0.640)	(0.639)	(0.653)	(0.660)
Growth$_{t-1}$	-1.135***	-1.135***	-1.149***	-1.147***
	(0.311)	(0.311)	(0.312)	(0.309)
Constant	-4.659	-4.666	-4.527	-4.547
	(3.401)	(3.391)	(3.539)	(3.586)
Observations	3,038	3,038	3,038	3,038
S.E. cluster	Industry	Industry	Industry	Industry
Adjusted R2	0.034	0.033	0.034	0.033

Appendix A. Variable definition

Variable names	Definitions	Sources
Firm political alignment (FPA):		
FPA1	Inverse hyperbolic sine transformation of the number of policy-aligned mentions in annual reports, based on the top 40 most frequently referenced policies in *People's Daily*	*Annual reports*
FPA1_Action	Inverse hyperbolic sine transformation of the number of action-based policy-aligned mentions in annual reports, based on the top 40 most frequently referenced policies in *People's Daily*	*Annual reports*
FPA1_Rhetoric	Inverse hyperbolic sine transformation of the number of rhetorical policy-aligned mentions in annual reports, based on the top 40 most frequently referenced policies in *People's Daily*	*Annual reports*
FPA2	Inverse hyperbolic sine transformation of the number of policy-aligned mentions in annual reports, based on the top 40 most frequently referenced policies in *Government Work Report*	*Annual reports*
FPA2_Action	Inverse hyperbolic sine transformation of the number of action-based policy-aligned mentions in annual reports, based on the top 40 most frequently referenced policies in *Government Work Report*	*Annual reports*
FPA2_Rhetoric	Inverse hyperbolic sine transformation of the number of rhetorical policy-aligned mentions in annual reports, based on the top 40 most frequently referenced policies in *Government Work Report*	*Annual reports*
FPA_Innov	Inverse hyperbolic sine transformation of the number of policy-aligned mentions about "indigenous innovation" in annual reports, i.e., "Indigenous Innovation (自主创新)", "Indigenous Intellectual Property (自主知识产权)", and "Indigenous Brands (自主品牌)"	*Annual reports*
FPA_Innov_Action	Inverse hyperbolic sine transformation of the number of action-based policy-aligned mentions about "indigenous innovation" in annual reports	*Annual reports*
FPA_Innov_Rhetoric	Inverse hyperbolic sine transformation of the number of rhetorical policy-aligned mentions about "indigenous innovation" in annual reports	*Annual reports*
FPA_Poverty	Inverse hyperbolic sine transformation of the number of policy-aligned mentions about "poverty alleviation" in annual reports, i.e., "Targeted Poverty Alleviation (精准扶贫)", "Fight Against Poverty (脱贫攻坚)"	*Annual reports*
FPA_Poverty_Action	In Inverse hyperbolic sine transformation of the number of action-based policy-aligned mentions about "poverty alleviation" in annual reports	*Annual reports*
FPA_Poverty_Rhetoric	Inverse hyperbolic sine transformation of the number of rhetorical policy-aligned mentions about "poverty alleviation" in annual reports	*Annual reports*

FPA_Envr	Inverse hyperbolic sine transformation of the number of policy-aligned mentions about "environmental protection" in annual reports, i.e., "Green Development (绿色发展)", "Circular Economy (循环经济)", "Beautiful China (美丽中国)", "Ecological Civilization (生态文明)", "Ecological Construction (生态建设)", "Ecological Environmental Protection (生态环境保护)", "Ecosystem" (生态系统), "Ecological Agriculture (生态农业)", "Ecological Security (生态安全)", "Returning Farmland To Forest (退耕还林)", "Sponge Cities (海绵城市)", and "River Chiefs System (河长制)"	*Annual reports*
FPA_Envr_Action	Inverse hyperbolic sine transformation of the number of action-based policy-aligned mentions about "environmental protection" in annual reports	*Annual reports*
FPA_Envr_Rhetoric	Inverse hyperbolic sine transformation of the number of rhetorical policy-aligned mentions about "environmental protection" in annual reports	*Annual reports*
FPA_MIC2025	Inverse hyperbolic sine transformation of the number of policy-aligned mentions about "Made in China 2025" (中国制造 2025) in annual reports.	*Annual reports*
FPA_BRI	Inverse hyperbolic sine transformation of the number of policy-aligned mentions about "BRI" in annual reports, i.e., "Belt and Road Initiative (一带一路)", "21st Century Maritime Silk Road (21 世纪海上丝绸之路)", and "The Silk Road Economic Belt (丝绸之路经济带)".	*Annual reports*
FPA1_Scope	Inverse hyperbolic sine transformation of the number of *unique* policies referenced in annual reports, based on the top 40 most referenced policies in *People's Daily*	*Annual reports*
FPA2_Scope	Inverse hyperbolic sine transformation of the number of *unique* policies referenced in annual reports, based on the top 40 most referenced policies in *Government Work Report*	*Annual reports*
FPA1_Scaled	The number of policy-aligned mentions in annual reports, based on the top 40 most frequently referenced policies in *People's Daily*, scaled by the number of pages of annual reports	*Annual reports*
FPA1_Scaled	The number of policy-aligned mentions in annual reports, based on the top 40 most frequently referenced policies in *Government Work Report*, scaled by the number of pages of annual reports	*Annual reports*
Policy1_Nonnegative	Inverse hyperbolic sine transformation of the number of nonnegative policy mentions in annual reports, based on the top 40 most referenced policies in *People's Daily*	*Annual reports*

Policy1_Negative	Inverse hyperbolic sine transformation of the number of negative policy mentions in annual reports, based on the top 40 most referenced policies in *People's Daily*	*Annual reports*
Policy2_Nonnegative	Inverse hyperbolic sine transformation of the number of nonnegative policy mentions in annual reports, based on the top 40 most referenced policies in *Government Work Report*	*Annual reports*
Policy2_Negative	Inverse hyperbolic sine transformation of the number of negative policy mentions in annual reports, based on the top 40 most referenced policies in *Government Work Report*	*Annual reports*
Firm characteristics:		
PoliticalConnection	An indicator variable that equals one if the CEO or Chairman is or was a member of Chinese People's Congress, Chinese People's Political Consultative Conference, Party Committee, Party Congress, or has worked in government agencies, and zero otherwise	*Author Calculation*
CC_Exec	An indicator variable that equals one if the firm ever has a central government-affiliated politician sitting on the board, and zero otherwise. A politician is deemed to have central government affiliation if she has ties to the Shanghai Gang, Princeling faction, Tsinghua clique, and Shaanxi Gang	*Author Calculation*
CC_HQ	An indicator variable that equals one if the firm is headquartered in Shannxi, Fujian, Zhejiang, Shanghai, Hebei or Beijing, and zero otherwise	*CSMAR*
SOE	An indicator variable that equals one if the government or a government entity (central or local) has ultimate controlling ownership, and zero otherwise	*CSMAR*
Leverage	Total liability divided by average total assets	*CSMAR*
Growth	Sales divided by sales in the previous year, minus one	*CSMAR*
ROA	Net income before extraordinary items divided by average total assets	*CSMAR*
Size	Natural logarithm of firm market value	*CSMAR*
Length	Natural logarithm of the number of pages in annual reports	*Annual reports*
EPU	Economic policy uncertainty index derived from the South China Morning Post	*Baker, Bloom and Davis (2016)*
CountryRisk	Textual measure for country risk derived from earnings conference calls	*Hassan et al., (2024)*
POST	An indicator variable that equals one from 2012 onward (including 2012), and zero otherwise	*CSMAR*
Common Prosperity Policy		
CRR	The cumulative raw return over the three-day window (i.e., August 16-18, 2021) centered on the announcement of the Common Prosperity Policy (August 17, 2021), in percentage	*CSMAR*

