Centralizing Policymaking: Examining the Origin and Diffusion of 116,000 Policies in China

[Preliminary and Incomplete]

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Abstract

Leveraging a comprehensive collection of Chinese policy documents and government work reports over the past two decades, we identify more than 116,000 distinct policies and systematically trace their initiation and diffusion processes. We document three main findings. First, China's policymaking landscape has been highly decentralized, with local officials playing a central role in both initiating new policies and facilitating their diffusion. Second, after 2013, the central government shifted the bureaucratic incentive structure by ceasing to reward bottom-up policy innovation and instead promoting diligent enforcement of centrally assigned policies, leading to significant centralization of policymaking. Third, focusing on industrial policies, we examine how centralization affects policy suitability and effectiveness. Top-down industrial policies tend to be less aligned with local conditions and less effective at spurring industrial growth, revealing the costs of centralization. Conversely, under decentralization, strategic competition among local officials can distort policy diffusion, undermining policy suitability and effectiveness. We estimate both distortions quantitatively and find that, over the past decade, the economic costs of centralizing policymaking in China have significantly outweighed its benefits.

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1 Introduction

A fundamental question in political economy concerns the appropriate level for making policy decisions — a matter that has sparked extensive debates over the merits of centralization versus decentralization (Hayek 1945; Rueschemeyer, Skocpol, and Evans 1985; Bardhan 2002; Besley and Coate 2003; Mookherjee 2015). This tension is especially relevant in governing large societies with high levels of regional heterogeneity: while top-down policy promotion may streamline adoption, internalize spillovers, and enhance efficiency, it often sacrifices the local suitability that bottom-up policy initiatives provide (Tiebout 1956; Oates 1972; Alesina and Spolaore 1997; Bolton and Roland 1997; Alesina, Baqir, and Hoxby 2004).

In this paper, we examine how centralization in policymaking affects the local suitability of policies. Despite its theoretical importance, empirical evidence on this topic remains scarce. Measuring centralization in policymaking is challenging because it requires systematically tracing the origins of all policies to capture the policymaking process comprehensively. Assessing its impact on policy outcomes is even more difficult, as it involves linking policies to both local conditions and desired results.

We focus on China's policymaking over the past four decades — a context in which the balance between centralization and decentralization is critically important and which allows us to address the empirical challenges outlined above. We investigate two questions: First, what proportion of local governments' policy portfolios is influenced by the central government's direct involvement, such as initiating or explicitly promoting policies from top-down? Second, does the central government's direct involvement undermine policy suitability and effectiveness at the local level?

For our analysis, we compile a comprehensive dataset of 151 thousand central government policy documents and 3.3 million local government policy documents and work reports. From this corpus, we identify over 116,000 distinct policies implemented from 2003 to 2023 and trace their origins and vertical and horizontal diffusion patterns. For the subset of industrial policies aimed at promoting industrial growth, we also measure policy suitability and effectiveness.

We document four main findings that address our research questions. First, policymaking in China is highly decentralized on average. Over the past two decades, 82% of the policies appearing in local governments' portfolios originated as local initiatives; of these, 74% diffused solely horizontally among local governments and never involved explicit central government action. Further analysis reveals that local bureaucrats are the primary drivers of decentralized policy initiation and diffusion.

Second, since 2013, decentralized policymaking has declined dramatically: the share of top-down policies in local governments' portfolios has risen by 30%, and the adoption rate of top-down initiatives has more than doubled. This shift appears linked to changes in career incentives for local politicians. Before 2013, local politicians earned promotions by pioneering new policies that eventually diffused widely. After 2013, however, promotions went to those who most actively implemented policies initiated or explicitly endorsed by the central government.

Third, locally initiated and horizontally diffused policies tend to be associated with higher *ex-ante* local suitability and better *ex-post* economic outcomes. Focusing on industrial policies aimed at promoting industrial growth and innovation, we find that those initiated or adopted by local governments without central involvement are better aligned with local conditions, as measured by *pre-existing* regional supply chains and private firms' *ex-ante* investment preferences. In contrast, industrial policies initiated or explicitly endorsed by the central government show systematically weaker alignment with local conditions. Furthermore, industrial policies better matched to local conditions prove significantly more effective, on average, at achieving policy objectives, including increased industrial output, new patents, and exports.

Fourth, the central government's explicit involvement reduces strategic competition among local governments, which can otherwise prevent them from learning from similar peer localities. In decentralized contexts, politicians with similar backgrounds often compete for the same promotions and avoid adopting each other's policies to prevent boosting their competitors' credentials. Because politically similar leaders are typically assigned to economically comparable localities, such strategic competition can hinder the spread of beneficial policies, reducing policy–locality compatibility and lowering economic outcomes. However, our calculations indicate that this benefit likely does not outweigh the drawbacks of reduced local policy suitability resulting from centralization.

Taken together, our evidence demonstrates the value of decentralized policymaking in achieving better policy suitability to local conditions. Since moving away from a centrally planned regime after 1979, China has experienced unprecedented economic growth — a phenomenon many social scientists attribute to the effective use of local initiatives in decentralized policymaking (Oi 1995; Montinola, Qian, and Weingast 1995; Xu 2011; Chen, Li, and Zhu 2024). The reversal of this trend over the past decade warrants attention, not only because of China's history of policy disasters from heavy-handed central planning (Lin 1990; Meng, Qian, and Yared 2015; Frank et al. 2024), but also because of the vast scale of China's economy and society, its diverse local landscape, and the increasing complexity of policymaking. Our estimates suggest that if China had maintained its 2012 share of

locally initiated industrial policies in the subsequent decade, export growth in treated sectors could have risen by approximately 61.1%. While this figure relies on strong assumptions and should be interpreted cautiously, the calculated costs consistently exceed the benefits by an order of magnitude, providing a clear caution against over-centralization.

This paper relates to three strands of literature. First, it contributes to the emerging literature on policy diffusion and innovation. A large body of work has demonstrated how policy innovation and diffusion in federalist societies can serve as a "laboratory of democracy" (Besley and Case 2003; Bernecker, Boyer, and Gathmann 2021; Caughey, Xu, and Warshaw 2017; Grumbach 2023; DellaVigna and Kim 2022). Yet, comparatively little is known about how authoritarian regimes acquire the decentralized information necessary to design and implement effective policies, given the typically limited scope for bottom-up participation in policy making in such settings.[1] A particularly relevant study is DellaVigna and Kim (2022), which documents several related aspects of policy innovation and diffusion in the United States. Our findings in the Chinese context reveal several notable contrasts between the policy-making models in the U.S. and China. For example: (a) although both countries rely heavily on decentralized policy making, in China local bureaucrats (rather than localities *per se*) are the primary drivers; (b) political dynamics complicate policy diffusion in both settings—party alignment facilitates diffusion in the U.S., while local political competition hinders it in China; and (c) while political polarization may undermine the efficiency of policy diffusion in some contexts, in China political centralization emerges as the most significant impediment.

Second, this paper contributes to the long-standing debate regarding centralization versus decentralization (Hayek 1945; Rueschemeyer, Skocpol, and Evans 1985; Bardhan 2002; Mookherjee 2015). On the one hand, our finding that bottom-up policies exhibit higher compatibility with local conditions lends empirical support to the theoretical literature emphasizing the importance of decentralized information in governance (Tiebout 1956; Oates 1972; Cremer, Estache, and Seabright 1994; Seabright 1996; Alesina and Spolaore 1997; Bolton and Roland 1997; Besley and Coate 2003; Alesina, Baqir, and Hoxby 2004). On the other hand, our results on strategic biases in bottom-up policy diffusion illustrate the distortions that can arise from decentralized regional competition (Blanchard and Shleifer 2001; Sonin 2003; Cai and Treisman 2004; Young 2000). Unlike much of the existing empirical literature — which typically examines the impact of (de)centralization on specific dimensions such as safety (Jia and Nie 2017), pollution (Lipscomb and Mo-

1. A notable exception is the literature on policy experimentation in China, which highlights the role of top-down pilots in policy learning (Montinola, Qian, and Weingast 1995; Cao, Qian, and Weingast 1999; Heilmann 2008; Wang and Yang 2025).

barak 2016; Wang and Wang 2020), or taxation (De Paula, Rasul, and Souza 2024) — our paper is among the first to offer a holistic account of the complete policy portfolios across all levels of government, thereby shedding unique light on both policy enforcement and policy *making*.

Third, our findings document the recent wave of re-centralization in China's policymaking process since 2013 and quantify the potential risks associated with this trend (Kornai 1960; Nove 1971). Following a series of drastic policy failures under the campaign-style top-down policy promotion of the central planning era, China's leadership, after 1970, shifted from top-down policy assignment to bottom-up policy experimentation—a move that later became a pillar of Chinese policy making and is widely credited with underpinning the country's economic success (Heilmann 2008; Rawski 1995; Roland 2000; Qian 2002; Chen, Li, and Zhu 2024; Wang and Yang 2025). When zooming in on industrial policies, our finding of a centralization trend—a pattern consistent with our broader documentation of centralization across all policies—echoes the trend reported in Fang, Li, and Lu (2025). We further demonstrate that, even though information asymmetry between central and local governments has substantially diminished in recent years (Martinez-Bravo et al. 2022), bottom-up policies remain markedly more compatible with local conditions and yield significantly superior outcomes, supporting the findings of Chen, Li, and Zhu (2024) for the 1980s and 1990s.

The remainder of this paper is organized as follows. Section 2 describes the data sources, defines policies, and traces their lifecycles. Section 3 provides an overview of China's decentralized policymaking environment. Section 4 documents the trend toward centralization in the post-2013 era and unpacks the underlying incentives. Section 5 introduces our measure of policy–locality compatibility and examines its relationship with policy effectiveness. Section 6 then uses these suitability measures to evaluate the costs and benefits of policy centralization. Section 7 concludes.

2 Background and data

In this section, we briefly describe the institutional background of governance and policymaking in China and introduce the policy documents and data construction process.

2.1 Governance and policymaking in China

2.1.1 Structure of government hierarchy

China's administrative system comprises five tiers: the central government, 31 provincial-level units, 333 prefectures, 2,853 counties, and 40,497 townships. Below the township level, urban communities and rural villages establish self-governing councils that support policy implementation, although they are not formal government entities. In practice, township governments primarily execute policies delegated to them, while substantive policymaking occurs at the county level or above.

At the apex, the State Council and the Chinese Communist Party's Politburo and Standing Committee in Beijing formulate national policies, develop five-year plans, and set broad strategic objectives. At the sub-national level, provincial, prefectural, and county governments—and their corresponding party committees—administer policy portfolios that blend directives from the central government with initiatives conceived locally.

Some policy areas, such as foreign affairs and national defense, remain the exclusive domain of the central government, whereas others, like community services and local governance, fall entirely under local authority. Nevertheless, most policy areas—from economic development and education to environmental protection—are governed through a collaborative process between central and local governments, with the exact degree of centralization varying substantially by sector, region, and over time.

This paper examines the division of labor between central and local governments, setting aside intra-local government dynamics. We focus on the policy portfolios of prefectural governments—the most detailed level at which a comprehensive policy record is available—to distinguish between centrally mandated policies and those initiated locally (the latter potentially originating from any sub-national level).

2.1.2 Typology of policies by central involvement

Both central and local governments can originate new policies. In the case of a central policy initiative, the proposal first appears in national documents—five-year plans, work reports or policy directives—and only later shows up in local policy documents and work reports after local adoption. Although some central directives specify firm timelines for nationwide rollout, the majority leave both which jurisdictions participate and when they implement the policy to local discretion. This latitude produces substantial variation in the coverage and speed of central policy diffusion.

Local policy initiatives, by contrast, emerge in local government documents and work

reports. Once a policy is launched locally, neighboring jurisdictions may observe it and adopt it themselves, generating horizontal diffusion. At some point the central government might take notice and respond in one of three ways: veto the proposal, endorse it for broader experimentation across other localities, or endorse it to be directly elevated to the national level.

Accordingly, any policy implemented by a given locality in a given year can be classified by the degree of central involvement as (a) centrally initiated, (b) locally initiated and endorsed by the central government, or (c) locally initiated without any central endorsement. The combined share of categories (a) and (b), relative to (c), provides a useful proxy for the strength of the central government's influence within China's policymaking landscape.

2.1.3 Policy documents

Accurately capturing the roles of central and local governments in China hinges on the comprehensiveness of policy documents, since these texts constitute the very foundation of enforcement. In practice, China's policy instruments—ranging from national Five-Year Plans to government work reports and policy directives—are far more than aspirational statements. They serve as the authoritative medium through which mandates are issued, monitored, and enforced across every administrative tier. Legitimacy, legality, and bureaucratic accountability all turn on the issuance and implementation of these documents, which together underpin the state's entire policy execution and compliance apparatus.

2.2 Construction of policy data

Our baseline policy dataset combines two primary sources. First, we assemble over 3.4 million policy documents issued by central, provincial, and prefectural governments between 1980 and 2023 from `www.pkulaw.com`, a leading legal search engine hosted by Peking University Law School and widely used by lawyers, judges, and academics.[2]

Second, we compile the complete set of annual prefectural government work reports for 2003–2020 from the Renmin database.[3] These reports enumerate the policies implemented in each prefecture in a given year, which we then match to the corresponding policy document(s) and supplement with additional local socio-economic indicators.

We describe these data sources in detail below and explain our choices for measurement and variable construction in the empirical analysis.

2. For more details about `www.pkulaw.com`, see Wang and Yang (2025).
3. Available at: https://data.people.com.cn/.

2.2.1 Defining and identifying a "policy"

A key step in our empirical approach involves the precise identification of "policies." To this end, we collect a comprehensive set of policy-related keywords from annual prefectural government reports between 2003 and 2020.

As shown in Panel (a) of Appendix Figure A.1, prefectural government reports follow a standardized format. Over the past 20 years, Section 1 always begins with a recap of prior policies and achievements, while Section 2 outlines plans for the coming year. For our purposes, we focus exclusively on the "recap" section to exclude policy ideas that are mentioned but never implemented.

To extract keywords from sentences, we first compile a stop-word list—including terms like "enhance," "further," and "implement"—so that we capture only the core elements that distinguish one policy from another. Each candidate keyword is then validated in two stages: initially by manual review from research assistants, and subsequently by ChatGPT o4-mini, which assesses whether the term can stand alone as a meaningful policy keyword.[4] Any keyword rejected in either step is removed from the master dataset.

Once extracted, we search for these keywords across the full corpus of policy documents to identify their initiation and track their diffusion. Appendix Table A.1 presents a random sample of policy keywords alongside its timing and location of initiation. This data-construction process enables us to reconstruct the full policy portfolio of any locality for any given year.

Two key assumptions underpin our definition of policy keywords. The first is that any substantive policy agenda implemented by a local government appears at least once in the corpus of government reports—whether in its own report or in those of subsequent adopters. The second is that the degree of aggregation chosen by politicians in these reports effectively captures the distinct features of individual policies.

While we regard both assumptions as generally valid, we also develop three alternative definitions of policy keywords to assess the robustness of our results. First, we extract keywords directly from the universe of policy titles—bypassing government work reports. Second, we disaggregate bundled policies by domain, so that each policy–domain pair constitutes a distinct policy initiative comparable to the rest of the sample.[5] Third,

4. As an example, we exclude "Promoting Environmental Protection" from our dataset but keep "River Chief System" and "Ecological Red Line Policy". We regard the former as a vague and overly broad slogan, while the latter two as solid agendas that refer to specific campaigns and policy actions.