CAR[-1,1]	The cumulative return adjusted by value-weighted portfolio return over the three-day window (i.e., August 16-18, 2021) centered on the announcement of the Common Prosperity Policy (August 17, 2021), or on the annual earnings announcements, in percentage	*CSMAR*
Action measures for flagship policy		
PovAmt	RMB spend on poverty alleviation campaign divided by average sales, multiplied by 1000	*CSMAR*
TPAPlan	An indicator variable that equals one if the firm-year has any follow-up plans on poverty alleviation, and zero otherwise	*CSMAR*
RDSpend	RMB spend on R&D divided by the average total sales, multiplied by 100	*CSMAR*
NumPatent	Number of patents applied and granted	*CSMAR*
EPInvest	RMB spend on environment-related investments in billions	*CSMAR*
NumEP	Number of environment protection projects	*CSMAR*
Government preferential treatment:		
Reg_Action	An indicator variable that equals one if a firm faces adverse actions from any Chinese government authorities via criticism, warning, condemnation, fine, confiscation of illegal income, revocation of business license, market entry ban, etc., and zero otherwise	*CSMAR*
BankLoan	Long-term loan plus short-term loan, in millions	*CSMAR*
Subsidy	Government subsidies, in millions	*CSMAR*
InterestRate	Interest charges in the income statement divided by bank loan	*CSMAR, Wind*
U.S.-related measurement		
Democratic leaning	The sum of the products of frequency of democratic phrases mentioned in section Item 1 and Item 7 in 10-K filings and their respective partisan scores from Gentzkow, Shapiro, and Taddy (2019), scaled by the total frequency of partisan phrases mentioned.	*Author Calculation*
Republican leaning	The sum of the products of frequency of republican phrases mentioned in section Item 1 and Item 7 in 10-K filings and their respective partisan scores from Gentzkow, Shapiro, and Taddy (2019), scaled by the total frequency of partisan phrases mentioned.	*Author Calculation*
Net partisan leaning	The difference between *Democratic leaning* and *Republican leaning*	*Author Calculation*

Appendix B. Annual reports parsing algorithm and GLLM application

Step 1. Parse annual reports

We analyze the text of annual reports using a keyword search methodology. Specifically, we examine each sentence for the presence of the two dictionaries based on the top 40 most frequently referenced polices from *People's Daily* and *Government Work Report*, respectively. This process yields 344,429 and 251,022 policy-mentioned sentences for Chinese publicly listed firms from 2003 to 2020.

Step 2. Identify action-based and rhetorical FPA by applying GPT-4 model

Following the framework of De Kok (2025), we utilize a zero-shot approach and process each sentence with the GPT-4 model in order to identify sentences indicating firm actions aligning with government goals. The zero-shot approach works by providing the GLLM only with our instructions and the sentences on which we want to perform the task, without providing examples. This approach works well with simple tasks such as identifying whether a section of an earnings conference call discusses political risks (De Kok 2025). For our paper, our specific instructions are as follows:

- Model: gpt-4
- Temperature: 0
- System message: You are a serious research assistant who follows exact instructions and returns only valid JSON.

Round 1: Classify whether the sentence below implies that the firm actively takes action to demonstrate its alignment with the government policy or goal: {policy}. Answer using JSON in the following format: {"Action": 0 or 1}

Round 2: Classify whether the sentence below implies that the firm expresses alignment with the government policy or goal: {policy}. Answer using JSON in the following format: {" Rhetorical": 0 or 1}

In Round 1, GPT helps identify sentences that indicate action-based alignment with government policies. In Round 2, GPT helps identify sentences that reflect verbal or rhetorical alignment with government policies. We exclude sentences where "Rhetorical" = 0 in Round 2, as these do not indicate any form of alignment. After filtering, we identify a total of 317,987 *policy-aligned* sentences for Chinese publicly listed firms from 2003 to 2020 based on *People's Daily*, including 235,159 action-based and 82,828 rhetorically aligned sentences. Based on the *Government Work Report*, we identify 242,820 *policy-aligned* sentences, including 184,264 action-based and 58,556 rhetorically aligned sentences.

Step 3. Human validation

We generate a random sample of sentences from the 119 policies derived from *People's Daily* (*Government Work Support*), selecting 5 sentences per policy per year whenever possible. If a policy has fewer than 5 sentences in a given year, we include all available sentences. Three independent research assistants then manually assess each sentence to determine whether it implies action-based or rhetorical alignment. We then aggregate their classifications to establish a gold standard for accurate classification and evaluate the GLLM-generated outcomes against this benchmark.