5. For example, the "Rural Revitalization Campaign," which is a large policy bundle initiated by multiple central government units, is broken down into "Rural Revitalization + Agriculture," "Rural Revitalization + Transportation," "Rural Revitalization + Education," "Rural Revitalization + Commerce," etc. For

we bundle policies that are sufficiently similar by computing pairwise textual distances based on document-vector representations of each keyword. In the Online Appendix, we describe these alternative constructions in greater detail and demonstrate that our main findings hold under each version of aggregation.

2.2.2 Tracing policy lifecycles

Once the keywords are extracted, we trace their diffusion across the full corpus of policy documents collected from `www.pkulaw.com`. Panels (b) and (c) of Appendix Figure A.1 provide examples of central and local policy documents. For each policy, we record its title, full text, issuing authority, effective date, area of law, and legal status as of December 2023.

Our final sample comprises 3,454,306 policy documents, of which 151,000 were issued by the central government. We merge this corpus with our keyword list, and use the Aho–Corasick algorithm to trace each policy across different policy documents—on average, each policy idea appears in documents issued by 22.92 distinct local-government ministries or bureaus.

Linking various policy documents based on policy keyword allows us to define the entire life cycle of each policy ever implemented in China over the past two decades—from local policy initiation, to horizontal diffusion, to vertical adoption, and eventually to national roll-out.

2.2.3 Supplementary data

Data on economic performance Policy objectives are inherently multidimensional. To evaluate policy effectiveness, Section 6 focuses on the subset of industrial policies in our sample. We classify industries using the four-digit codes of China's national standard GB/T 4754 (2017), a hierarchical system maintained by the National Bureau of Statistics for categorizing economic activities. This system is analogous to NAICS in the U.S. or NACE in the EU, and the four-digit level provides the most granular and widely used classification.

We draw equity investment data from the Business Registration Database, maintained by the State Administration for Industry and Commerce. This comprehensive registry covers over 250 million firm records from 1980 to 2023 and includes detailed information on firm location, ownership structure, legal representatives, shareholders, executives, reg-

each bundled policy, its corresponding domains are defined as the set of local department types that issue documents related to its topic.

istered capital, industry classification, founding year, and subsequent updates. Each firm is assigned a four-digit industry code corresponding to its primary business activities.

We measure firm-level performance using the Annual Survey of Industrial Enterprises, maintained by the National Bureau of Statistics. It contains detailed input and output data for all manufacturing firms with annual revenue exceeding 5 million RMB before 2011 and 20 million RMB thereafter. Each firm is classified into a four-digit industry code by the National Bureau of Statistics.

We collect export revenue data from the Detailed Records of Imports and Exports, compiled by the General Administration of Customs of China. This dataset records the city-level origin and HS codes of all customs export transactions from 2000 to 2016. To convert HS codes into the four-digit industrial codes used in our analysis, we first map them to the United Nations ISIC codes and then translate those ISIC codes into four-digit industrial codes using official Chinese government documentation. To improve conversion accuracy, we further apply NLP methods to identify the semantically closest code pairs.

Finally, we collect patent information from the China National Intellectual Property Administration. The patent dataset covers approximately 11 million patents filed by Chinese companies between 1990 and 2020. Each patent is linked to an industry classified by a four-digit code. Additionally, we link the patent data to the company database based on the filing party's identifier.

Data on politicians Following Wang and Yang (2025) and Wang, Zhang, and Zhou (2020), we compile detailed biographical information on the universe of Chinese central ministers and local (provincial and prefectural) leaders over our two-decade sample period. For each politician, we record hometown, date of birth, education level, current title, past work history, and other observable characteristics. We also estimate each politician's *ex ante* promotion prospects in each year as a flexible function of age, official rank, and the vector of these characteristics, which serves as a proxy for career-advancement incentives.[6]

3 Basic facts about policy making in China

In this section, we document some basic facts about policy making in China, and investigate the driving forces behind policy innovation and diffusion.

6. Appendix Appendix C explains the incentive measure in greater detail.

3.1 Overview

Among the 115,679 distinct policies identified between 2003 and 2023, 20,994 (18.15%) were initially introduced by the central government. For example, in 2005 the Ministry of Education issued a policy to provide "full tuition waivers for primary and secondary education in rural areas"—a central policy that had not been attempted by any local government before.

The remaining 94,685 policies were first introduced by local governments. Among these, 29,957 (31.64%) were "one-off" policies—implemented only in the prefecture or province where they originated and never diffused to other localities or adopted by higher-level governments. For instance, one such policy, Industrial Cluster for Petrochemicals, Energy, and Advanced Materials, enacted in Guangdong in 2018, was not adopted elsewhere. In contrast, 64,728 (68.36%) locally initiated policies diffused to at least one other locality. For example, Zhejiang province introduced a policy on the "Village Shareholder System" in 2005, which was later adopted by 25 other provinces.

Among all the locally initiated policies, 24,322 (25.68%) eventually had some central government involvement. This process typically involves some initial local diffusion that draws the central government's attention, leading it to adopt the bottom-up policy idea either through further evaluation via centrally led experimentation or by directly promoting it as a top-down national policy (Heilmann 2008).

3.2 Bureaucrats' roles in policy innovation

To measure the policy innovativeness of each locality in a given year, we follow Gerrish and Blei (2010) and Kelly et al. (2021) to define a policy innovation index:

$$\text{Innovation}_{i,t} = \frac{1}{|U|} \times \sum_{p \in U} \frac{\text{totalAdopt}_p}{\text{ranking}_{i,p}} \tag{1}$$

where U is the set of bottom-up policy that prefecture i carried out at year t. This measure simultaneously captures both how fast you are moving and how important a policy is: for example, if prefecture i is the initiator of policy p ($\text{ranking}_{i,p} = 1$), and policy p eventually became a national policy (totalAdopt_p = the total number of prefectures in China), then the innovation index will be driven up accordingly. Similarly, we can measure the eagerness of each locality in each year in terms of implementing central policies from top down, by defining the compliance index.[7]

7. Compliance index is defined as: $\text{Compliance}_{i,t} = \frac{1}{|\tilde{U}|} \times \sum_{p \in \tilde{U}} \frac{\text{totalAdopt}_p}{\text{ranking}_{i,p}}$, where $\tilde{U}$ is the set of top-down policy that prefecture i carried out at year t.

For example, according to our calculation, local policy innovation spiked during Xi Jinping's tenure as Zhejiang's Party Secretary: the innovation index reached 7.50, ranking number 1 out of all 31 provinces in China. This surge was driven by several policies he initiated that later diffused widely, such as the "fiscal expenditure performance evaluation" program—launched in 2006 and adopted as national policy in 2011—and the "subsidized hospitalization" program, which was eventually adopted by nine other provinces.

A key question is whether policy innovation is primarily driven by innovative bureaucrats or if some localities inherently provide a more nurturing environment for innovation. To address this, we exploit the fact that Chinese bureaucrats are frequently rotated across localities and follow the Abowd, Kramarz, and Margolis (1999) approach to separately identify "bureaucrat fixed effects" and "locality fixed effects" in driving policy innovations:

$$Y_{ijt} = \alpha_i + \Psi_{j(i,t)} + \gamma_t + \varepsilon_{ijt} \tag{2}$$

where Y_{ijt} is the policy innovation index of prefecture i, led by bureaucrat j, in year t. α_i is prefecture fixed effect, $\Psi_{j(i,t)}$ is bureaucrat fixed effect, and γ_t is year fixed effect. Those parameters are solely identified from politicians who moved between localities.

As shown in Table 1, bureaucrat fixed effects explain seven times more variation in the innovation index than locality fixed effects. This suggests that bureaucrats, rather than localities, play the central role in shaping bottom-up policy innovation. In addition, year fixed effects also appear important in shaping policy innovation, highlighting the importance of evolving policymaking dynamics, which we discuss in greater detail in Section 4.

As Andrews et al. (2008) pointed out, if prefectures are weakly connected to one another because of limited mobility of politicians across localities, AKM estimates of the contribution of locality effects to variance of innovation are biased *upwards*, while estimates of the contribution of politician effects to variance are biased *downwards*. Therefore, our estimates of the relative importance of politician fixed effects with respect to locality fixed effects can be interpreted as a lower bound.

3.3 Bureaucrats' roles in policy diffusion

In addition to driving bottom-up policy innovation, do local bureaucrats also play a significant role in shaping policy diffusion across various localities? To investigate this, we examine how policy diffusion evolves after a prefectural leader departs from his position. Specifically, we estimate the following event study model:

$$Y_{pit} = \sum_{T} \beta_T T_{it} + \phi_p + \lambda_t + \varepsilon_{pit} \tag{3}$$

where Y_{pit} is the number of adoptions in year t for policy p, which was initiated by prefecture i. T_{it} represents the event study dummy variables: T_{it} equals one if, in year t, T years have passed since prefecture i experienced a turnover of its political leader, and zero otherwise. We further control for the full set of policy fixed effect and year fixed effect, and cluster the standard errors at the prefecture level. For robustness, we follow also Sun and Abraham (2021) to account for heterogeneous treatment effects in staggered event study designs.

As shown in Figure 1, the future departure of a local politician—resulting from rotation, promotion, demotion, or retirement—is orthogonal to prior trends in the diffusion of locally initiated policies. However, once the local politician leaves his position, there is a stark 41.6% reduction in the speed of policy diffusion, and it never recovers to baseline levels in the subsequent years. This pattern exists for all types of political turnover, and is particularly pronounced when the departing politician is *not* promoted to a higher position.

These results suggest that policy diffusion depends on incentivized bureaucrats actively "marketing" their innovations: when the inventor of a new policy can no longer claim full credit for its success, other politicians have little incentive to adopt it. Because local bureaucrats—rather than their central counterparts—initiate the lion's share of policies in China, they also drive policy diffusion.

Taken together, the findings in Sections 3.2 and 3.3 underscore the critical role of local bureaucrats in China's decentralized policymaking process, serving as the driving force behind both policy innovation and diffusion.

4 The centralization of policy making

In this section, we document the notable changes in China's policymaking process over the past decade. In Section 4.1, we examine how local bureaucrats' incentives regarding policy innovation versus compliance have evolved over time. In Section 4.2, we illustrate the emerging trend toward centralization in policymaking.

4.1 Incentives for policy innovation vs. compliance

In order to stand out among their peers in the policy making process, local bureaucrats can potentially allocate their effort across two visible dimensions: (a) initiate innovative new policies from bottom-up that can diffuse widely or even get picked up by the central government for national roll-out; and (b) be an early adopter of top-down policies

assigned by the central government to demonstrate compliance and loyalty.

To understand local policy decisions, it is therefore important to examine the incentive schemes faced by local bureaucrats: are they rewarded for policy innovation, or policy compliance? To answer this question, for each given year, we identify all the prefectural leaders that finished their terms within a 5-year moving window around it, and compare the prefectural leaders that received promotion versus those that did not by estimating the following equation:

$$Promotion_i = \alpha + \beta_1 \cdot innovation_i + \beta_2 \cdot compliance_i + X_i\Gamma + \varepsilon_i \tag{4}$$

where $Promotion_i$ is a binary variable indicating whether prefectural leader i was promoted to a higher position by the end of their term. For the right-hand side variable, $innovation_i$ and $compliance_i$, we compute the average innovation/compliance index—defined in Section 3.2—for each prefectural leader i over their entire term in office. Control variables X_i include their year of departure and their official rank within the hierarchy.

Figure 2 plots the estimated coefficients by year. As shown in Panel A, from 2005 to 2012, the innovation index strongly predicted subsequent promotion, with this effect intensifying over time. After 2013, however, the relationship between promotion and the innovation index declined rapidly and converged to zero within three years. These patterns support the interpretation that, prior to 2013, local bureaucrats were rewarded by the central government for policy innovation, a practice that ceased after 2013.

Panel B of Figure 2 presents a mirror image for the rewards to the compliance index. Between 2005 and 2012, there was no significant correlation between the *ex ante* compliance index and subsequent promotion; however, after 2013, this correlation became positive and significant. This finding suggests that the incentives for local officials shifted from rewarding policy innovation to rewarding compliance after 2013.

Panel A of Appendix Table A.6 quantifies these graphical patterns. Before 2013, a one standard deviation increase in the innovation index was, on average, associated with an 8.2 pp increase in the likelihood of promotion, while the correlation became statistically indistinguishable from zero in the post-2013 era. In contrast, prior to 2013, the compliance index was uncorrelated with promotion; thereafter, a one standard deviation increase in the compliance index was associated with a 7.8% higher chance of promotion. These estimates remain robust after controlling for the bureaucrats' cohort, the hierarchical level of the prefectural cities, as well as the bureaucrats' age and education levels.

Panel B of Table A.6 shows that our results are robust to alternative proxies for innovation and compliance. Specifically, instead of the innovation index, we count the

number of locally initiated policies that became national policies in the last three years; and instead of the compliance index, we count the number of times a locality adopted a national policy within the first three years. Our main empirical patterns persist under these alternative measures.

4.2 Trend in policy centralization

Given the reversal in political incentives concerning policy innovation versus compliance, bureaucrats might adjust their behavior accordingly by reallocating effort from bottom-up policy innovation to compliance with top-down policies.

Figure 5, Panel A illustrates such reallocation. For each year, we compute the average ratio of the compliance index to the innovation index, which serves as a proxy for the relative allocation of bureaucratic effort across these two dimensions. As shown, in 2005 the innovation index was roughly on par with the compliance index, and this ratio quickly increased by 20% in 2012. After 2013, the ratio continues to increase, representing an increase of more than 40% in relative magnitude within the period of seven years.

Figure 5, Panel B plots the relative share of bottom-up versus top-down policies in an average prefectural government's policy portfolio in any given year, which exhibits a similar trend. The share of top-down policies remained relatively stable at around 40% prior to 2012, and then rose sharply to 52% between 2013 and 2020—a 30% increase from the baseline, confirming a notable trend toward policy centralization over the past decade.

Figure 5, Panel C underscores that the rise in policy centralization since 2013 stems primarily from a sharp increase in local compliance with centrally mandated policies. For each new top-down policy, we measure how many prefectures adopt it within three years of its issuance. Before 2013, a typical central policy reached about ten prefectures in that window; since 2013, that number has nearly tripled, highlighting a substantial jump in compliance. In contrast, bottom-up policies still diffuse to roughly five prefectures within three years—a rate that remains essentially unchanged before and after 2013.

Taken together, the patterns in Figure 5 suggest a decline in bottom-up policy innovation alongside an increase in compliance with top-down directives, jointly driving a rapid trend toward policy centralization.

The timing of this shift toward centralized policymaking — with 2013 as the clear inflection point — aligns with our results in Figure 2 and Table A.6, which document a reversal in political incentives from innovation to compliance. Qualitative accounts likewise suggest that after Xi Jinping assumed power in late 2012, authority was rapidly consolidated at the center, suppressing local experimentation (Heilmann 2018, Naughton

2021). In particular, the heightened rewards for local compliance and the wider diffusion of central directives mirror Beijing's own critique at the time that "government orders never leave Zhongnanhai" (the central leadership compound in Beijing), a problem Xi made resolving a top priority upon taking office.[8]

That said, in addition to the consolidation of political power by the new leadership since 2013, numerous other factors may have influenced policymaking during this period, including evolving internal and external conditions for the Chinese economy. Thus, although we document empirical facts on promotion patterns and innovation–compliance trends, we do not assert any specific causal mechanism for these observations.