Appendix C. Examples of policy-aligned sentences in annual reports

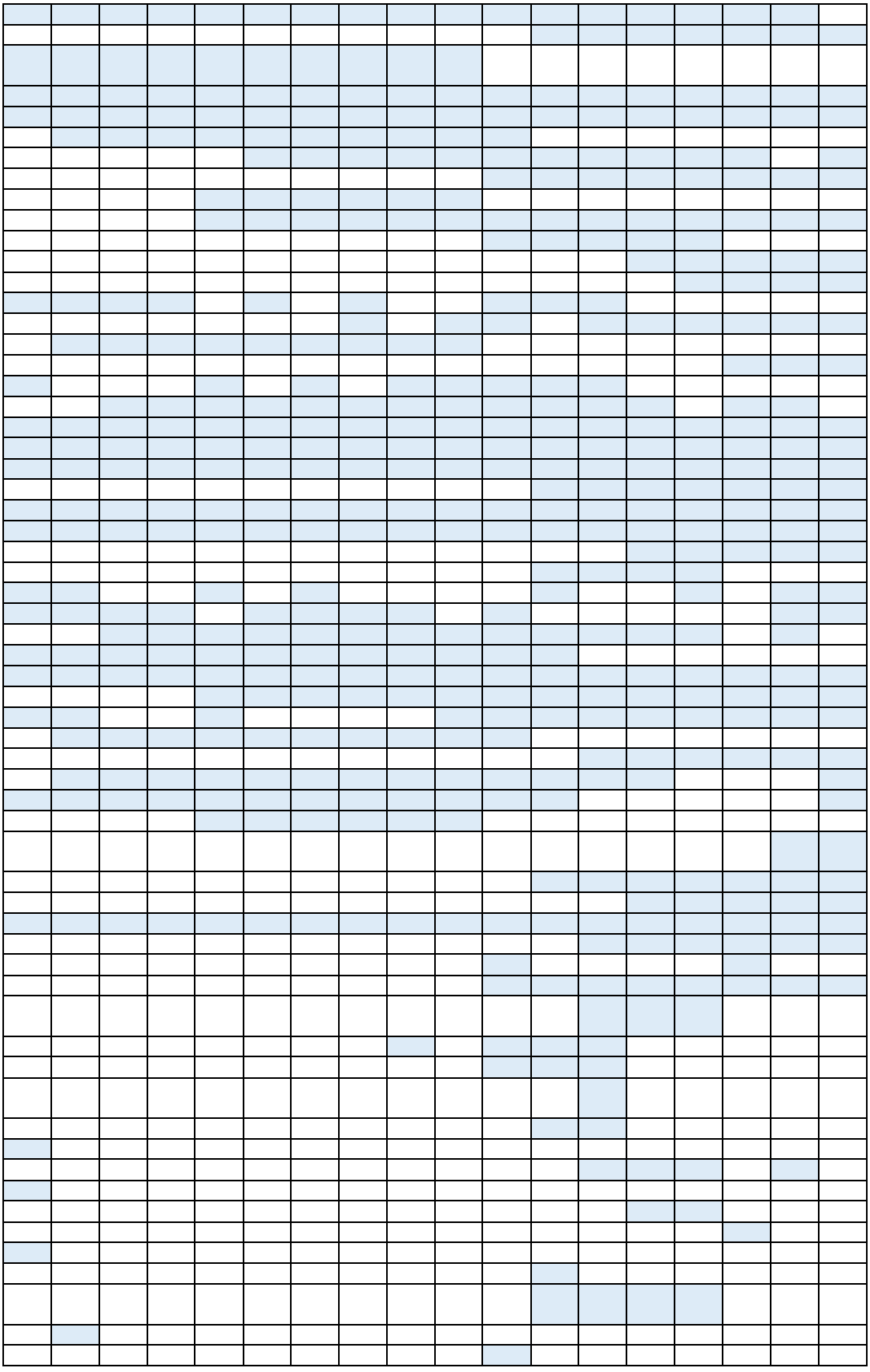
Policy	Sentence	Action-based alignment	Rhetorical alignment
Poverty Alleviation	The company will continue to actively pursue **Poverty Alleviation** efforts for the next three to five years, based on the requirements and plans of various government departments and the Gansu Province Charity Federation. (Gansu Guofang Ind&Trd Grp Ltd by Shr Ltd, 2017)	Yes	
	The **Poverty Alleviation** is the essence and highlight of the Party and country's poverty relief efforts in the new era, and it's a crucial safeguard for achieving the comprehensive well-off society and realizing the great "Chinese Dream." (Keshun Waterproof Technologies Co. Ltd, 2019)		Yes
Made in China 2025	The company advances in integrated circuits, 5G communications, aircraft engines, new energy vehicles, and new materials. The company also targets equipment shortfalls, fosters industrial Internet platforms, and creates a **Made in China 2025** demonstration area. (Changsha Jingjia Microelectronics Co Ltd, 2019)	Yes	
	The national strategies such as **Made in China 2025**, big data, cloud computing, and "Internet+" provide opportunities but also pose challenges and growing pains for traditional industry transformation. (KEHUA DATA CO, 2015)		Yes
Belt and Road Initiative	The company actively adheres to the Party Central Committee and State Council's guidance, focusing on international operations and expansion into **Belt and Road Initiative** countries, leveraging its strengths to secure overseas projects. (Poly Union Chemical Holding Group Co Ltd, 2019)	Yes	
	The **Belt and Road Initiative** offers a unique opportunity for the wire and cable industry. (Suzhou Good-Ark Electronics, 2019)		Yes
Sustainable Development	Through innovation and lean management, the company adopts wastewater treatment, water recycling, and waste recovery to promote a circular economy, enhance resource efficiency, and support **Sustainable Development**. (Shandong Weida Machinery Co Ltd, 2014)	Yes	
	Since the 18th Party Congress, ecological civilization has gained unprecedented importance—reflecting the Party's commitment to making "environmental protection a core policy and **Sustainable Development** a national strategy. (LingNan Eco & Culture-Tourism Co Ltd, 2018)		Yes
High-quality Development	The company is committed to enhancing development quality and boosting economic efficiency. Guided by the principle of **High-quality Development**, we prioritize customer service and environmental safety. Our core mission is to improve the quality and efficiency of our work. (YTO Express Group Co Ltd, 2017)	Yes	
	As China's economy shifts to **High-quality Development** and power supply-demand balance, changes in industry policies and laws introduce unforeseeable future risks for the industry. (Guodian Nanjing Automation Co. Ltd., 2019)		Yes
Indigenous Innovation	The company advances R&D in distributed energy by integrating diverse technologies to build high-efficiency energy systems, foster **Indigenous Innovation** in key areas, and drive transformation and industrialization. (XiAn Shaangu Power Co Ltd, 2016)	Yes	
	With industrial upgrading and widespread high-tech adoption, China is set to enhance its **Indigenous Innovation** and technological advancement in fine chemicals, becoming a major global producer and consumer in the sector. (Sichuan Dowell Science and Technology Inc, 2020)		Yes

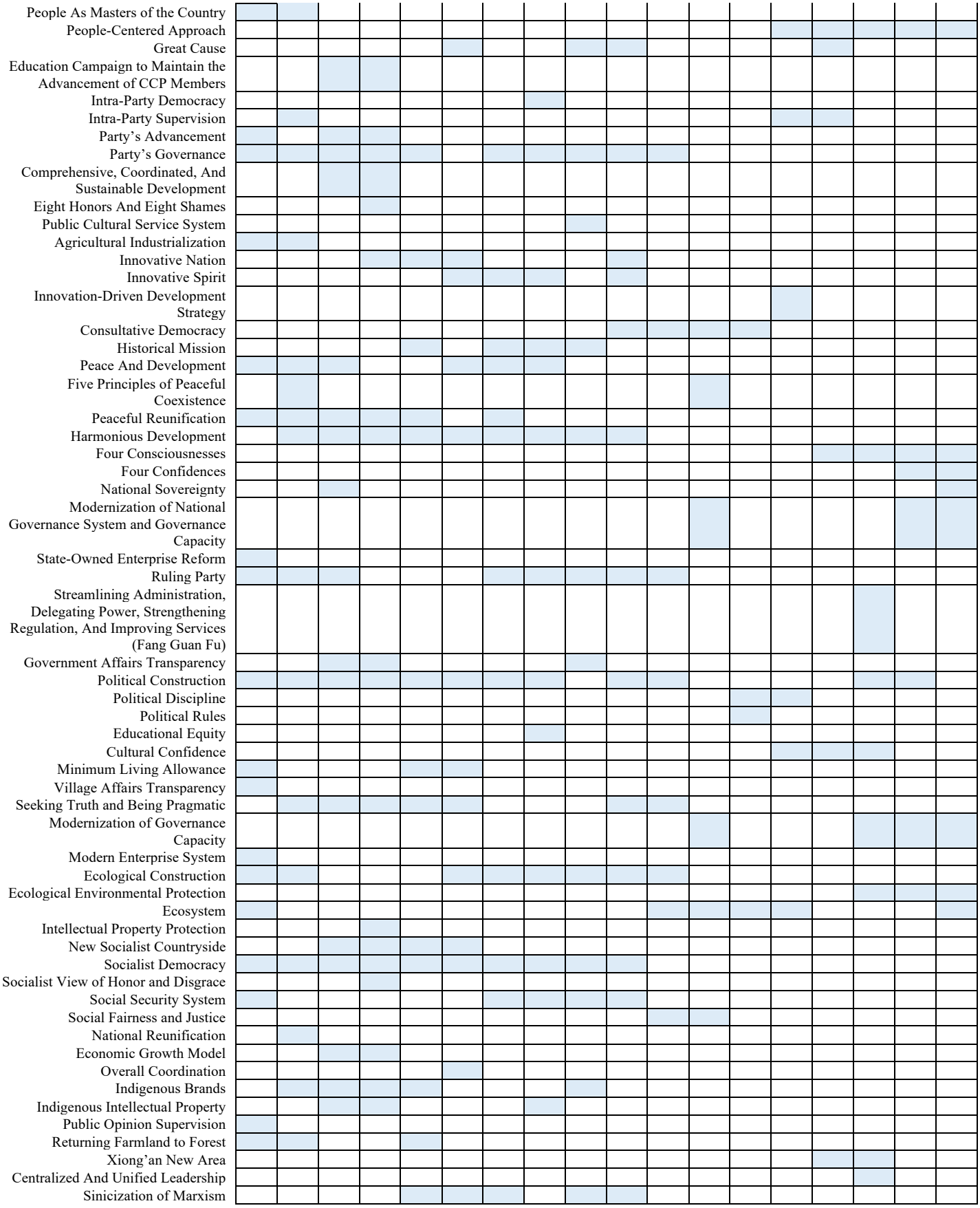
Online Appendix for "Firm Political Alignment: Measurement and Effects"

Online Appendix A. Time-varying dictionaries based on *People's Daily* and *Government Work Report*