4.3 Zooming in to industrial policies

So far, we have documented that China's policymaking process relies substantially on bottom-up innovation (Section 3), but has been quickly shifting toward greater centralization since 2013 (Section 4). In light of these findings, a natural question is to what extent such centralization in policymaking would affect policy suitability and effectiveness.

Our baseline sample covers around 116,000 distinct policies across all policy domains, which makes it particularly challenging to holistically quantify policy effectiveness. For instance, consider an education policy that provides free lunches to middle school students; its goal could be to improve students' health outcomes, raise their grades, or reduce dropout rates, etc. Given the multiplicity of policy goals—and without knowing the government's exact objective function—it is difficult to evaluate a policy's effectiveness. Furthermore, comparing policies across domains is even trickier. For example, even if we have a clear measure of an education policy's effectiveness, we lack a systematic benchmark to compare it with the effectiveness of a health or environmental policy, which focus on entirely different outcomes.

To systematically evaluate the consequences of policy centralization, in the remainder of this paper, we restrict our analysis to a subsample of industrial policies, which, as shown in Appendix Figure A.6, exhibit a similar trend of centralization since 2013. For these industrial policies, the government explicitly states that its primary goal is to promote the growth of a specific industry, as measured by industrial output, exports, and patent filings—common indicators used by the central government to evaluate industrial policy success (Fu 2015, Glaser 2022, Fang, Li, and Lu 2025).

With the focus on industrial policies, the empirical question becomes: given the government's goal of promoting industrial growth through industrial policies, what are the

8. See: https://www.voachinese.com/a/regulatory-system-china-20130123/1589175.html

tradeoffs associated with relying on top-down versus bottom-up approaches, and to what extent has policy centralization since 2013 affected the government's overall effectiveness in achieving its objectives? We break this inquiry into two parts. In Section 5, we explain how we measure the compatibility between industrial policies and localities, and how this measure relates to industrial policy effectiveness. In Section 6, we discuss the impacts of policy centralization on policy–locality compatibility and, in turn, on policy effectiveness.

5 Policy-Locality Compatibility

The effectiveness of a policy in a given locality depends critically on how well its design and implementation align with local conditions. For instance, an effort to promote the mass installation of solar panels in a rainy area may prove futile. Motivated by this, in Section 5.1, we construct measures of compatibility between each industrial policy and the implemented locality. In Section in Section 5.2, we demonstrate that such compatibility is indeed an important predictor of policy effectiveness (in generating industrial growth and innovation).

5.1 Measurement of compatibility

We measure the compatibility between an industrial policy and a locality in two different (but related) ways.

5.1.1 Alignment with pre-existing regional supply chains

The first approach is to directly measure the predetermined observable characteristics that make a locality particularly conducive to a specific industry. In particular, for a given industry to grow, one important condition is having easy access to its key upstream suppliers, as demonstrated by the extensive literature on industrial agglomeration effects (Greenstone, Hornbeck, and Moretti 2010; Kline and Moretti 2014).

Motivated by this, for each industrial policy aimed at promoting industry p in prefectural city c, we first directly measure the extent to which c has a relative *pre-existing*

strength in the supply chain of industry p:[9]

$$S_{cp} = \sum_{j \neq p} \alpha_{jp} \cdot I_{cj} \tag{5}$$

where α_{jp} represents the share of key upstream industry j in the input composition of industry p, as extracted from China's national input-output table. I_{cj} denotes the accumulated investment in industry j in prefectural city c over the decade preceding the industrial policy. The weighted average S_{cp} thus reflects the absolute strength of prefectural city c in industry p, from the perspective of supply chain access.[10]

Furthermore, we benchmark S_{cp} against both prefectural city c's strengths in other industries and other prefectural cities' strengths in industry p:

$$Supply\text{-}chain\ compatibility_{cp} = \frac{S_{cp} / \sum_{p' \in P} S_{cp'}}{\sum_{c' \in C} S_{c'p} / \sum_{c' \in C, p' \in P} S_{c'p'}} \tag{6}$$

where the numerator measures prefectural city c's strength in industry p's supply chain relative to all other industries, and the denominator measures the rest of the country's strength in industry p's supply chain relative to all other industries. Therefore, the ratio captures the relative strength of prefectural city c in industry p, from the perspective of *pre-existing* supply chain access.

5.1.2 Alignment with entrepreneurs' revealed preferences

From China's business registration records, we extract every equity investment made in a given prefecture-industry-year, capturing both the entry of new firms and additional investments in existing firms. Specifically, we compute I_{cp}, which represents the accumulated equity investment in prefectural city c in industry p during the decade preceding the initiation of an industrial policy. This *ex ante* investment accumulation reflects the absolute level of entrepreneurial enthusiasm for industry p in prefectural city c, as indicated by their business investment decisions.

Based on I_{cp}, we further calculate the entrepreneurs' relative enthusiasm for a given

9. We retain only the key upstream industries—those supplying more than 10 percent of a downstream industry's inputs, as measured in the supply chain. To further identify spatially sensitive industries, we proceed as follows: for each industry–upstream industry pair, we take its five largest prefectures and, for each one, compute the distance to the five largest prefectures in the corresponding upstream industry. If each prefecture can find a corresponding upstream-industry prefecture within a 500 km radius, the industry–upstream industry pair is classified as spatially sensitive.

10. Our findings remain quantitatively similar when we measure supply chain strength within a 500 km radius rather than within the same prefecture. These results are available upon request.

industry in a specific prefecture:

$$Investment\ Compatibility_{cp} = \frac{I_{cp} / \sum_{p' \in P} I_{cp'}}{\sum_{c' \in C} I_{c'p} / \sum_{c' \in C, p' \in P} I_{c'p'}} \tag{7}$$

where the numerator $\frac{I_{cp}}{\sum_{p' \in P} I_{cp'}}$ captures, for a given prefecture c, the concentration of investments in industry p relative to other industries. The denominator measures this relative concentration for the entire nation, so that the resulting ratio reflects the "additional entrepreneur preference" for a particular industry in a specific locality compared to all other industry-locality clusters.

Given this definition, for each industrial policy—whether top-down or bottom-up—that is aimed at promoting industry p in prefectural city c, we can measure the extent to which the policy aligns with or deviates from the preferences of entrepreneurs, as revealed by their business investment decisions prior to the policy's initiation.

Our construction of "entrepreneurs' revealed relative preference" based on business registration records is similar in spirit to that constructed in Fang, Li, and Lu (2025), but with two important distinctions: (a) we restrict our calculation to investments made within the decade *before* the issuance of an industrial policy, thereby capturing the revealed preference of business investors in the *absence* of policy interventions—preferences that likely reflect local fundamentals such as natural endowments and regional supply chains; and (b) we disaggregate investments by private versus state-owned enterprises to examine whether they align differently with top-down versus bottom-up industrial policies.

5.1.3 Descriptive patterns

As shown in Appendix Figure A.12, the compatibility measure based on supply chain strength and that based on investment flows are strongly positively correlated, consistent with supply chain strength being an important consideration in entrepreneurs' investment decisions.

Appendix Figure A.3 plots the average compatibility of adopting localities against years since policy inception. We observe a clear downward trend, indicating that high-compatibility localities tend to be early adopters under decentralized policymaking. This pattern implies two things: (i) our compatibility measures capture meaningful variation across policy–locality pairs; and (ii) local policymakers indeed value alignment between industrial policies and their localities' economic conditions.

Appendix Figure A.11 plots the spatial distribution of these measures of policy–locality compatibility using the automobile industry as an example. This figure further verifies

that the compatibility measures—whether inferred from revealed preferences or defined based on supply chains—are highly correlated. It is worth noting, however, that when we measure relative strength based on *ex ante* cumulative equity investment, the versions based on private enterprise investment and state-owned enterprise investment, while correlated, show notable differences. This pattern likely indicates that these two types of firms may have different preferences when making investment decisions, and this distinction allows us to examine whether an industrial policy is more closely aligned with the revealed preferences of private firms or those of SOEs.

5.2 Policy Compatibility and policy effectiveness

Do industrial policies that are more compatible with local economic conditions actually deliver more desirable policy outcomes?

To answer this question, we compare the dynamic impacts of industrial policies that promote industries in line with local strengths versus those that defy local strengths. Specifically, we estimate the following empirical model:

$$Y_{pct} = \sum_{T} \alpha_T T_{ipct} + \sum_{T} \beta_T T_{ipct} Compatibility_{pc} + \phi_{cp} + \gamma_{pt} + \lambda_{ct} + \varepsilon_{pct} \tag{8}$$

where Y_{pct} is the outcome of interest for industry p in prefectural city c in year t. T_{it} represents the event-study dummy variables, which equal one if, in year t, T years have passed since prefectural city c implemented a policy promoting industry p, and zero otherwise. $Compatibility_{ip}$ is the continuous compatibility score between prefectural city c and industry p, measured using either equity investment or local supply chain, prior to the initiation of an industrial policy. β_T represents the coefficients of interest, capturing the role of industry-locality compatibility in determining the effectiveness of an industrial policy. We control for full sets of two-dimensional fixed effects: prefecture-by-year, industry-by-year, and prefecture-by-industry. The standard errors are two-way clustered at the prefecture and industry levels.

We examine various outcome variables, including industrial output, patent filings, and export values, which are the most frequently mentioned target outcomes of industrial policies in China, and also the common KPIs used to evaluate local officials' effectiveness in promoting industrial development. It is worth noting that these measures of industrial policy consequence reflect policy effectiveness through the lens of the government's own goals, which may or may not align with the broader welfare of society.

As shown in Figure 3, industrial policies that align with local strengths, according to both pre-existing supply chains or business investment stock, are significantly more

effective in delivering industrial growth compared to those that are incompatible with local conditions. Such compatibility premium appears to be growing over time, suggesting that the gap in industrial policy effectiveness is likely persistent. This heterogeneity is unlikely to be explained by endogenous policy selection, as the two groups exhibit similar trends prior to the initiation of the industrial policies.

Table A.3 quantifies these patterns. Specifically, when an industrial policy is launched in a locality with a one-standard-deviation higher comparative advantage in pre-existing supply chains, it yields, on average, an additional 12% increase in exports, 41.2% growth in industrial output, and 197%more patent filings. Similarly, after policy initiation, a one-standard-deviation increase in the investment-based compatibility measure is associated with an additional 46.9% increase in exports, 236%growth in industrial output, and 757% more patent filings. This robustness is consistent with the fact that these two comparative-advantage measures are highly correlated.

Interestingly, Appendix TableA.4 shows that the heterogeneity disappears when we measure policy–locality compatibility based on SOEs' revealed preferences (i.e., pre-policy investments by SOEs rather than by private firms). This finding is consistent with the interpretation that, on average, the private market is better than the state at understanding local economic conditions—such as whether a particular sector may be profitable given regional supply chains—and that following private market investment patterns can lead to more desirable outcomes in terms of promoting industrial growth and innovation.

6 Tradeoffs of policy centralization

In Sections 6.1 and 6.2, we assess, respectively, the costs and benefits of centralized policymaking through the lens of policy-locality compatibility. Leveraging the findings reported in these two sections, in Section 6.3, we quantitatively compare the costs and benefits of China's policy centralization since 2013.

Our analysis of the trade-offs associated with policy centralization focuses on policy–locality compatibility, a key concern in the theoretical literature (Tiebout 1956; Oates 1972; Alesina and Spolaore 1997; Bolton and Roland 1997; Besley and Coate 2003; Alesina, Baqir, and Hoxby 2004), and likely of first-order importance in this context. Although examining all potential considerations related to centralization is beyond the scope of this paper, we briefly discuss several alternative objectives that might justify centralization and assess their empirical relevance.

6.1 Centralization's negative impact on policy suitability

Centralized policymaking, by sacrificing valuable decentralized local information, may reduce compatibility between localities and policies, thereby undermining policy effectiveness. We examine this hypothesis using a subset of industrial policies, evaluating their suitability to local conditions and their effectiveness in promoting industrial growth and innovation.

6.1.1 Anecdotal example: wind energy development

A clear example of policy centralization leading to reduced policy-locality compatibility can be found in China's development of wind power.

In the 2000s, wind energy was an emerging industry in China that relied heavily on bottom-up industrial policy promotions. The decentralized promotion of wind energy initially concentrated in regions with favorable natural conditions—namely, the northwestern provinces such as Gansu, Xinjiang, and Inner Mongolia—where the vast Gobi deserts and steppes, characterized by high wind density (>300 W/m^2) and minimal land acquisition costs, provided an ideal setting for constructing large-scale wind farms. Under this bottom-up approach, by 2010, China had surpassed the U.S. as the world's largest wind power installer, with over 75% of its capacity concentrated in the northwest.

After 2013, however, policy shifts led to increased top-down pushes for wind energy development. Many low-wind provinces, such as Hunan and Hubei, eager to signal responsiveness to central policy initiatives, rushed to replicate the northwestern model. As a result, many of these newly constructed wind farms—built in regions with wind densities below 200 W/m^2 and lacking access to ultra-high voltage transmission lines—operated at low capacity and were eventually abandoned, earning the moniker "ghost wind farms."[11]

This example illustrates the potential cost of centralizing industrial policymaking: regions less suited for such policies might adopt them, thereby lowering policy effectiveness compared to a scenario in which each locality implements policies tailored to its specific conditions.

6.1.2 Quantitative evidence

To verify whether the forces at play in the wind energy example is generalizable to other domains in China's policy making, we quantitatively examine the difference in average policy-locality compatibility, for top-down vs. bottom-up industrial policies. Specifically,

11. Source: https://news.bjx.com.cn/html/20170221/809616-1.shtml

for each industrial policy, we compute the extent to which it complies with local conditions, according to the two compatibility measures defined in Section 5.

As shown in Table 2, among all the industrial policies implemented by a given prefecture in a given year, those assigned from top-down are significantly less compatible with local economic conditions, as measured by *pre-existing* regional supply chain strength and *ex ante* business investment flows. The results are robust regardless of whether we use binary or continuous measures of compatibility. On average, compared to bottom-up industrial policies, top-down ones promote industries that are 6-16% less suitable for the given prefecture.

Consistent with this cross-sectional comparison between top-down and bottom-up industrial policies, in Appendix Table A.2 we show that when a given industrial policy is endorsed by the central government, there is a sharp decline in the compatibility of subsequent adopters, compared to those who previously adopted the *same* policy under horizontal diffusion. This is consistent with the interpretation that central endorsement leads to a crowd of less-compatible localities taking up the policy to signal compliance and loyalty.

Taken together, our findings show the salience of lowered policy-locality compatibility under centralization, which, combined with the association between policy-locality compatibility and policy effectiveness documented in Section 5.2, imply that top-down industrial policies would on averaged end up being less effective in generating industrial growth than their bottom-up counterparts.[12]

6.2 Centralization's positive impact on policy suitability

It has been well documented that decentralized competition among Chinese local bureaucrats leads to various distortions (Jia and Nie 2017; Wang and Wang 2020; Wang and Yang 2025). To what extent does decentralized competition bias policy-making, and how might centralization mitigate such bias?

Specifically, with respect to the "policy compatibility" dimension we focus on in this paper, a key issue under decentralized policy-making is strategic bias in policy diffusion across localities. Rich qualitative evidence suggests that when local politicians compete for the same promotion opportunities, they may avoid learning from one another—so as not to enhance their competitors' credentials—and thereby forgo opportunities to adopt otherwise suitable and effective policies.

12. This hypothesis is confirmed by Appendix Table A.5, which documents that top-down policies lead to significantly lower industrial growth and innovation, as compared to their bottom-up counterparts.