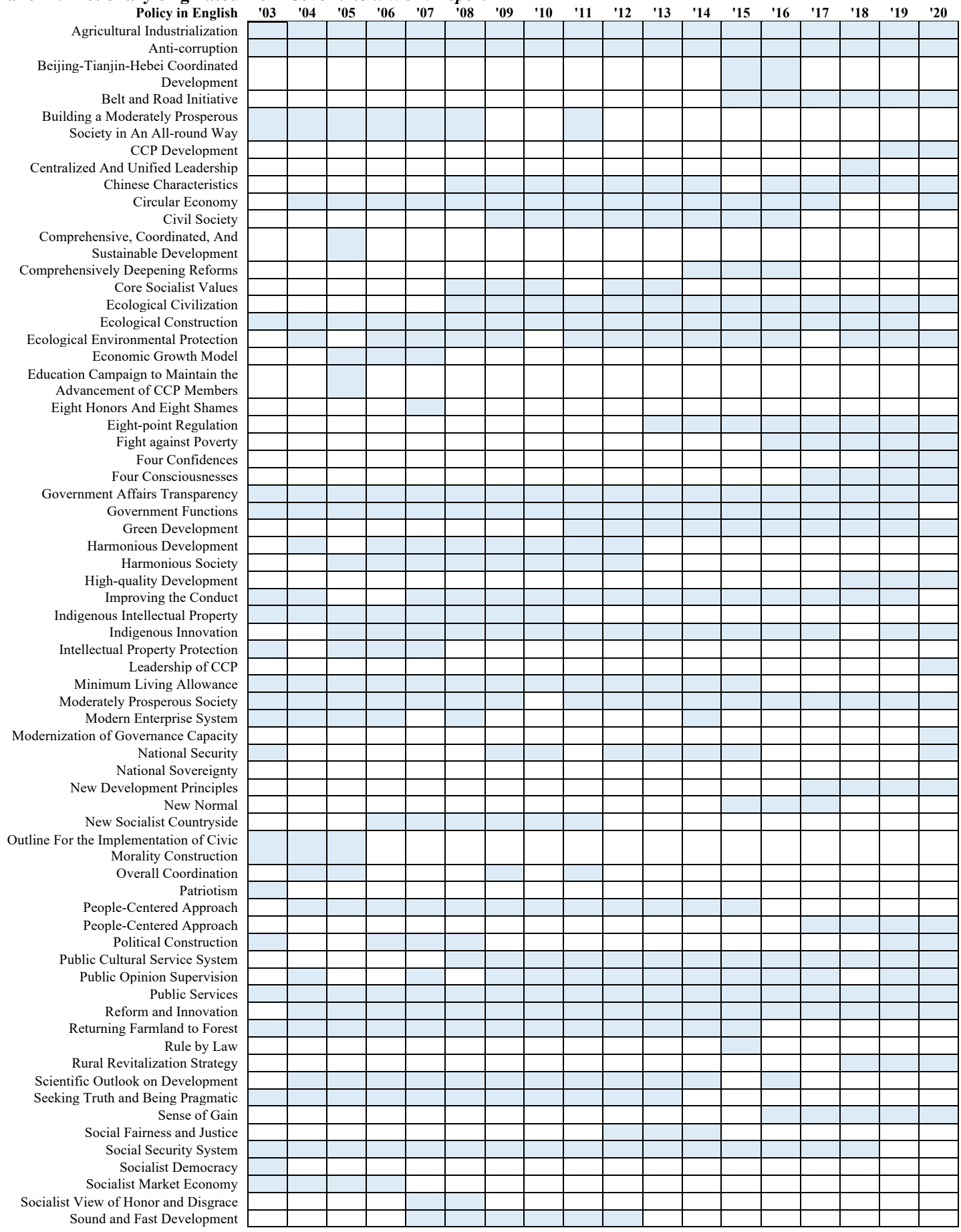
Panels A and B show dictionaries from *People's Daily* and *Government Work Report*, respectively. Filled cells indicate policies ranking among the top 40 most mentioned in each source that year.

Panel A. Dictionary originated from *People's Daily*




People As Masters of the Country
People-Centered Approach
Great Cause
Education Campaign to Maintain the Advancement of CCP Members
Intra-Party Democracy
Intra-Party Supervision
Party's Advancement
Party's Governance
Comprehensive, Coordinated, And Sustainable Development
Eight Honors And Eight Shames
Public Cultural Service System
Agricultural Industrialization
Innovative Nation
Innovative Spirit
Innovation-Driven Development Strategy
Consultative Democracy
Historical Mission
Peace And Development
Five Principles of Peaceful Coexistence
Peaceful Reunification
Harmonious Development
Four Consciousnesses
Four Confidences
National Sovereignty
Modernization of National Governance System and Governance Capacity
State-Owned Enterprise Reform
Ruling Party
Streamlining Administration, Delegating Power, Strengthening Regulation, And Improving Services (Fang Guan Fu)
Government Affairs Transparency
Political Construction
Political Discipline
Political Rules
Educational Equity
Cultural Confidence
Minimum Living Allowance
Village Affairs Transparency
Seeking Truth and Being Pragmatic
Modernization of Governance Capacity
Modern Enterprise System
Ecological Construction
Ecological Environmental Protection
Ecosystem
Intellectual Property Protection
New Socialist Countryside
Socialist Democracy
Socialist View of Honor and Disgrace
Social Security System
Social Fairness and Justice
National Reunification
Economic Growth Model
Overall Coordination
Indigenous Brands
Indigenous Intellectual Property
Public Opinion Supervision
Returning Farmland to Forest
Xiong'an New Area
Centralized And Unified Leadership
Sinicization of Marxism

Panel B. Dictionary originated from *Government Work Report*



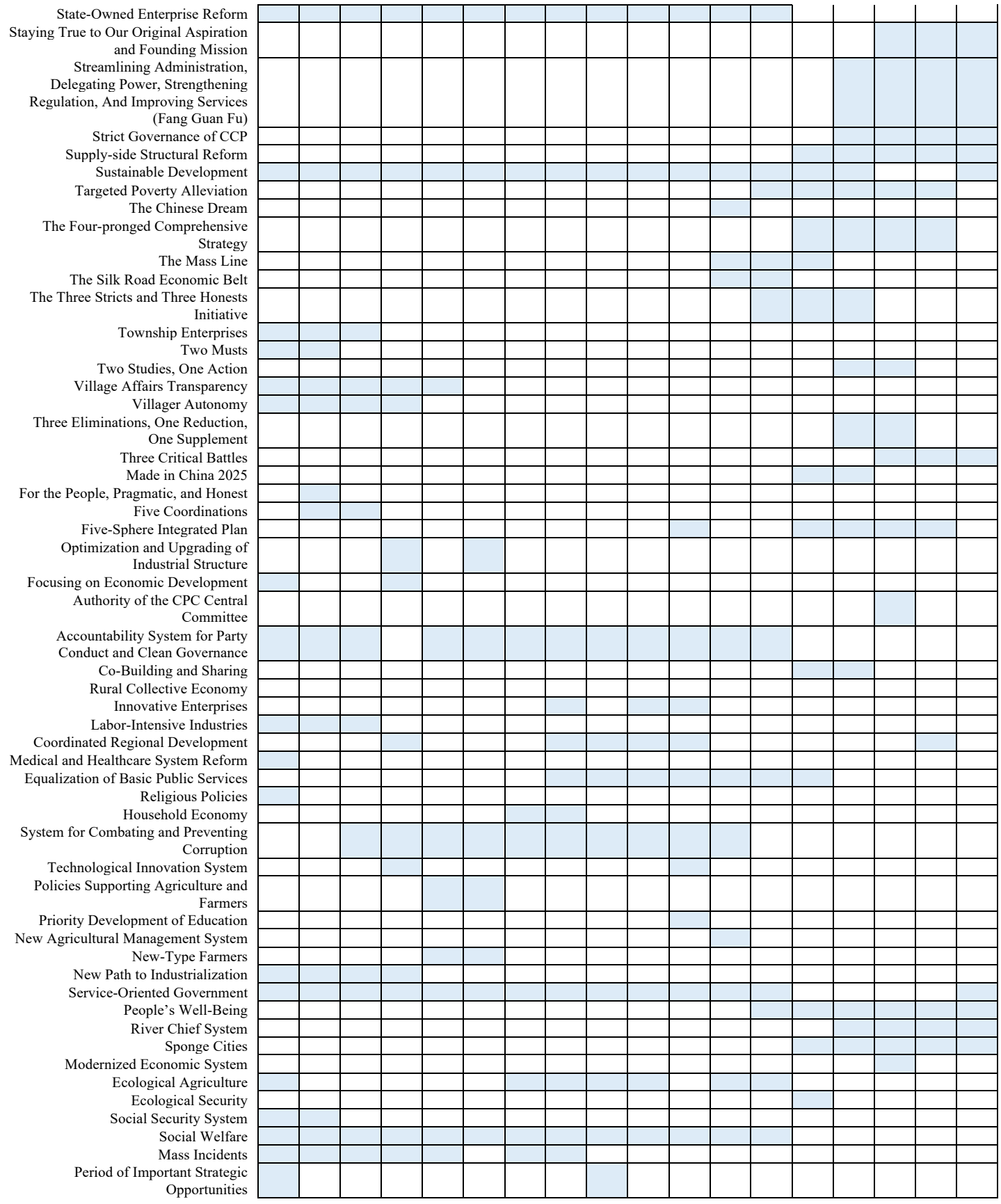

State-Owned Enterprise Reform
Staying True to Our Original Aspiration and Founding Mission
Streamlining Administration, Delegating Power, Strengthening Regulation, And Improving Services (Fang Guan Fu)
Strict Governance of CCP
Supply-side Structural Reform
Sustainable Development
Targeted Poverty Alleviation
The Chinese Dream
The Four-pronged Comprehensive Strategy
The Mass Line
The Silk Road Economic Belt
The Three Stricts and Three Honests Initiative
Township Enterprises
Two Musts
Two Studies, One Action
Village Affairs Transparency
Villager Autonomy
Three Eliminations, One Reduction, One Supplement
Three Critical Battles
Made in China 2025
For the People, Pragmatic, and Honest
Five Coordinations
Five-Sphere Integrated Plan
Optimization and Upgrading of Industrial Structure
Focusing on Economic Development
Authority of the CPC Central Committee
Accountability System for Party Conduct and Clean Governance
Co-Building and Sharing
Rural Collective Economy
Innovative Enterprises
Labor-Intensive Industries
Coordinated Regional Development
Medical and Healthcare System Reform
Equalization of Basic Public Services
Religious Policies
Household Economy
System for Combating and Preventing Corruption
Technological Innovation System
Policies Supporting Agriculture and Farmers
Priority Development of Education
New Agricultural Management System
New-Type Farmers
New Path to Industrialization
Service-Oriented Government
People's Well-Being
River Chief System
Sponge Cities
Modernized Economic System
Ecological Agriculture
Ecological Security
Social Security System
Social Welfare
Mass Incidents
Period of Important Strategic Opportunities

Table OA1. Summary statistics for the three flagship policies

This table presents summary statistics for the variables used in the three flagship policies analyses (Table 3 of the manuscript). All variable definitions are provided in Appendix A.

Statistic	N	Mean	St. Dev.	Min	Median	Max
Indigenous Innovation Policy						
FPA_Innov (untransformed)	26,847	1.233	2.15	0	0	59
FPA_Innov_Action (untransformed)	26,847	1.107	1.956	0	0	56
FPA_Innov_Rhetoric (untransformed)	26,847	0.126	0.464	0	0	10
RDSpend	26,847	3.199	6.469	0	1.753	618
NumPatent	26,847	0.469	0.803	0	0	6
Poverty Alleviation Policy						
FPA_Poverty (untransformed)	15,110	2.753	4.079	0	1	48
FPA_Poverty_Action (untransformed)	15,110	1.556	3.287	0	0	40
FPA_Poverty_Rhetoric (untransformed)	15,110	1.196	1.685	0	1	12
TPAPlan	15,110	0.208	0.406	0	0	1
PovAmt	15,110	0.0002	0.01	0	0	0.947
Environmental Protection Policy						
FPA_Envr (untransformed)	28,921	1.046	3.3	0	0	139
FPA_Envr_Action (untransformed)	28,921	0.779	2.584	0	0	134
FPA_Envr_Rhetoric (untransformed)	28,921	0.267	1.142	0	0	36
EPInvest	28,921	0.133	10.532	0	0	1,370
NumEP	28,921	0.147	0.964	0	0	39

Table OA2. Determinants of Action-based FPA and Rhetorical FPA

This table reports the regression results on the determinants of action-based and rhetorical FPA. The firm-year level sample covers 2008-2018. *FPA1_Action* and *FPA1_Rhetoric* are measured as the inverse hyperbolic sine transformation of the number of action-based and rhetorical policy-aligned mentions in annual reports, based on the *People's Daily* dictionary. *FPA2_Action* and *FPA2_Rhetoric* are measured similarly, but based on the *Government Work Report* dictionary. For these two pairs of variables, Panel A reports the results for estimating equation (1): the determinants of action-based and rhetorical FPA. Panel B reports the results estimating equation (3): examining the relationship between central leadership connection and action-based and rhetorical FPA around the Anti-Corruption Campaign. All variable definitions are provided in Appendix A. Standard errors are clustered at the industry level and presented in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

Panel A. Determinants of Action-based FPA and Rhetorical FPA

Dependent variable:	*FPA1_Action*		*FPA1_Rhetoric*		*FPA2_Action*		*FPA2_Rhetoric*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
POST		0.471***		0.531***		0.207***		0.305***
		(0.016)		(0.017)		(0.029)		(0.026)
$CountryRisk_{t-1}$	0.003***	0.0003	0.003***	-0.001**	0.003***	0.001	0.002***	-0.0004
	(0.0002)	(0.0003)	(0.0003)	(0.0003)	(0.001)	(0.001)	(0.0003)	(0.0004)
$Size_{t-1}$	0.180***	0.150***	0.398***	0.364***	0.180***	0.167***	0.475***	0.456***
	(0.030)	(0.028)	(0.015)	(0.014)	(0.035)	(0.033)	(0.015)	(0.014)
ROA_{t-1}	0.182	0.553*	-1.878***	-1.460***	-0.276	-0.114	-2.360***	-2.120***
	(0.220)	(0.276)	(0.219)	(0.167)	(0.283)	(0.295)	(0.237)	(0.216)
SOE_{t-1}	0.039	0.081**	-0.082**	-0.035	0.084	0.102*	-0.071**	-0.044
	(0.036)	(0.038)	(0.038)	(0.029)	(0.058)	(0.057)	(0.029)	(0.026)
$Leverage_{t-1}$	0.166**	0.169**	0.285***	0.289***	-0.003	-0.002	0.170**	0.172**
	(0.078)	(0.070)	(0.073)	(0.069)	(0.072)	(0.068)	(0.066)	(0.065)
$Growth_{t-1}$	-0.074***	-0.048**	-0.086***	-0.057**	-0.040	-0.028	-0.067***	-0.050**
	(0.018)	(0.021)	(0.018)	(0.020)	(0.025)	(0.025)	(0.021)	(0.018)
$Length_t$	0.132***	-0.048**	0.157***	-0.046**	0.021	-0.058***	0.177***	0.061**
	(0.020)	(0.018)	(0.018)	(0.017)	(0.021)	(0.020)	(0.026)	(0.021)
Observations	21,738	21,738	21,738	21,738	21,738	21,738	21,738	21,738
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	No	No	No	No
S.E. cluster	Industry	Industry	Industry	Industry	Industry	Industry	Industry	Industry
Adjusted R2	0.381	0.409	0.327	0.369	0.360	0.365	0.330	0.344