In this section, we first present qualitative examples of such behavior, then quantitatively assess its prevalence in our context, and finally examine the extent to which policy centralization can mitigate these biases. While this paper centers on policy-locality compatibility, we also briefly discuss several other potential benefits of centralization.

6.2.1 Anecdotal example: vehicle restriction policy

In the 1990s and 2000s, vehicle ownership grew rapidly in China, causing severe congestion and pollution problems in major cities. In response, Shanghai initially experimented with various forms of a license plate auction system, eventually launching a multi-unit, discriminatory (pay-as-you-bid), dynamic auction in which residents bid for plates in monthly auctions, with revenues directed toward public transportation upgrades. The policy is widely praised for its allocative efficiency as well as the substantial financial support generated for public transportation (which benefits the poor).

Instead of adopting the Shanghai model—which had proven effective and refined its design details over more than a decade of gradual experimentation—Beijing opted to implement an alternative system in 2011. This system used free, random lotteries to allocate license plates to registered citizens. Due to the low lottery success rate, many citizens without an urgent need for vehicles participated preemptively in the lottery. Moreover, since license plates cannot be "banked" or "resold," citizens with low willingness to pay (WTP) for vehicles often purchased cars ahead of their high-WTP counterparts, thereby generating substantial welfare loss due to misallocation (Li 2018).

Many observers speculate that Beijing intentionally deviated from the Shanghai model of license plate auctions because of the political rivalry between the two major cities. When challenged on this point, a government official asserted that Beijing would *never* auction license plates, claiming that it "aims to protect the interests of the poor" (Wang and Zhao 2017).

6.2.2 Quantitative evidence

In order to quantify the prevalence of such strategic distortions in policy diffusion, we examine whether political competition is a determinant of decentralized policy diffusion, and if so, how it might affect the compatibility between localities and policies, and whether centralization can help mitigate such impacts.

Determinants of policy diffusion We define policy similarity across each pair of prefectures in China in a given year, and investigate what factors, such as pairwise geographic,

economic, and political proximity can explain the changes in policy proximity.

Specifically, for each prefecture i in each year t, we construct a vector representing its entire policy portfolio covering all policy dimensions: $\vec{V}_{it} = (v_{i1t}, v_{i2t}, v_{i3t}, ..., v_{iNt})$. We then calculate, for each prefecture pair in a given year, their similarity in policy portfolios, as measured by the (opposite) distance between their policy portfolio vectors: $S_{ijt} = -||\vec{V}_{it} - \vec{V}_{jt}||$.

Similarly, for each pair of prefectures, we further compute their economic proximity in a given year ($\text{Proximity}_{ijt,econ}$), as measured by difference in per capita GDP; [13] and political proximity in a given year ($\text{Proximity}_{ijt,pol}$), as measured by the two prefectural leaders' similarity in promotion likelihoods, which are projected based on their backgrounds. [14]

We estimate the follow equation:

$$S_{ijt} = \alpha \cdot \text{Proximity}_{ijt,m} + \lambda_t + \gamma_i + \sigma_j + \varepsilon_{ijt} \tag{9}$$

where $m \in \{\text{Econ}, \text{Pol}\}$ denote different measures of proximity. λ_t, γ_i, σ_j represents year, origin, and destination fixed effects, respectively. The standard errors are two-way clustered at the origin and destination levels.

As shown in panel (a) of Figure 4, economic similarity between prefectures is a strong, positive predictor of policy similarity. In other words, neighboring prefectures and those with comparable economic conditions are more likely to adopt similar policies. This finding is intuitive: if a policy has been demonstrated to work in another locality with similar socio-economic conditions, it is more likely to succeed here.

In stark contrast, as shown in panel (b), when two prefectural leaders are more politically similar—a proxy for increased competition for promotions—policy similarity declines significantly. This suggests that politicians, in order to avoid enhancing their competitors' credentials, tend not to learn from their peers, thereby distorting the policy diffusion process.

Table A.14 quantifies these patterns: a one-standard-deviation increase in economic similarity is associated with a 1.04-point (2.5%) rise in policy similarity, whereas a one-standard-deviation increase in political similarity corresponds to a 0.08-point (0.2%) decline in policy similarity.

Importantly, as shown in Table A.14 Panel B, in our political similarity analysis we

13. Our findings are robust to using alternative measures of economic similarity, based on fiscal income, unweighted GDP, fiscal expenditure etc.

14. See Appendix C for details on the construction of this variable. Our result is robust to alternative measures of political competition. For example, instead of taking the difference between promotion incentives, we can compute the Mahalanobis distance between two politicians' "feature vectors" – those include their start-age, hierarchical status, gender, ethnicity, education, central government experience as well as previous experience. See Appendix Figure **??**

control for a stringent set of "prefecture-pair fixed effects," holding constant the baseline rate of policy diffusion between any two localities and exploiting only the variation in political similarity generated by bureaucratic turnovers over time. Furthermore, in a more stringent specification, we control for "politician-by-target-location" fixed effects, isolating variation created solely by political turnover at the other prefecture. This enables us to assess whether changes in local political leadership affect a prefecture's propensity to adopt policies from an origin prefecture whose leader remains unchanged. Our findings remain robust under these more demanding specifications, suggesting a causal role for political competition in policy diffusion.

Our result is robust to alternative measures of policy learning. Instead of comparing policy portfolio each year between localities, we can model learning more explicitly. In this specification, we define an instance of policy learning (Learning_{ijt}) as prefecture i adopting, at year t, a policy initiated by prefecture j. We then estimate the following model:

$$\text{Learning}_{ijt} = \beta \cdot \text{Proximity}_{ijt,m} + \gamma_{ij} + \lambda_t + \varepsilon_{ijt} \tag{10}$$

Appendix Table A.15 presents the results, we find that while economic proximity once again positively predicts policy learning, an increase in political competition decreases the propensity of policy learning. In the more stringent specifications, we control for prefecture-pair fixed effects, thereby exploiting variation that solely comes from politician rotation. We find that a one standard deviation increase in political competition leads to a 1.2% decrease in the likelihood of directed policy learning.

Economic similarity and political similarity To what extent do the patterns documented in Table A.14 affect the average policy–locality compatibility in China? If politically similar bureaucrats tend to work in economically different localities, then the lack of policy diffusion driven by political competition would not be costly, as adopting a policy from a prefecture with vastly different socio-economic conditions would not be highly beneficial anyway. Conversely, if competing politicians are assigned to lead socio-economically similar localities, the absence of policy diffusion resulting from their strategic competition becomes costly, as it prevents the adoption of potentially fruitful policies.

As revealed by Appendix Figure A.14, the economic similarity between two prefectures is strongly and positively associated with their political similarity. In other words, politicians with similar backgrounds tend to be assigned by the central government to localities with comparable economic conditions—an expected pattern if the central government aims to maximize an objective that depends on both local conditions and bureaucratic capabilities.

This finding implies that strategic political competition interferes with the diffusion of policies across localities with similar socio-economic conditions, thereby hindering the adoption of new policies that might otherwise prove highly effective.

Decentralization and policy-locality compatibility Holding the policy capacity of a locality constant, strategic political competition leads to substitutions in policy adoption. Instead of adopting policies from one's political competitors—which have been proven effective in jurisdictions with comparable socio-economic conditions—a prefectural leader may opt for alternative policies from jurisdictions that are less socio-economically similar, or adopt central government policies that are less tailored to local needs.

Specifically, among all other prefectures (i) whose GDP per capita differs by no more than 0.43 standard deviation (50th percentile of pairwise difference in GDP pc) from that of a given prefecture; (ii) who are within the same province (hierarchical neighbors); and (iii) who are among the top 30 closest in distance (geographic neighbors), we count what proportion of them are led by politicians whose promotion incentives are within the top 5% fiercest competitors of the leader in question.[15]

Figure **??** panel (a) shows the results. We show that a 10% increase in the share of political competitors among economic neighbors is associated with a 4.4% loss in average locality–policy compatibility in that year, confirming the hypothesis that strategic competition prevents the diffusion of beneficial policies. Reassuringly, in Appendix Table **??** Panel A, we verify that the "share of political competitors among economic neighbors" is uncorrelated with the overall number of policies adopted in a given year, confirming that the "extensive margin" remains unaffected. In Table 4, Panel A, we find that the compatibility of central policies remain largely unaffected by inter-regional competition, while such effect is pronounced in the local policy subsample.[16]

This finding, combined with the result that lower policy-locality compatibility is associated with reduced policy effectiveness, underscores the economic cost of decentralized policy making.

Centralization mitigating distortions in policy diffusion To the extent that strategic distortion in decentralized policy diffusion is driven by political competition among local bureaucrats for career advancement, the post-2013 removal of political rewards for

15. Our findings are robust to various alternative definitions of economic and geographic neighbors, as shown in the Online Appendix.

16. We repeat the analysis using the share of political competitors among geographic neighbors and the share of political competitors within the same province; in all three cases, we observe that heightened political competition among regions with similar characteristics corresponds to reduced policy–locality compatibility. The results are presented in Appendix Table A.17.

bottom-up policy innovation—documented in Section 4—may have inadvertently tamed these distortions. Specifically, under more centralized policy making after 2013, politicians could become less concerned about boosting their peers' credentials and, consequently, more willing to adopt policies proven effective in peer localities with similar socio-economic conditions.

Panels (c) and (d) of Figure 4 verify these changing diffusion patterns under centralized policy making. After 2013, the positive correlation between economic similarity and policy diffusion weakens, consistent with centralization leading to the adoption of policies less tailored to local conditions. Importantly, Panel (d) shows that the negative association between political proximity and policy diffusion also significantly weakens post-2013, confirming that centralization helps mitigate biases in decentralized diffusion.

Figure **??** panel (b) shows that, after 2013, a higher share of political competitors among economic neighbors no longer predicts lower policy suitability. Table 4 Panel B confirms this: the negative correlation between average policy–locality compatibility and the share of similar localities led by political competitors becomes statistically insignificant post-2013. This suggests that centralization—shifting incentives from bottom-up innovation toward top-down compliance—mitigates the distortions inherent in decentralized policy diffusion.

6.3 Back of the envelope calculation: cost vs. benefit (preliminary)

As shown in Sections 6.1 and 6.2, the centralization of policymaking has mixed impacts on policy–locality compatibility. By linking these countervailing forces to the relationship between compatibility and policy effectiveness in Section 5.2, we perform a back-of-the-envelope calculation to quantify the economic trade-offs of centralization. Below, we outline its main components (see Section Appendix B for details and robustness checks).

Compared to the 2012 level of decentralization, the post-2013 centralization trend converted 2,562 prefecture-level industrial policies from bottom-up to top-down. Based on our estimates in Section 6.1, each top-down policy is 16% less compatible with local conditions than a bottom-up one. Linking this compatibility gap to the differential effectiveness of compatible versus incompatible policies in driving industrial growth and innovation, we calculate that the yearly cost of the post-2013 centralization in policy making is 197 billion RMB in industrial output, 15 billion in export and 1090 patent filings.

Meanwhile, Section 6.2 shows that for each additional political competitor among economic neighbors, post-2013 centralization mitigates the negative impact on average compatibility by 0.009. Given the average prefecture has 4 competitors among its eco-

nomic neighbors, this raises its average compatibility by 0.036. Applying this to the 9,376 bottom-up industrial policies implemented each year—and again using the differential effectiveness estimates—we calculate that the yearly benefit of post-2013 centralization is 129 billion RMB in industrial output, 10 billion in export and 715 patent filings.

Taken together, these calculations indicate that, in this context, centralization's costs consistently exceed its benefits by roughly 50%, cautioning against over-centralization in policymaking.

6.4 Different policy objectives between central and local governments?

Through the lens of policy-locality compatibility, a key tradeoff associated with centralization, our calculations indicate that centralization might conflict with the government's stated objectives of promoting industrial growth and innovation. That said, it remains plausible that the central government pursues additional goals beyond policy-locality compatibility, which could explain its differential selection of industrial policies. For instance, the central government may prioritize industries with higher long-run potential or those of strategic importance, such as military applications. In such cases, evaluating industrial policies solely on the basis of local suitability and industrial growth might underestimate the returns to top-down policies.

It is worth noting that if the central government pursues additional policy goals distinct from those of local governments, this might lead to the promotion of industries that do not align with China's current *national* comparative advantage (relative to other countries). However, even conditional on these industries, if the central government wants to effectively promote their growth, it should not, when choosing localities *within* China, allocate industrial policies to areas lacking the relevant supply chains or deemed less suitable by private investors—yet our data systematically reveal these patterns.

Nevertheless, we address the issue of alternative policy goals by explicitly investigating the central government's potential goals. First, we examine whether the central government's industrial policies indeed target more "ambitious" industries. Using ComTrade data, we compute the 2024 global market size (total import value summed across all countries) for each industry and map this information to China's industrial policies. As shown in Panel (a) of Appendix Table A.7, top-down industrial policies do not appear to select significantly larger industries in the long run, compared to their bottom-up counterparts. Given that local governments initiate significantly more industrial policies than the central government, in Panel (b), we further restrict the bottom-up sample to local policies targeting industries with the highest future output values, ensuring that the

number of central and local policies is balanced. Under such comparison, local governments actually target *more* ambitious industries.

Second, we investigate whether top-down policies are more focused on industries pertinent to national security, and assess the extent to which this focus affects our findings on industry-locality compatibility. Specifically, we identify industries included on the "export ban" list to China by the US government and confirm that the central government is indeed more likely to promote such "key" industries than local governments (Panel (a) of Appendix Table A.8). That said, as shown in Appendix Table A.13, even after accounting for these national security-related industries, our main findings regarding the reduced locality–policy compatibility for top-down policies persist (with even larger magnitudes), suggesting that the costs of centralization cannot be attributed to national security considerations.

Third, the central government may have a longer policy horizon than local governments, causing it to favor more "forward-looking" industries—those in which China currently lacks a comparative advantage, but have high potentials in the long run. To test this, we use UN Comtrade data to calculate China's revealed comparative advantage (RCA) in exporting, in both 2000 and 2024. We then calculate, for each industry, the difference in these two RCA measures, which serves as a proxy for China's long-term growth in it. As shown in Panel (a) of Appendix Table A.9, the centrally initiated or endorsed policies do not appear to target industries with higher long-run growth, as compared to their local counterparts. Furthermore, Panel (b) reveals that when the number of central and local policies is held equal (i.e., stratifying local policies by highest long-run growth), industries with the highest long-run potential appear to be promoted more by the local governments instead of the central government. These findings suggest that central authorities are not inherently more forward-looking than local governments when selecting industrial policies.

Fourth, as pointed out by Liu (2019), within a production network, market distortions accumulate via backward demand linkages, causing upstream sectors to suffer the greatest size distortions. In such settings, there may be a rationale for the central government to promote these upstream sectors to maximize national output. As shown in Appendix Table A.10, we find no evidence that the central government targets such industries more than local governments do.

Fifth, the central government might additionally promote sectors with high economies of scale to maximize national productivity—objectives that may lie beyond the scope of individual local governments. Using the sector-level economies of scale estimated in Atkin, Costinot, and Fukui (2021), we confirm that the central government is indeed

marginally more likely to endorse high–economies of scale sectors (Appendix Table A.11), but this cannot explain the lower compatibility associated with top-down policies (Appendix Table

Finally, certain industries generate pollution externalities that affect neighboring jurisdictions. To better coordinate spatial environmental spillovers, it might be more efficient for the central government, rather than decentralized local governments, to take the lead in promoting such industries. Following He, Wang, and Zhang (2020), we identify key manufacturing industries classified as "polluting" by the Ministry of Ecology and Environment. As reported in Appendix Table A.12, the central government is indeed more likely to promote these sectors than local governments. However, Appendix Table A.13 shows that accounting for such polluting sectors does not alter our baseline finding that centrally endorsed policies have lower compatibility.