Table OA2. Determinants of Action-based FPA and Rhetorical FPA (continued)

Panel B. Central leadership connection and FPA around the Anti-Corruption Campaign

Dependent variable:	*FPA1_Action*	*FPA1_Rhetoric*	*FPA1_Action*	*FPA1_Rhetoric*	*FPA2_Action*	*FPA2_Rhetoric*	*FPA2_Action*	*FPA2_Rhetoric*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
POST* × *CC_Exec	**-0.293*** **	**-0.366*** **			**-0.193** **	**-0.183** **		
	(0.099)	**(0.080)**			**(0.088)**	**(0.076)**		
POST* × *CC_HQ			**-0.151*** **	**-0.207*** **			**-0.118*** **	**-0.094*** **
			(0.037)	**(0.030)**			**(0.029)**	**(0.024)**
$Size_{t-1}$	0.095***	0.083***	0.096***	0.084***	0.0002	0.044***	0.001	0.044***
	(0.028)	(0.012)	(0.027)	(0.012)	(0.031)	(0.014)	(0.030)	(0.014)
SOE_{t-1}	0.082**	-0.010	0.081**	-0.012	0.098*	-0.009	0.097*	-0.010
	(0.035)	(0.031)	(0.037)	(0.030)	(0.052)	(0.030)	(0.053)	(0.029)
ROA_{t-1}	0.928***	0.378**	0.920***	0.368**	1.015***	0.294	1.010***	0.289
	(0.215)	(0.142)	(0.210)	(0.142)	(0.246)	(0.171)	(0.240)	(0.170)
$Leverage_{t-1}$	0.139*	0.268***	0.132*	0.259***	0.046	0.178***	0.041	0.174***
	(0.069)	(0.059)	(0.071)	(0.058)	(0.067)	(0.053)	(0.068)	(0.053)
$Growth_{t-1}$	-0.020	0.005	-0.020	0.006	-0.006	-0.018	-0.006	-0.017
	(0.020)	(0.017)	(0.020)	(0.017)	(0.021)	(0.014)	(0.021)	(0.014)
$Length_t$	-0.046*	-0.103***	-0.044*	-0.099***	-0.031	-0.045**	-0.029	-0.043**
	(0.022)	(0.020)	(0.022)	(0.019)	(0.029)	(0.017)	(0.029)	(0.016)
Observations	21,738	21,738	21,738	21,738	21,738	21,738	21,738	21,738
Firm, year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
S.E. cluster	Industry	Industry	Industry	Industry	Industry	Industry	Industry	Industry
Adjusted R2	0.435	0.432	0.436	0.433	0.397	0.457	0.397	0.457
Chi-square test on the equality of *POST*×*CC*	0.574		1.188		-0.088		-0.658	

Table OA3. FPA using the top 30 and top 50 most frequently referenced policies

This table reports the main regression results using alternative FPA measures, derived using the top 30 and top 50 most frequently referenced policy phrases, instead of top 40. Specifically, *FPA1_Top30 (FPA1_Top50)* is measured as the inverse hyperbolic sine transformation of the number of policy-aligned mentions sourced from the top 30 (top 50) most frequently referenced policies in *People's Daily*. *FPA2_Top30* and *FPA2_Top50* are measured similarly, but based on *Government Work Report*. The firm-year level sample covers 2008-2018. Panel A reports the results for estimating equation (1): the determinants of alternative FPA. Panel B reports the results estimating equation (3): examining the relationship between central leadership connection and alternative FPA around the Anti-Corruption Campaign. Panel C reports the results estimating equation (4), examining the relationship between alternative FPA and government preferential treatment. Panel D reports the results estimating equation (5), examining the market reaction to the announcement of the Common Prosperity Policy on August 17th, 2021. All variable definitions are provided in Appendix A. Standard errors are clustered at the industry level and presented in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

Panel A. Determinants of Top30/50 FPA

Dependent variable:	*FPA1_Top30*		*FPA2_Top30*		*FPA1_Top50*		*FPA2_Top50*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
POST		0.620***		0.310***		0.524***		0.370***
		(0.028)		(0.030)		(0.029)		(0.023)
$CountryRisk_{t-1}$	0.001**	-0.003***	0.002***	0.0004	0.005***	0.002***	-0.001***	-0.003***
	(0.0003)	(0.0003)	(0.001)	(0.001)	(0.0003)	(0.0004)	(0.0003)	(0.0004)
$Size_{t-1}$	0.151***	0.111***	0.302***	0.283***	0.375***	0.341***	0.329***	0.305***
	(0.032)	(0.028)	(0.029)	(0.025)	(0.021)	(0.017)	(0.025)	(0.022)
ROA_{t-1}	0.319	0.807***	-0.815***	-0.571**	-0.954***	-0.542***	-1.225***	-0.933***
	(0.186)	(0.224)	(0.200)	(0.221)	(0.122)	(0.152)	(0.168)	(0.182)
SOE_{t-1}	0.013	0.067**	0.048	0.076**	-0.011	0.035	0.019	0.052
	(0.035)	(0.032)	(0.030)	(0.029)	(0.027)	(0.021)	(0.037)	(0.037)
$Leverage_{t-1}$	0.220**	0.224***	0.167**	0.169**	0.194**	0.198***	0.113	0.116*
	(0.090)	(0.077)	(0.071)	(0.067)	(0.073)	(0.066)	(0.070)	(0.064)
$Growth_{t-1}$	-0.021	0.013	-0.058***	-0.041*	-0.054***	-0.025	-0.043***	-0.022**
	(0.016)	(0.016)	(0.018)	(0.019)	(0.018)	(0.021)	(0.011)	(0.010)
$Length_t$	0.228***	-0.009	0.082***	-0.037	0.161***	-0.039*	0.146***	0.004
	(0.023)	(0.022)	(0.025)	(0.022)	(0.022)	(0.021)	(0.020)	(0.022)
Observations	21,738	21,738	21,738	21,738	21,738	21,738	21,738	21,738
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	No	No	No	No
S.E. cluster	Industry	Industry	Industry	Industry	Industry	Industry	Industry	Industry
Adjusted R2	0.366	0.418	0.369	0.380	0.418	0.458	0.375	0.393

Table OA3. FPA using the top 30 and top 50 most frequently referenced policies (continued)

Panel B. Central leadership connection and Top30/50 FPA around the Anti-Corruption Campaign

Dependent variable:	*FPA2_Top30*		*FPA2_Top30*		*FPA1_Top50*		*FPA2_Top50*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
POST* × *CC_Exec	**-0.449*** **		**-0.219***		**-0.335*** **		**-0.265*** **	
	(0.099)		**(0.104)**		**(0.103)**		**(0.089)**	
POST* × *CC_HQ		**-0.201*** **		**-0.132*** **		**-0.170*** **		**-0.137*** **
		(0.031)		**(0.035)**		**(0.028)**		**(0.031)**
Observations	21,738	21,738	21,738	21,738	21,738	21,738	21,738	21,738
Firm, year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
S.E. cluster	Industry	Industry	Industry	Industry	Industry	Industry	Industry	Industry
Adjusted R2	0.434	0.435	0.417	0.418	0.497	0.498	0.478	0.478