Taken together, our findings indicate that these alternative considerations regarding centralization—while potentially relevant to some industrial policy decisions—are quantitatively not of first-order importance in our setting, relative to the baseline results on the cost of centralization. Therefore, our main message remains unchanged after accounting for these additional considerations.

7 Conclusion

In this paper, we map the comprehensive landscape of China's policymaking process. By tracing the full arc of over 116,000 distinct policies—-from inception to diffusion and adoption-—we uncover salient features of an institutional setup once characterized by decentralized experimentation. We then pinpoint the incentive changes that fueled the transition to an increasingly centralized regime. We offer a conceptual and empirical investigation into the pros and cons of the centralization trend, pointing out a tension between the compatibility of locally tailored policies and the distortions arising from horizontal differentiation in political tournaments.

These trade-offs are not unique to China. As governments around the world grapple with challenges that demand both coordination and customization—from climate mitigation to industrial policy—understanding the optimal hierarchical level for decision-making and the associated tradeoffs becomes increasingly imperative. By illuminating the mechanisms and consequences of China's policymaking centralization, this paper contributes new evidence and invites a rethinking of how large states can design institutions that balance initiative with integration.

At a broader level, our paper alludes to widespread policy misallocation driven by

institutional constraints and bureaucratic incentive structures. We refrain from taking a stance on the determinants of policy space: while we find that political incentives explain the quantity of policy innovations, we say little about the *quality* of policies that could have been adopted but were strangled in the cradle, since we observe only those that ultimately appeared on paper. Understanding how institutional changes affect the direction and quality of policy *innovation* is a fascinating direction for future work.

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Figures

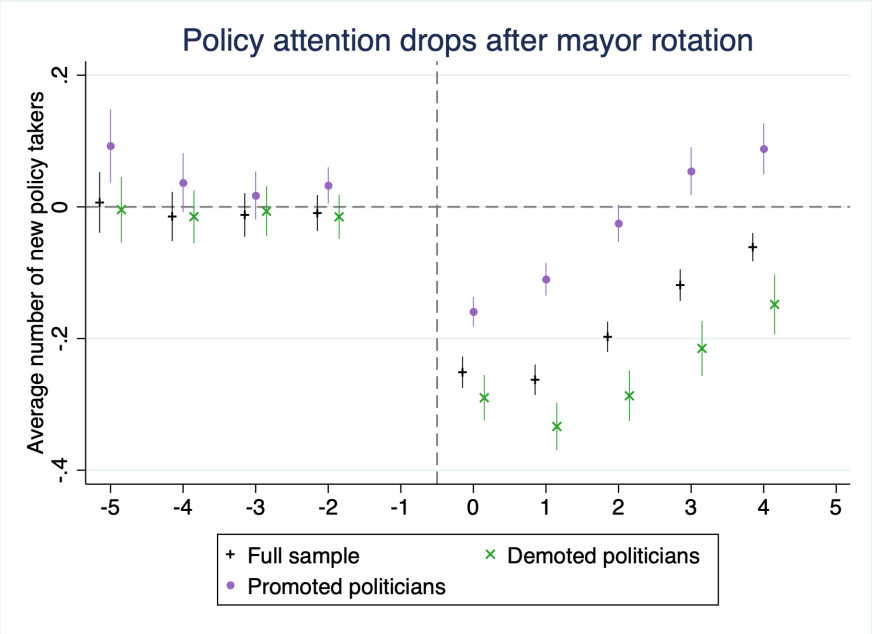
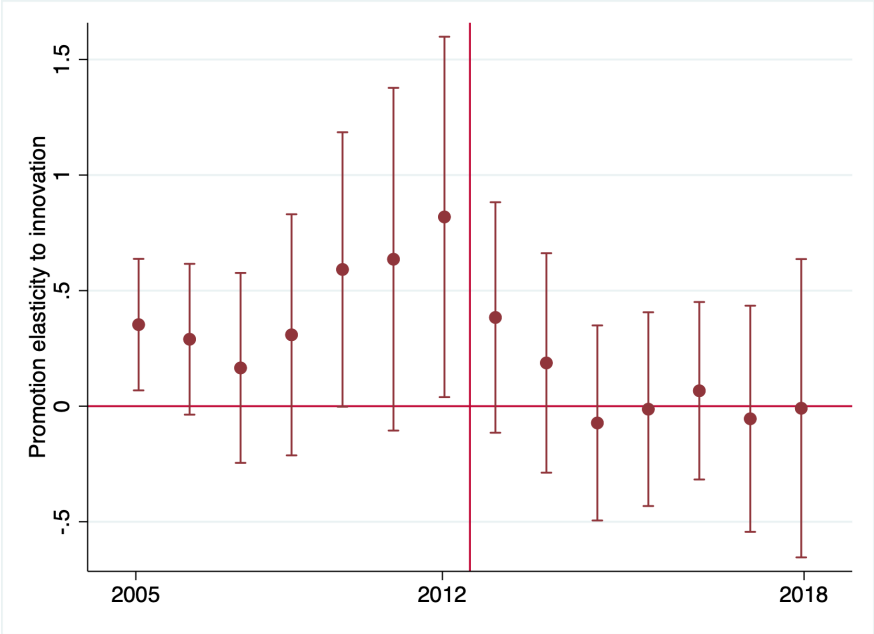
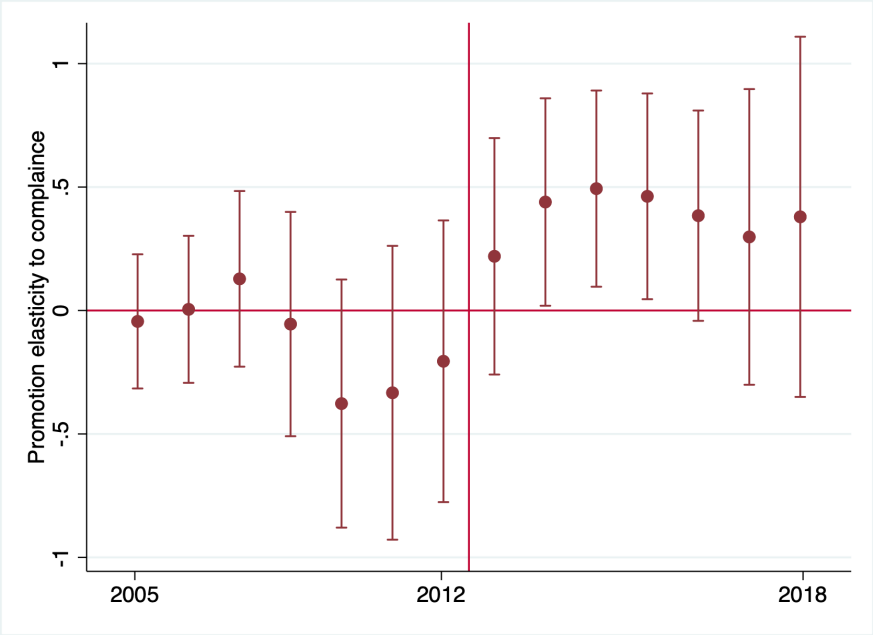


Figure 1: This figure plots the event study estimates illustrating the decrease in number of policy adoption after prefectural party secretary departure. We cluster standard errors at prefectural level, and compare baseline estimates with cases where the departing politicians got promoted or demoted.

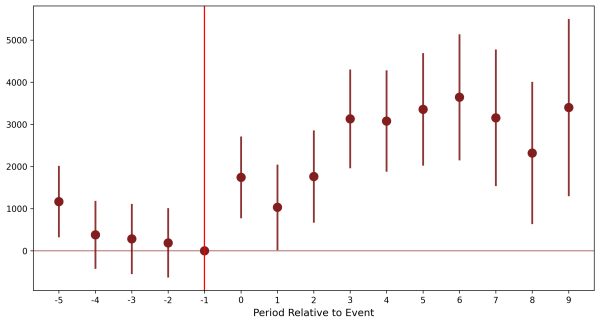


Panel A: Promotion elasticity wrt. innovation

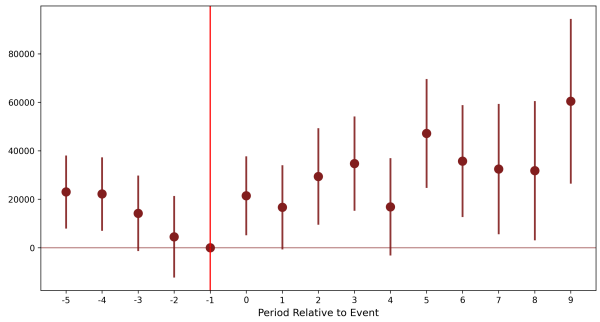


Panel B: Promotion elasticity wrt. compliance

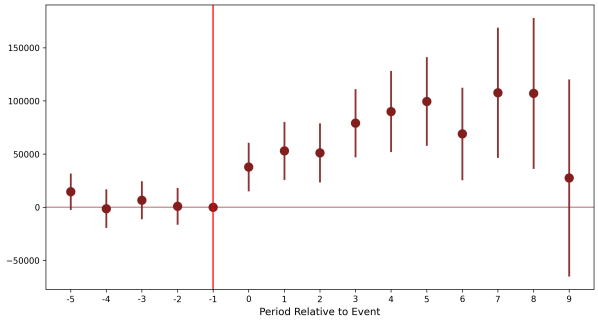
Figure 2: The two figures above plot the point estimates and 90% confidence intervals of a series of cross-sectional regressions. In each regression, we focus on a sliding-window of politicians who depart from office during $[t-2, t+2]$. We regress their job outcome (promotion$\in \{0,1\}$) on both an index for innovation and another for compliance. We parse out the effect of GDP growth on promotion. Both indices are scaled by the mean of dependent variable so that the estimated coefficients can be interpreted as the elasticity of promotion probability with respect to changes in innovation (compliance). Standard errors are clustered at prefecture level.



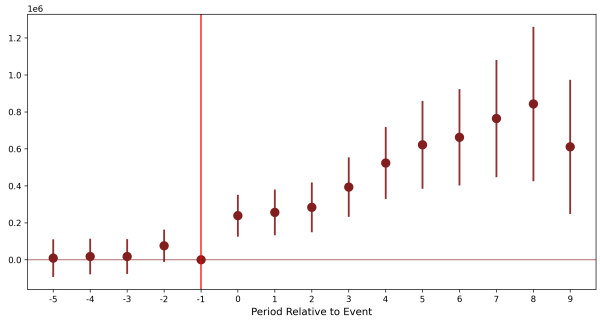
Panel A.1: Export value (1 thousand yuan), Supply-chain compatibility



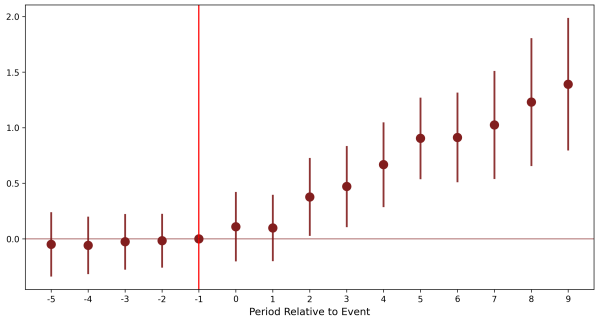
Panel B.1: Export value (1 thousand yuan), Investment compatibility



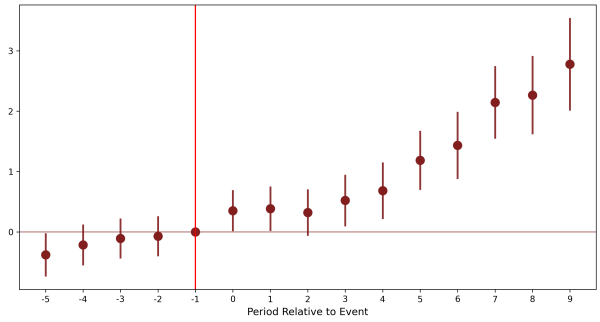
Panel A.2: Total revenue (1 thousand yuan), Supply-chain compatibility



Panel B.2: Total revenue (1 thousand yuan), Investment compatibility

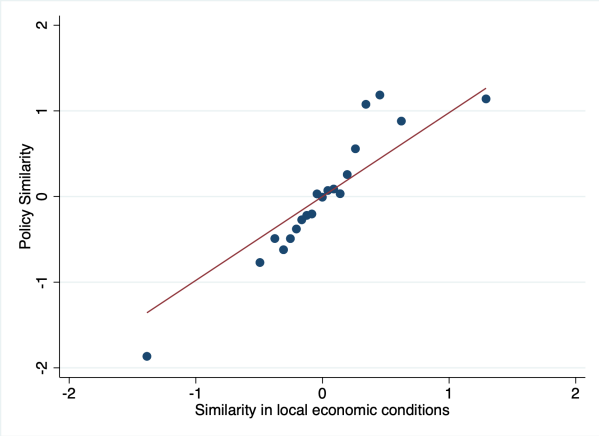


Panel A.3: Patent (counts), Supply-chain compatibility

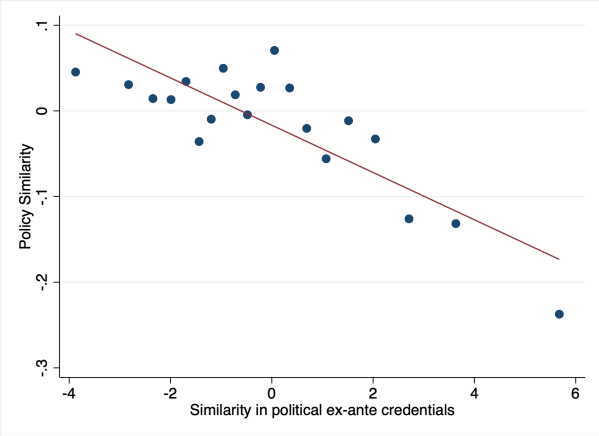


Panel B.3: Patent (counts), Investment compatibility

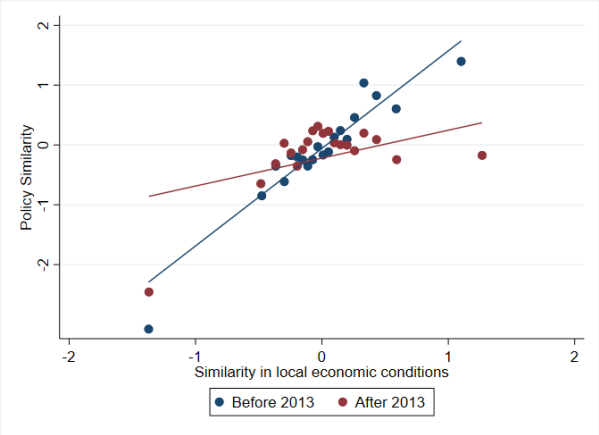
Figure 3: This figure demonstrates the divergence in policy effectiveness as a function of ex-ante compatibility, using a triple-difference strategy, where the key treatment is the promotion of an industrial policy $\times$ the compatibility of such industry with the prefecture. Panels A.1–A.3 show results by ex-ante supply-chain compatibility; Panels B.1–B.3 by ex-ante investment compatibility. Outcomes include export value, firm revenue, and patent registrations. Each regression includes prefecture-by-year, prefecture-by-industry, and industry-by-year fixed effects. Standard errors are clustered at the prefecture level.



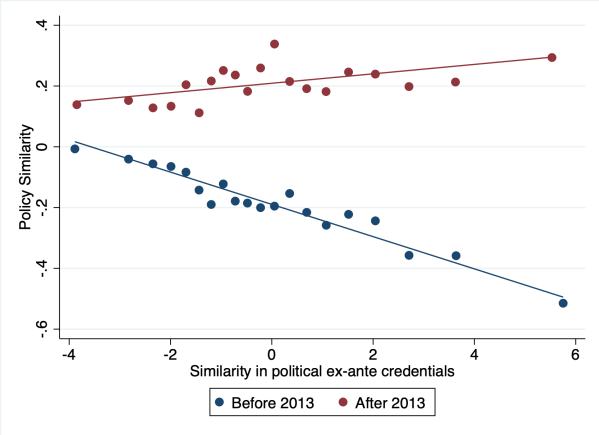
Panel A: Policy portfolio and economic proximity



Panel B: Policy portfolio and political proximity

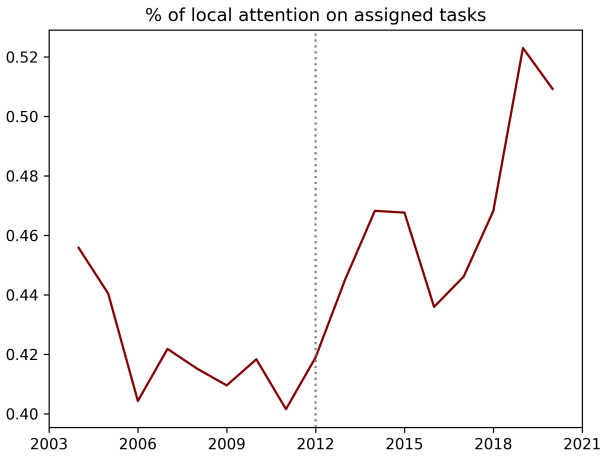


Panel C: Policy portfolio and economic proximity: Before and After 2013

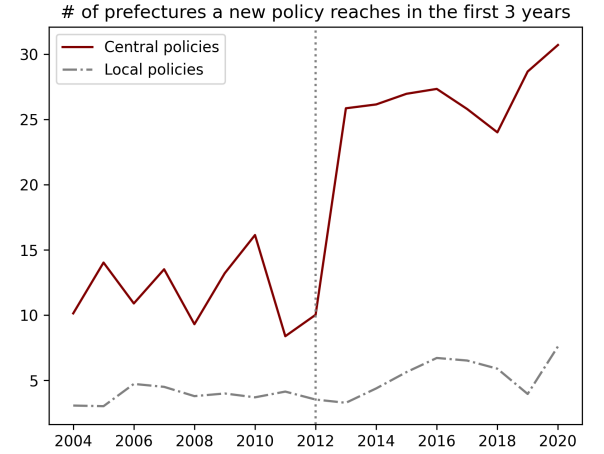


Panel D: Policy portfolio and political proximity: Before and After 2013.

Figure 4: This figure illustrates the similarity of policy space between city-pairs with respect to their economic / political proximity. The dependent variable, policy similarity, is the euclidean distance between the two vectors of dummy variables v_{pct} indicating whether a document about policy p is implemented in city c in year t. In Panel A, we plot such similarity against distance in standard deviations of GDP per capita, net of origin, destination, and year fixed effects. In panel B, we plot it against distance in promotion incentives. The independent variable, political credential similarity, is the Mahalanobis distance between the full vector of all observable politician characteristics prior to their term, including their start-age, hierarchical status, gender, ethnicity, education, central government experience as well as previous experience. In Panel C & Panel D, we plot the contrast before and after 2013.



Panel A



Panel B

Figure 5: This figure illustrates the increasing centralization of policymaking post-2013. Panel A plots the percentage of local attention on assigned tasks by year. For each locality-year, we compute the percentage of policies already endorsed by central government among the set of policies it implements, and then average the attention across localities. In Panel B, we focus on central-government initiated policies, and plot the number of prefectures adopting the policy in the first 3 years by year of policy-initiation. In both cases, we see a sharp increase in the degree of centralization.

Table 1: Decomposition of innovation between bureaucrats and locality

Decomposing innovation and compliance			
	$\tau_{\text{politician}}$	$\tau_{\text{prefecture}}$	τ_{year}
	(1)	(2)	(3)
Panel A: Decomposing innovation			
Variation of Y explained	0.304***	0.059*	0.132***
	(0.037)	(0.033)	(0.014)
Panel B: Decomposing compliance			
Variation of Y explained	0.196***	0.088**	0.308***
	(0.046)	(0.043)	(0.016)

Notes: In this table, we follow Abowd, Kramarz, and Margolis (1999) to decompose innovation index into bureaucrat fixed effects, locality fixed effects, and calendar year controls. Akin to employer-employee matched design, identification exploits variation of innovation index within (rotating) bureaucrats across the places they hold office. After the decomposition, we report the normalized correlation between each set of fixed effects and the outcome variable. In the parentheses below the estimates, we report standard errors with 1,000 bootstraps.

Table 2: Centralization and policy compatibility

	Investment		Supply-chain	
	% compatible	compatibility	% compatible	compatibility
Central endorsement	-0.0217**	-0.127***	-0.0156*	-0.0542***
	(0.0100)	(0.0175)	(0.00889)	(0.0206)
# of obs.	118,104	118,104	116,133	116,333
Mean of DV	0.23	0.78	0.35	0.90
SD of DV	0.42	1.31	0.47	0.79
Prefecture $\times$ Year FE	Yes	Yes	Yes	Yes

Notes: This table presents the point estimates of the differential of policy locality compatibility between centrally-endorsed policy and local initiative policy. Specifically, we regress the of policy compatibility, either with investment (columns 1-2), or with supply chain (columns 3-4) on an indicator variable suggesting whether the industrial policy had been promoted by a central government planning document. Prefecture by year fixed effects are controlled across columns. Standard errors clustered at the prefecture-year level are reported below the estimates.

Table 3: Policy portfolio and proximity

	Similarity in policy portfolio		
	(1)	(2)	(3)
Panel A: Economic Proximity			
-Δ GDP per capita	3.164***	2.226***	0.979***
	(0.395)	(0.369)	(0.210)
Year FE	Yes	No	Yes
Origin FE	No	Yes	Yes
Destination FE	No	Yes	Yes
Panel B: Political Proximity			
- Δ politician characteristics	-0.00798**	-0.0276***	-0.0279***
	(0.00360)	(0.00379)	(0.00501)
Year FE	Yes	Yes	Yes
Origin FE	Yes	No	No
Destination FE	Yes	No	Yes
Prefecture-pair FE	No	Yes	No
Politician(o) × prefecture(d) FE	No	No	Yes

Notes: We compute pairwise similarity between vectors denoting policy portfolios across all prefecture pairs from 2003-2020. Distance is computed via Euclidean norm. In Panel A, we measure economic proximity by the difference between city pairs of GDP per capita in units of standard deviation. Normalizing by year eliminates the mechanical variation attributable to increasing scale. In Panel B, we measure political proximity by the difference between city pairs of political promotion incentive, which we describe in detail in Section 2. Across columns in Panel B, we sequentially control for calendar year fixed effects, origin and destination fixed effects, origin-by-destination fixed effects, as well as politician × target location fixed effects. Standard errors clustered at the prefecture-pair level are reported below the estimates.

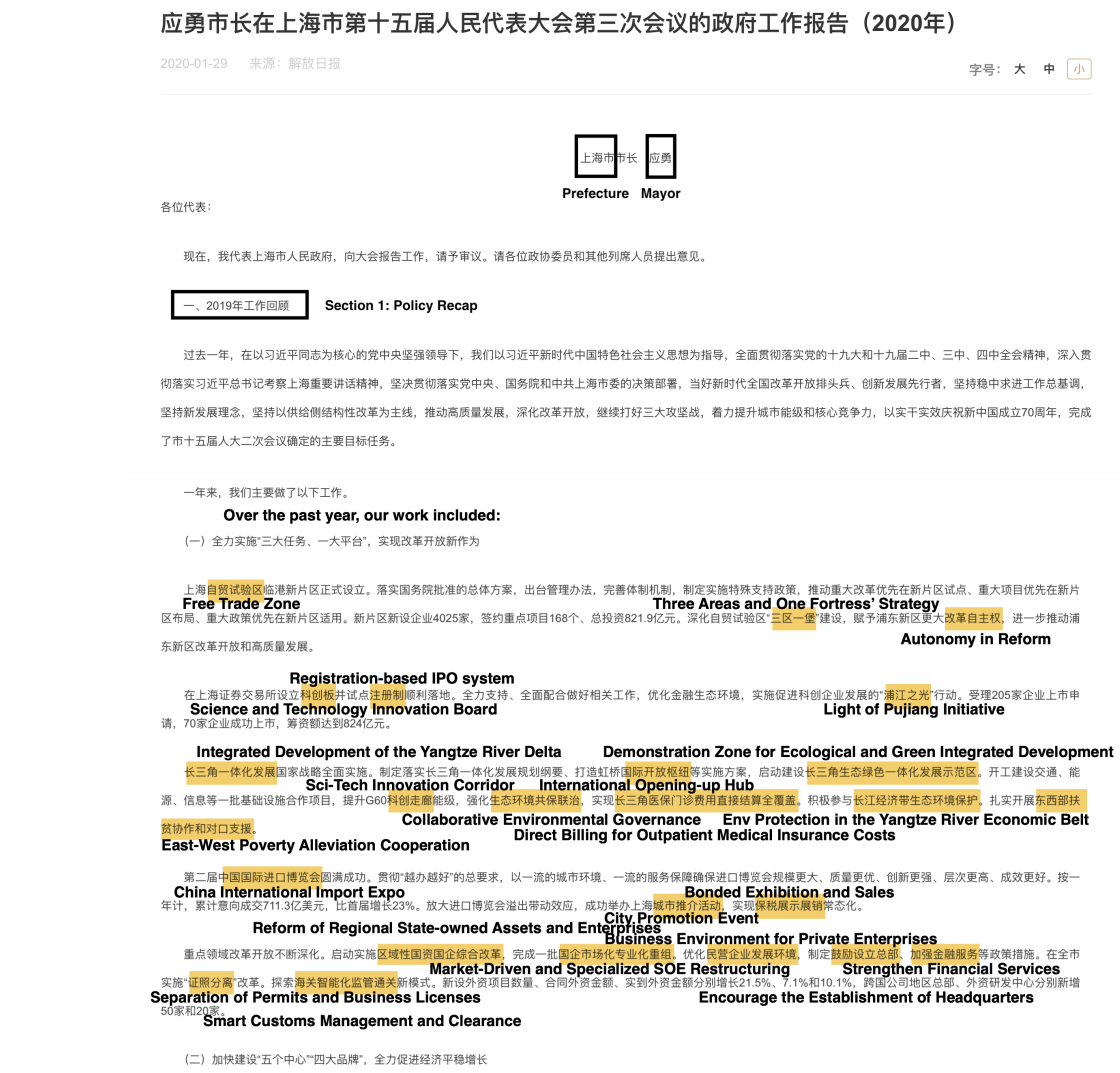
Table 4: Competition among economic neighbors

	Investment Compatibility			Supply-Chain Compatibility		
	All Policy	Local Policy	Central Policy	All Policy	Local Policy	Central Policy
Panel A: Strategic competition						
Competitors	-0.00537***	-0.0104***	-0.00397***	-0.0108***	-0.0314***	-0.00660***
	(0.00129)	(0.00276)	(0.00126)	(0.00329)	(0.0105)	(0.00251)
# of obs	4,010	3,079	3,985	4,010	3,079	3,985
Panel B: Strategic competition before and after 2013						
Competitors × Post 2013	0.00881***	0.0138***	0.00785***	0.00798*	0.0237**	0.00463
	(0.00202)	(0.00435)	(0.00199)	(0.00464)	(0.0117)	(0.00360)
Competitors	-0.00952***	-0.0156***	-0.00782***	-0.0146***	-0.0403***	-0.00887***
	(0.00190)	(0.00345)	(0.00183)	(0.00425)	(0.0105)	(0.00342)
# of obs	4,010	3,079	3,985	4,010	3,079	3,985
Prefecture FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the effects of the number of economically competing prefectures on the compatibility of policies adopted by local governments, across two dimensions of policy alignment: investment compatibility (columns 1–3) and supply-chain compatibility (columns 4–6). The analysis distinguishes among three types of policies: all policies (All Policy), central policies implemented by local governments (Central Policy), and locally diffused policies (Local Policy). Panel B shows that the intensity of such competition was mitigated after 2013. All specifications include prefecture and year fixed effects, with robust standard errors clustered at the prefectural level.

Online Appendix

Appendix A Additional figures and tables



Panel (a): Example of government report (Shanghai, 2020)

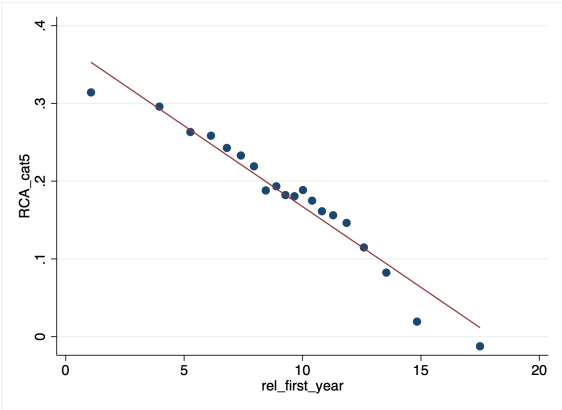


Panel (b): Five-year plan document

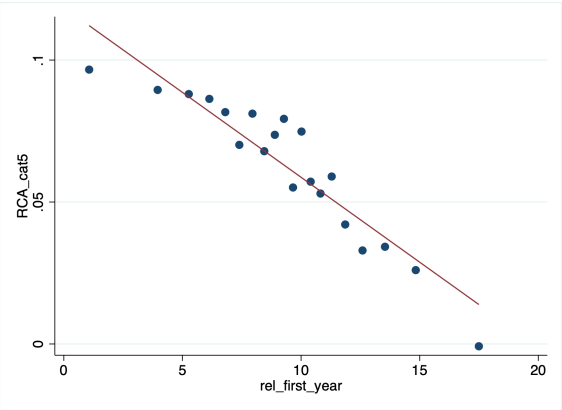


Panel (c): Prefectural policy document

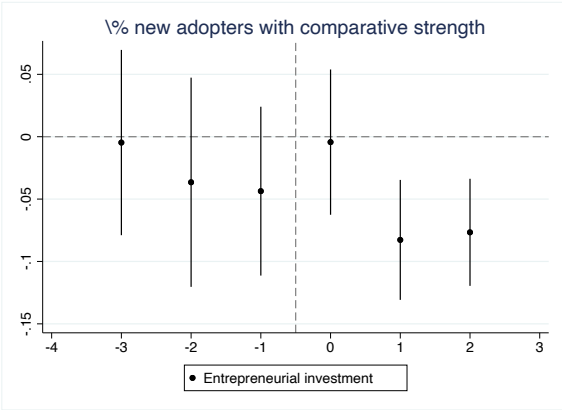
Figure A.1: (a) Example of government reports from Shanghai (2020), used to illustrate the policy-keyword extraction procedure. (b) Central government five-year plan document from PKULaw. (c) Prefectural policy document from PKULaw, linked by the keyword "developing a water-saving society."