Panel C. Top30/50 FPA and government preferential treatment

Dependent variable:	*Reg_Action*$_{t+1}$		*Log(BankLoan*$_{t+1}$*)*		*Log(Subsidy*$_{t+1}$*)*		*InterestRate*$_{t+1}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Top 30:								
FPA1_Top30	-0.007**		0.506***		0.313***		0.0002	
	(0.003)		(0.096)		(0.068)		(0.0004)	
FPA2_Top30		-0.010***		0.486***		0.336***		-0.0001
		(0.002)		(0.031)		(0.055)		(0.0003)
Top 50:								
FPA1_Top50	-0.009***		0.541***		0.407***		0.00005	
	(0.002)		(0.078)		(0.067)		(0.0004)	
FPA2_Top50		-0.011***		0.501***		0.388***		0.0001
		(0.002)		(0.044)		(0.071)		(0.0003)
Observations	23,688	23,688	23,688	23,688	23,688	23,688	16,981	16,981
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry, year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
S.E. cluster	Industry	Industry	Industry	Industry	Industry	Industry	Industry	Industry
Adjusted R2 (Top30)	0.057	0.058	0.298	0.298	0.142	0.143	0.037	0.037
Adjusted R2 (Top50)	0.057	0.058	0.298	0.298	0.143	0.143	0.037	0.037

Table OA3. FPA using the top 30 and top 50 most frequently referenced policies (continued)

Panel D. Top30/50 FPA and market reaction to "Common Prosperity Policy" announcement

Dependent variable:	*CAR[-1,1]*			
	(1)	(2)	(3)	(4)
FPA1_Top30$_{t-1}$	0.185***			
	(0.055)			
FPA2_Top30$_{t-1}$		0.255***		
		(0.054)		
FPA1_Top50$_{t-1}$			0.178***	
			(0.067)	
FPA2_Top50$_{t-1}$				0.213***
				(0.065)
Observations	3,038	3,038	3,038	3,038
Controls	Yes	Yes	Yes	Yes
S.E. cluster	Industry	Industry	Industry	Industry
Adjusted R2	0.034	0.037	0.033	0.034

Table OA4. FPA scope

This table reports the main regression results using alternative FPA measures, *FPA1_scope* and *FPA2_Scope.* Specifically, *FPA1_Scope (FPA2_Scope)* is measured as the inverse hyperbolic sine transformation of the number of mentions of unique policies, based on the two dictionaries (*People's Daily* and *Government Work Report*). The firm-year level sample covers 2008-2018. Panel A reports the results for estimating equation (1): the determinants of alternative FPA. Panel B reports the results estimating equation (3): examining the relationship between central leadership connection and alternative FPA around the Anti-Corruption Campaign. Panel C reports the results estimating equation (4), examining the relationship between alternative FPA and government preferential treatment. Panel D reports the results estimating equation (5), examining the market reaction to the announcement of the Common Prosperity Policy on August 17th, 2021. All variable definitions are provided in Appendix A. Standard errors are clustered at the industry level and presented in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

Panel A. Determinants of FPA scope

Dependent variable:	*FPA1_Scope*		*FPA2_Scope*	
	(1)	(2)	(3)	(4)
POST		0.340***		0.171***
		(0.019)		(0.030)
$CountryRisk_{t-1}$	0.002***	-0.0003	0.002***	0.001
	(0.0003)	(0.0002)	(0.001)	(0.001)
$Size_{t-1}$	0.159***	0.138***	0.208***	0.197***
	(0.018)	(0.016)	(0.021)	(0.019)
SOE_{t-1}	0.028	0.059**	0.072**	0.087***
	(0.023)	(0.020)	(0.027)	(0.026)
ROA_{t-1}	-0.238**	0.037	-0.672***	-0.538***
	(0.102)	(0.099)	(0.140)	(0.142)
$Leverage_{t-1}$	0.133**	0.136**	0.037	0.039
	(0.063)	(0.056)	(0.055)	(0.052)
$Growth_{t-1}$	-0.035***	-0.017	-0.032*	-0.023
	(0.011)	(0.015)	(0.016)	(0.017)
$Length_t$	-0.116	-0.014	-0.017	-0.048***
	(0.015)	(0.014)	(0.022)	(0.015)
Observations	21,738	21,738	21,738	21,738
Firm FE	Yes	Yes	Yes	Yes
Year FE	No	No	No	No
S.E. cluster	Industry	Industry	Industry	Industry
Adjusted R2	0.337	0.372	0.334	0.342

Table OA4. FPA scope (continued)

Panel B. Central leadership connection and FPA scope around the Anti-Corruption Campaign

Dependent variable:	*FPA1_Scope*		*FPA2_Scope*	
	(1)	(2)	(3)	(4)
POST* × *CC_Exec	**-0.220*** **		**-0.181** **	
	(0.062)		**(0.063)**	
POST* × *CC_HQ		**-0.125*** **		**-0.069** **
		(0.034)		**(0.032)**
Sample period	2008-2018			
Observations	21,738	21,738	21,738	21,738
Controls	Yes	Yes	Yes	Yes
Firm, year FE	Yes	Yes	Yes	Yes
S.E. cluster	Industry	Industry	Industry	Industry
Adjusted R2	0.373	0.374	0.342	0.342

Panel C. FPA scope and government preferential treatment

Dependent variable:	*Reg_Action*$_{t+1}$		*Log(BankLoan*$_{t+1}$*)*		*Log(Subsidy*$_{t+1}$*)*		*InterestRate*$_{t+1}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
***FPA1_Scope*$_t$**	**-0.018*** **		**0.362*** **		**0.167*** **		**0.0004**	
	(0.003)		**(0.039)**		**(0.025)**		**(0.001)**	
***FPA2_Scope*$_t$**		**-0.017*** **		**0.331*** **		**0.167*** **		**0.0003**
		(0.003)		**(0.029)**		**(0.028)**		**(0.0004)**
Observations	23,688	23,688	23,688	23,688	23,688	23,688	16,981	16,981
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry, year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
S.E. cluster	Industry	Industry	Industry	Industry	Industry	Industry	Industry	Industry
Adjusted R2	0.058	0.502	0.502	0.306	0.307	0.037	0.037	0.101

Panel D. FPA scope and market reaction to the announcement of "Common Prosperity Policy"

Dependent variable:	*CAR[-1,1]*	
	(1)	(2)
***FPA1_Scope*$_{t-1}$**	**0.585*** **	
	(0.149)	
***FPA2_Scope*$_{t-1}$**		**0.395*** **
		(0.101)
Observations	3,038	3,038
Controls	Yes	Yes
S.E. cluster	Industry	Industry
Adjusted R2	0.036	0.035

Table OA5. Scaled FPA

This table reports the main regression results using alternative FPA measures, scaled by annual report length. Specifically, *FPA1_Scaled* and *FPA2_ Scaled* are measured as the number of policy-aligned mentions based on the two dictionaries (*People's Daily* and *Government Work Report*), respectively, scaled by the number of pages in annual reports. The firm-year level sample covers 2008-2018. Panel A reports the results for estimating equation (1): the determinants of alternative FPA. Panel B reports the results estimating equation (3): examining the relationship between central leadership connection and alternative FPA around the Anti-Corruption Campaign. Panel C reports the results estimating equation (4), examining the relationship between alternative FPA and government preferential treatment. Panel D reports the results estimating equation (5), examining the market reaction to the announcement of the Common Prosperity Policy on August 17th, 2021. All variable definitions are provided in Appendix A. Standard errors are clustered at the industry level and presented in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