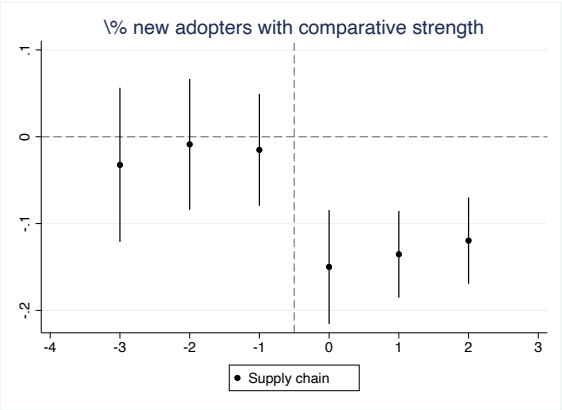
Panel A: Investment Compatibility



Panel B: Supply Chain Compatibility

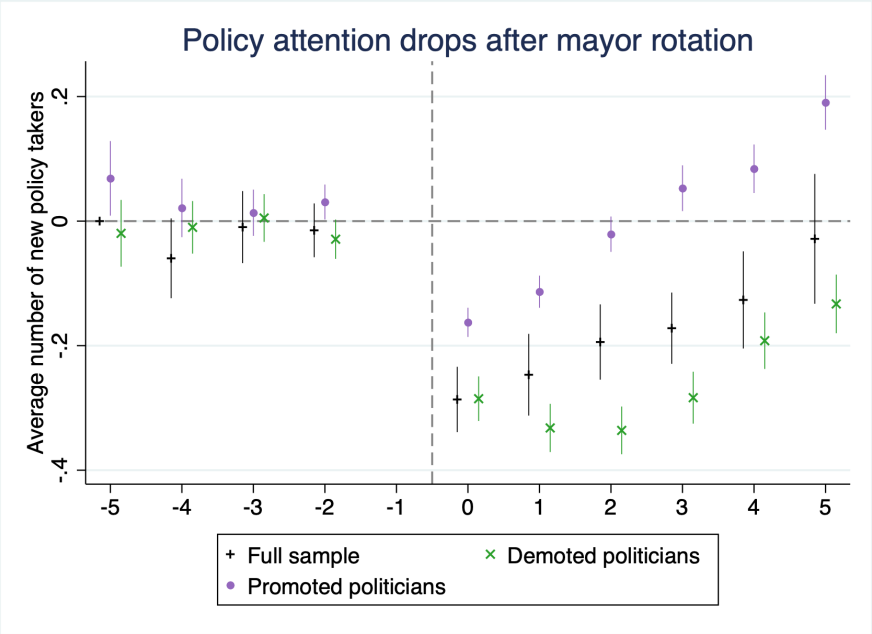


Panel C: Investment Compatibility



Panel D: Supply Chain Compatibility

Figure A.2: Evolution of Industry suitability during policy diffusion. This figure tracks the decline in ex-ante industry suitability during policy diffusion. For each year t relative to initial policy adoption, we plot the average industry-locality compatibility measure among adopting prefectures, with prefecture and industry fixed effects removed. Panel A measures compatibility based on alignment with entrepreneurial preferences, while Panel B evaluates compatibility through local supply chain alignment. The results demonstrate how policy effectiveness varies with pre-existing economic conditions.



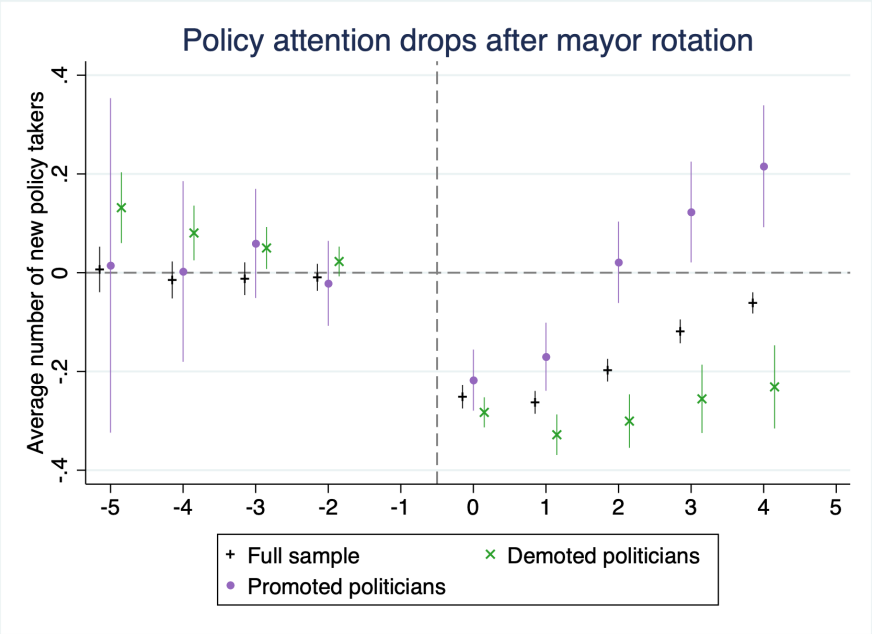


Figure A.3: This set of figures plot the event study estimates illustrating the decrease in number of policy adoption after prefectural party secretary departure. We cluster standard errors at prefectural level, and compare baseline estimates with cases where the departing politicians got promoted or demoted. In panel A, we follow Sun and Abraham (2021) to adjust for negative weights present in TWFE regressions. We treat the last cohort to depart from office in our data (2022) as our never-treated control group. In panel B, we impose a much more stringent definition of promotion, counting only promotions to provincial governor, or provincial party secretary (3%).

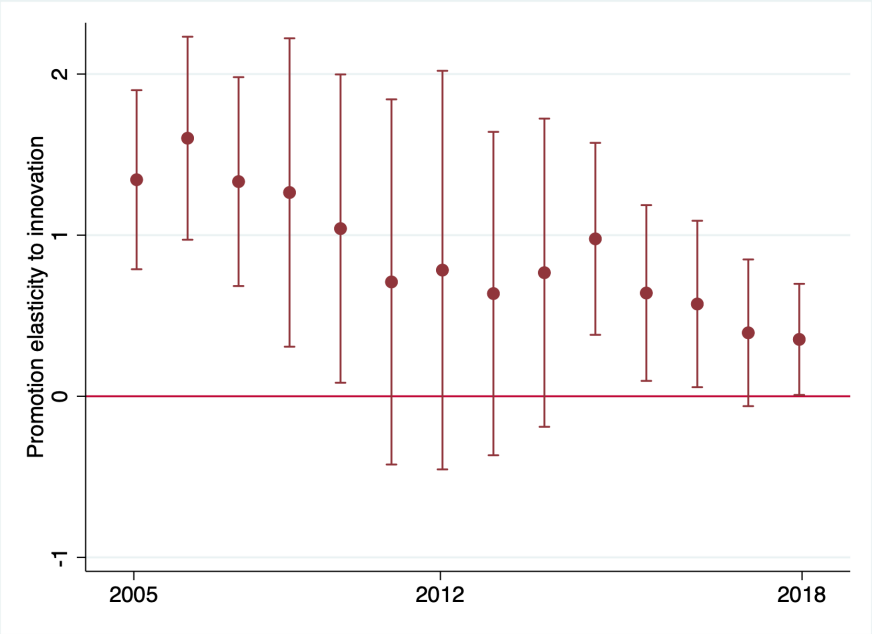
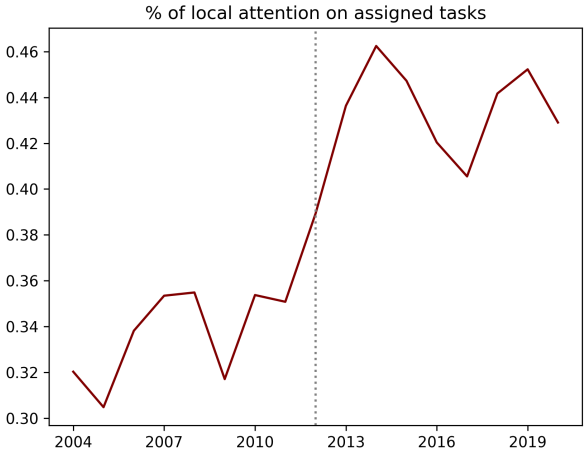
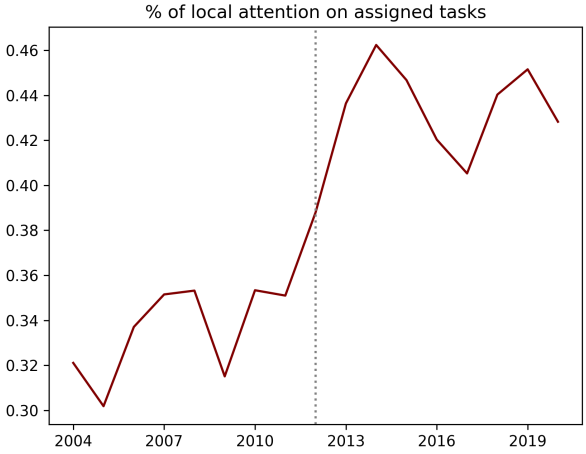


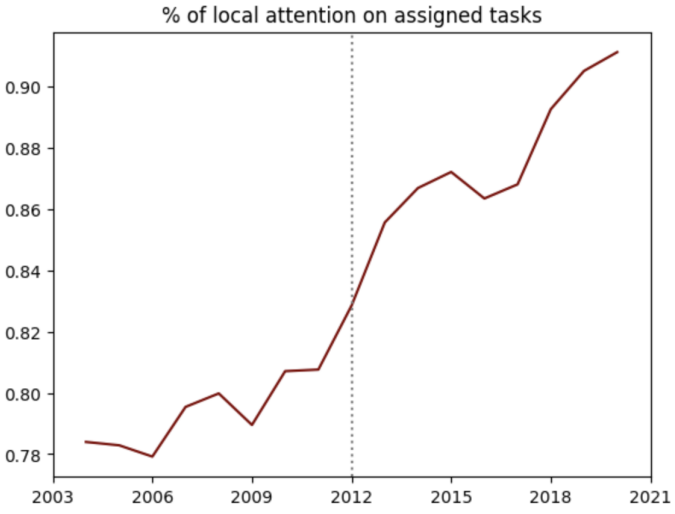
Figure A.4: This figure plots the point estimates and confidence intervals of a series of cross-sectional regressions. In each regression, we focus on a sliding-window of politicians who depart from office during $[t-2, t+2]$. We regress their job outcome (promotion$\in \{0, 1\}$ on both an index for innovation, another for compliance, and a third for GDP growth – the canonical predictor à la Li and Zhou (2005)). Standard errors are clustered at prefecture level.



Panel A



Panel B



Panel C

Figure A.5: This figure illustrates the increasing centralization of policymaking post-2013 under alternative specifications. All three panels plot the percentage of local attention on assigned tasks by year. For each locality-year, we compute the percentage of policies already endorsed by central government among the set of policies it implements, and then average the attention across localities. In Panel A, we disaggregate large policy bundles into comparable agendas with the rest of the sample by treating a policy $\times$ domain, instead of a policy, as our unit of observation. In Panel B, we aggregate policies that are sufficiently close to each other together – defined as a Jaccard similarity > 0.8. In Panel C, we use an alternative set of keywords extracted by GPT-4o.

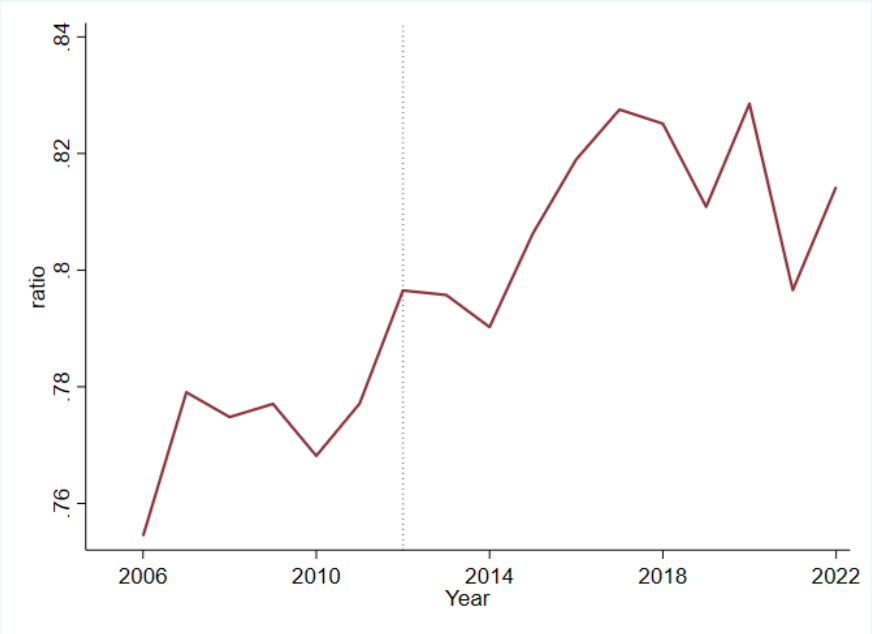


Figure A.6: This figure illustrates the increasing centralization of policymaking for industrial policies in post-2013. Panel A plots the percentage of local attention on assigned tasks by year. For each locality-year, we compute the percentage of policies already endorsed by central government among the set of policies it implements, and then average the attention across localities. In Panel B, we focus on central-government initiated policies, and plot the number of prefectures adopting the policy in the first 3 years by year of policy-initiation for industrial policies. In both cases, we see a sharp increase in the degree of centralization.

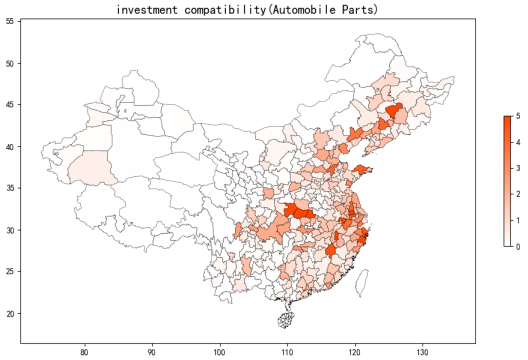


Figure A.7: Automobile:Investment Compatibility

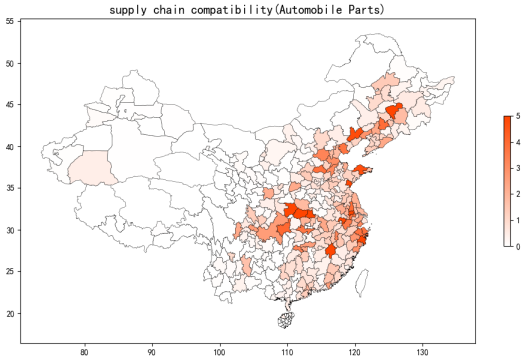


Figure A.8: Automobile:Supply Chain Compatibility

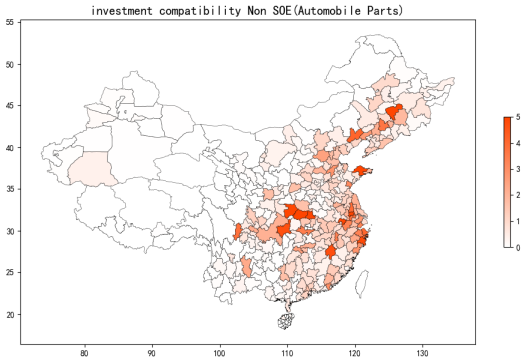


Figure A.9: Automobile:Investment Compatibility,non SOE Company

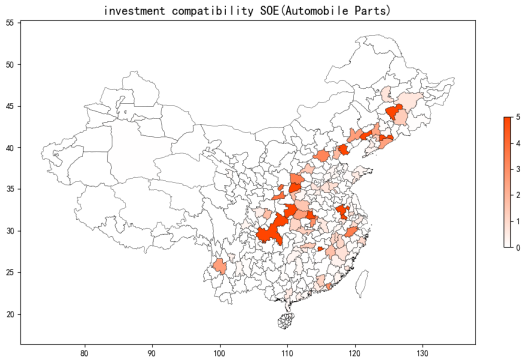


Figure A.10: Automobile:Investment Compatibility,SOE Company

Figure A.11: This figure plots the spatial distribution of the compatibility of automobile industry across China. In the left panel, we construct the measure using new investment from private firms, while on the right, we focus on state-owned enterprises.