Panel A. Determinants of scaled FPA

Dependent variable:	*FPA1 Scaled*		*FPA2 Scaled*	
	(1)	(2)	(3)	(4)
POST		0.021***		0.010***
		(0.001)		(0.001)
$CountryRisk_{t-1}$	0.0001***	0.00001	0.0001***	-0.0001
	(0.00001)	(0.00001)	(0.00002)	(0.00002)
$Size_{t-1}$	0.011***	0.010***	0.011***	0.011***
	(0.001)	(0.001)	(0.001)	(0.001)
SOE_{t-1}	0.001	0.003**	0.001	0.002*
	(0.001)	(0.001)	(0.001)	(0.001)
ROA_{t-1}	-0.020**	-0.003	-0.036***	-0.028***
	(0.007)	(0.008)	(0.008)	(0.008)
$Leverage_{t-1}$	0.007**	0.007***	0.002	0.002
	(0.003)	(0.006)	(0.002)	(0.002)
$Growth_{t-1}$	-0.004***	-0.002***	-0.002***	-0.002***
	(0.001)	(0.001)	(0.001)	(0.001)
$Length_t$	-0.029***	-0.037***	-0.025***	-0.029***
	(0.001)	(0.001)	(0.001)	(0.001)
Observations	21,738	21,738	21,738	21,738
Firm FE	Yes	Yes	Yes	Yes
Year FE	No	No	No	No
S.E. cluster	Industry	Industry	Industry	Industry
Adjusted R2	0.414	0.452	0.410	0.422

Table OA5. Scaled FPA (continued)

Panel B. Central leadership connection and scaled FPA around the Anti-Corruption Campaign

Dependent variable:	*FPA1_Scaled*		*FPA2_Scaled*	
	(1)	(2)	(3)	(4)
POST* × *CC_Exec	**-0.011****		**-0.005**	
	(0.004)		**(0.003)**	
POST* × *CC_HQ		**-0.007*****		**-0.005****
		(0.001)		**(0.001)**
Observations	21,738	21,738	21,738	21,738
Controls	Yes	Yes	Yes	Yes
Firm, year FE	Yes	Yes	Yes	Yes
S.E. cluster	Industry	Industry	Industry	Industry
Adjusted R2	0.487	0.488	0.481	0.482

Panel C. Scaled FPA and government preferential treatment

Dependent variable:	*Reg_Action*$_{t+1}$		*Log(BankLoan*$_{t+1}$*)*		*Log(Subsidy*$_{t+1}$*)*		*InterestRate*$_{t+1}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
***FPA1_Scaled*$_t$**	**-0.142*****		**8.531*****		**5.885*****		**-0.0003**	
	(0.025)		**(1.371)**		**(1.061)**		**(0.006)**	
***FPA2_Scaled*$_t$**		**-0.208*****		**11.962*****		**7.986*****		**-0.0001**
		(0.040)		**(1.231)**		**(1.403)**		**(0.008)**
Observations	23,688	23,688	23,688	23,688	23,688	23,688	16,981	16,981
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry, year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
S.E. cluster	Industry	Industry	Industry	Industry	Industry	Industry	Industry	Industry
Adjusted R2	0.057	0.057	0.298	0.298	0.143	0.143	0.037	0.037

Panel D. Scaled FPA and market reaction to the announcement of "Common Prosperity Policy"

Dependent variable:	*CAR[-1,1]*	
	(1)	(2)
***FPA1_Scaled*$_{t-1}$**	**4.030*****	
	(1.145)	
***FPA2_Scaled*$_{t-1}$**		**4.094*****
		(1.390)
Observations	3,038	3,038
Controls	Yes	Yes
S.E. cluster	Industry	Industry
Adjusted R2	0.034	0.033

Table OA6. Policy sentiment

This table reports the regression results examining the association between policy sentiment and governmental preferential treatment (Panel A) and market reaction to policy shock (Panel B). *Policy1_Negative* (*Policy1_Nonnegative*) is measured as the inverse hyperbolic sine transformation of the number of policy mentions expressing negative (nonnegative) sentiment, based on the *People's Daily* dictionary. *Policy2_Negative* (*Policy2_Nonnegative*) is measured similarly, but based on the *Government Work Report* dictionary. Around 1% of sentences containing political policies exhibit negative sentiment. All variable definitions are provided in Appendix A. Standard errors are clustered at the industry level and presented in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

Panel A. Policy sentiment and government preferential treatment

Dependent variable:	*Reg_Action*$_{t+1}$		*Log(BankLoan*$_{t+1}$*)*		*Log(Subsidy*$_{t+1}$*)*		*InterestRate*$_{t+1}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Policy1_Nonnegative	-0.013***		0.430***		0.339***		-0.00005	
	(0.002)		(0.093)		(0.071)		(0.0004)	
Policy1_Negative	-0.002		-0.123		-0.106		0.001	
	(0.007)		(0.135)		(0.088)		(0.001)	
Policy2_Nonnegative		-0.009***		0.544***		0.393***		0.0002
		(0.002)		(0.033)		(0.067)		(0.0003)
Policy2_Negative		0.001		0.102		-0.086		0.001
		(0.011)		(0.151)		(0.073)		(0.002)
Observations	23,688	23,688	23,688	23,688	23,688	23,688	16,981	16,981
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry, year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
S.E. cluster	Industry	Industry	Industry	Industry	Industry	Industry	Industry	Industry
Adjusted R2	0.058	0.057	0.297	0.299	0.143	0.144	0.037	0.037

Table OA6. Policy sentiment (continued)

Panel B. Policy sentiment and market reaction to the announcement of "Common Prosperity Policy"

Dependent variable:	*CAR[-1,1]*	
	(1)	(2)
Policy1_Nonnegative$_{t-1}$	0.119	
	(0.077)	
Policy1_Negative$_{t-1}$	0.194	
	(0.230)	
Policy2_Nonnegative$_{t-1}$		0.166**
		(0.068)
Policy2_Negative$_{t-1}$		0.308
		(0.233)
Observations	3,038	3,038
Controls	Yes	Yes
S.E. cluster	Industry	Industry
Adjusted R2	0.034	0.034

Table OA7. Summary statistics of partisanship in U.S. 10-K filings

This table reports average frequency and partisan leaning in the Item 1 and Item 7 sections of U.S. 10-K filings from 2012 to 2023. It presents phrase-level metrics for the 20 most Democrats-leaned and Republicans-leaned phrases, respectively. Phrase-level partisan leaning is calculated as the product of phrase frequency and the phrase-level partisan scores from Gentzkow, Shapiro, and Taddy (2019).

Top 20 partisan phrases used by Democrats			**Top 20 partisan phrases used by Republicans**		
Partisan phrase	**Average Freq**	**Phrase-level partisan leaning**	**Partisan phrase**	**Average Freq**	**Phrase-level partisan leaning**
insur compani	4.371	4.581	tax rate	5.224	2.865
student loan	4.373	4.441	american peopl	1.278	2.227
middl class	1.425	4.087	medic devic	8.718	2.069
care act	3.173	4.047	yucca mountain	3.298	1.896
interest rate	6.797	4.020	farm bureau	23.464	1.829
afford care	2.957	3.574	health plan	4.593	1.595
prescript drug	4.610	3.172	job creator	1.000	1.478
clean air	2.540	2.256	nuclear wast	2.757	1.467
health reform	10.259	2.228	tax reform	3.305	1.411
oil compani	2.221	2.016	cord blood	7.612	1.364
immigr reform	1.029	1.827	busi owner	1.655	1.237
farm bill	2.414	1.820	job creation	1.244	1.229
breast cancer	7.806	1.599	govern spend	1.270	1.133
feder reserv	13.238	1.561	ballist missil	2.447	1.091
million american	1.408	1.538	hydraul fractur	11.335	1.075
public health	1.922	1.538	econom growth	1.499	0.991
clean energi	3.487	1.514	american energi	1.331	0.935
air act	2.668	1.497	energi product	1.866	0.894
tax credit	2.508	1.456	train wreck	2.500	0.811
tax break	1.035	1.438	nation debt	1.054	0.774