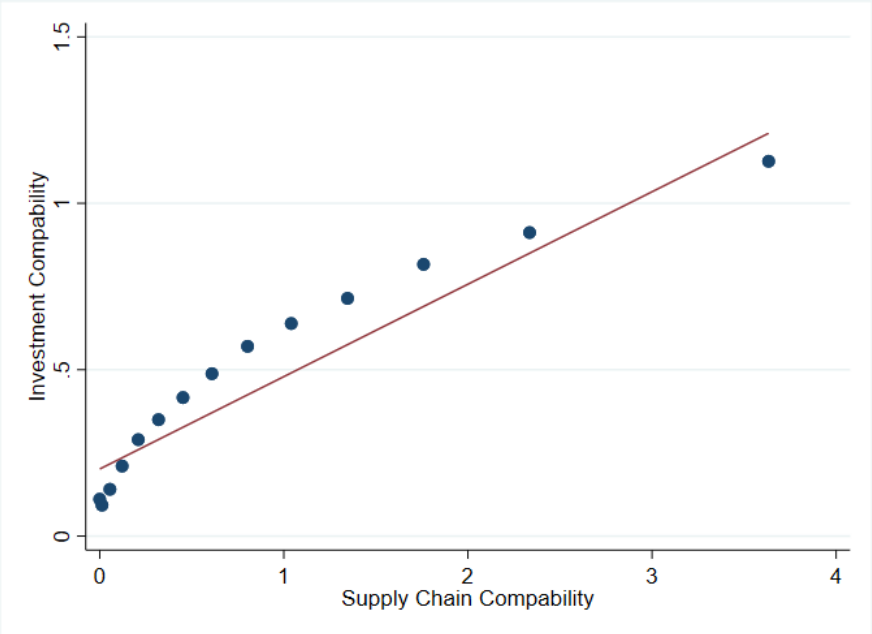
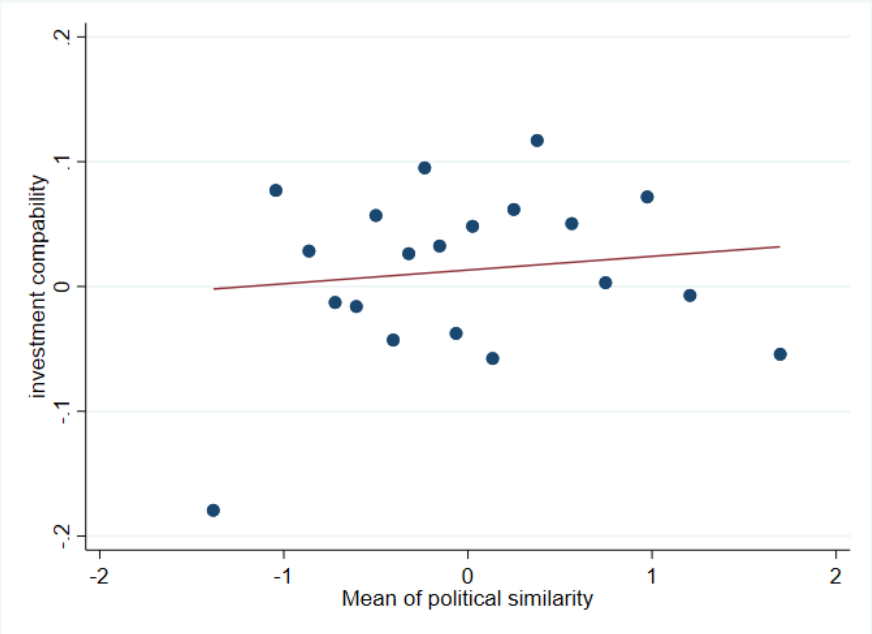
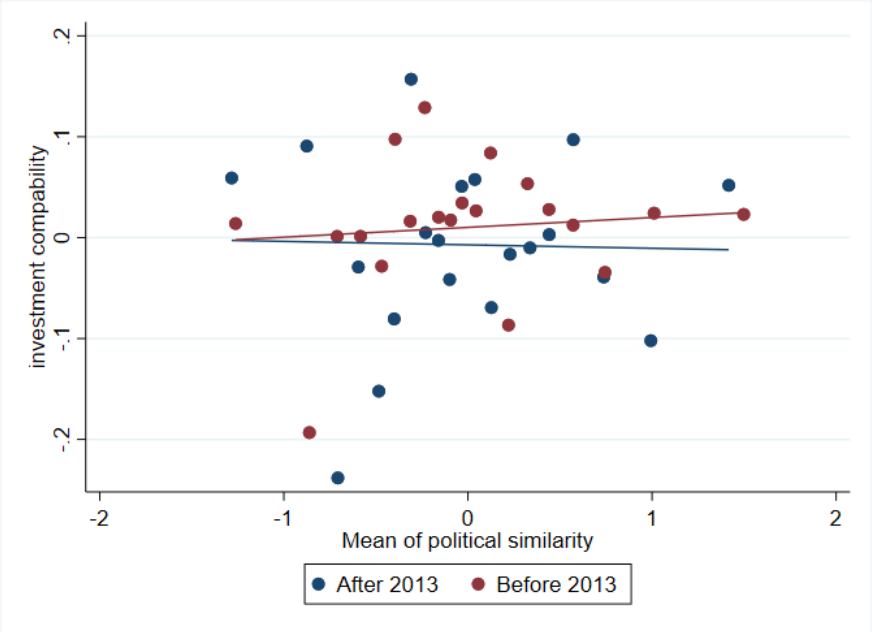


Figure A.12: This figure plots the correlation between Investment Compatibility with Supply Chain Compatibility. For a given locality, the two measures are positively associated with each other.



Panel A:Local policy competition



Panel B: Competition before and after 2013

Figure A.13: This figure plots the reduced-form relationship between average policy compatibility and political competition. In Panel A, with prefecture-year data, we present a binned-scatter plot illustrating the correlation between the average policy compatibility with ex-ante entrepreneurial investment against the number of their economic neighbors (closest 20 cities) who are also political competitors (closest 20 cities). In Panel B, we zoom into central-endorsed policies – industries that got picked up in the past 3 years – and plot the average compatibility within those sectors against the intensity of political competition.

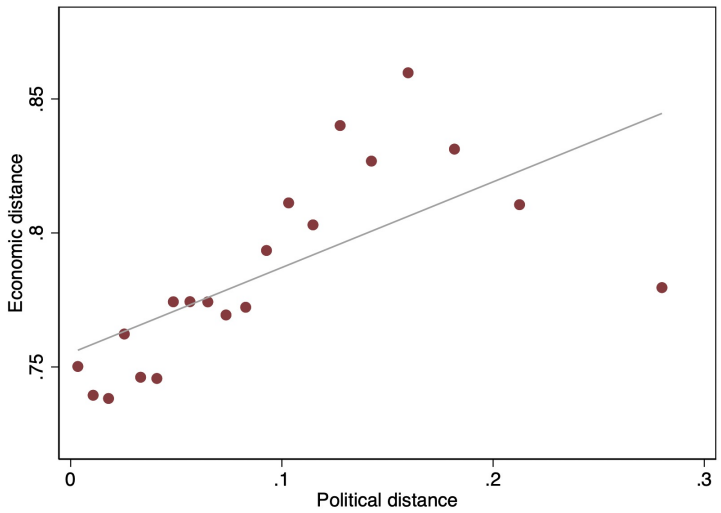


Figure A.14: This figure illustrates the sorting between economic conditions and politician characteristics. We draw a bin-scatter plot of economic distance (measured by GDP per capita dispersion) against political distance (measured by ex-ante projected promotion probability differentials). We observe a strong, positive relationship between the two.

Table A.1: Policy examples

Policy	Inception year	First adopter
Primary and Secondary School Teacher Title System Reform	2009	Sha'anxi, Shanghai
Cross-Region Housing Provident Fund Loans	2010	Liaoning, Hubei
Long-Term Management of Village Environment	2012	Jiangsu, Fujian
Control and Demolition of Illegal Constructions	2004	Hunan
Oil and Gas Recovery at Gas Stations	2007	Tianjin
Pilot of New Rural Cooperative Finance	2014	Shandong, Beijing, Hebei
Detailed Survey of Soil Pollution	2013	Jiangsu
River Chief System	2003	Zhejiang
Overseas Chinese Investment and Talent Introduction	2002	Chongqing
End-to-End Online Processing	2008	Shanxi

Table A.2: Centralization and policy compatibility

	Investment		Supply-chain	
	% compatible		% compatible	
Central endorsement	-0.0528***	-0.178***	-0.0788***	-0.119***
	(0.0154)	(0.0184)	(0.00969)	(0.0148)
# relative years	-0.00909***	-0.00999***	-0.00718***	-0.00747***
	(0.00123)	(0.00124)	(0.00116)	(0.00116)
Central endorsement × # relative years		0.0223***		0.00717***
		(0.00328)		(0.00181)
# of obs.	15,028	15,028	15,028	15,028
Prefecture FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes

Notes: Sample 2004-2020. Central endorsement: local policies implemented within 3 years of first central policy. Data organized at prefecture industry level where each observation is an instance where industry i got promoted in prefecture p *for the first time*. Dependent variable is the compatibility at year $t-1$. Standard errors are clustered at the prefectural level.

Table A.3: Divergence in Policy Effectiveness: Triple Differences

	Exports	**Sales**	**Patents**
	(1)	(2)	(3)
Panel A: Investment Compatibility			
Policy × Compatibility	34,156***	435,890***	2.412***
	(6,042)	(61,441)	(0.250)
# of obs	2,108,939	2,481,648	3,477,600
Panel B: Supply Chain Compatibility			
Policy × Compatibility	8,719***	76,140***	1.466***
	(1464.7)	(12,740)	(0.131)
# of obs	1,720,998	2,042,456	2,884,000
Mean of DV	72,802	184,527	5.33
Prefecture × Year FE	Yes	Yes	Yes
Prefecture × Industry FE	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes

Notes: This table reports triple-differences estimates examining how policy effectiveness varies with compatibility, across three outcome variables: exports (column 1), sales (column 2), and patents (column 3).Panel A focuses on Investment Compatibility and Panel B focuses on Supply Chain Compatibility.Prefecture-by-year, prefecture-by-industry, and industry-by-year fixed effects are controlled across columns. Standard errors are clustered at prefecture level. Standard errors are clustered at the prefectural level.

Table A.4: Divergence in Policy Effectiveness: Triple Differences based on SOE

	Exports Total	**Exports Within SOE**	**Sales Total**	**Sales Within SOE**
	(1)	(2)	(3)	(4)
Panel A: Investment Compatibility				
Policy × SOE Compatibility	19,355**	7,638*	194,961	59,323**
	(8,658)	(4,220)	(168,758)	(24,135)
# of obs.	2,088,994	2,088,994	2,481,648	2,481,648
Panel B: Supply Chain Compatibility				
Policy ×SOE Compatibility	3,583	2,348	4,094	22,242***
	(3,640)	(1,581)	(4,317)	(7,058)
# of obs.	1,711,366	1,711,366	2,290,752	2,290,752
Mean of DV	72,802	72,802	184,527	184,527
Prefecture × Year FE	Yes	Yes	Yes	Yes
Prefecture × Industry FE	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes

Notes: This table reports triple-differences estimates examining how policy effectiveness varies with compatibility, across three outcome variables: exports (column 1), sales (column 2), and patents (column 3).The compatibility is calculated by investment data of the State-Owned Enterprise(SOE),rather than private companies .Panel A focuses on Investment Compatibility and Panel B focuses on Supply Chain Compatibility.Prefecture-by-year, prefecture-by-industry, and industry-by-year fixed effects are controlled across columns. Standard errors are clustered at the prefectural level.

Table A.5: Top down bottom up policy outcome

	Exports	**Sales**	**Patents**
	(1)	(2)	(3)
Policy × Top Down	-16,451	-3,594	-1.138***
	(12,318)	(3,276)	(0.270)
# of obs.	2,228,356	2,672,544	7,782,390
Mean of dependent variable	72,802	184,527	0.195
Prefecture × Year FE	Yes	Yes	Yes
Prefecture × Industry FE	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes

Notes: This table reports how policy effectiveness varies between central and local policies, across three outcome variables: exports (column 1), sales (column 2), and patents (column 3).Prefecture-by-year, prefecture-by-industry, and industry-by-year fixed effects are controlled across columns. Standard errors are clustered at prefecture level. Standard errors are clustered at the prefectural level.

Table A.6: Innovation, compliance and promotion likelihood

	Promotion					
	Before 2012			After 2012		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Baseline: innovation / compliance index						
Average innovation index	0.202***	0.196***	0.173**	0.011	0.020	0.020
	(0.072)	(0.072)	(0.072)	(0.076)	(0.080)	(0.080)
Average compliance index	-0.069	-0.053	-0.065	0.177**	0.166**	0.166**
	(0.067)	(0.068)	(0.068)	(0.079)	(0.082)	(0.082)
Δ GDP	1.157***	1.145***	1.241***	0.357**	0.340**	0.341**
	(0.331)	(0.339)	(0.331)	(0.159)	(0.161)	(0.162)
Panel B: Sum of successful innovations / early follow-ups						
Successful innovation	0.005***	0.005***	0.004***	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Early adopters	-0.003	-0.000	-0.001	0.011**	0.011**	0.011**
	(0.009)	(0.009)	(0.009)	(0.005)	(0.005)	(0.005)
Panel C: Robustness: alternative measures of innovation / compliance						
$\sum$ innovation index	0.149***	0.139***	0.120***	-0.046	-0.051	-0.051
	(0.040)	(0.041)	(0.041)	(0.041)	(0.042)	(0.042)
$\sum$ compliance index	-0.084**	-0.072*	-0.061	0.103**	0.108**	0.109**
	(0.038)	(0.039)	(0.038)	(0.047)	(0.048)	(0.048)
Panel D: Placebo: muted effects for politicians $>$ 55 years old						
Average innovation index	0.038	0.148	0.118	0.138	0.165	0.148
	(0.366)	(0.361)	(0.376)	(0.211)	(0.203)	(0.203)
Average compliance index	0.285	0.248	0.237	0.004	-0.003	0.003
	(0.303)	(0.297)	(0.298)	(0.226)	(0.228)	(0.232)
Δ GDP	-0.915	-0.493	-0.498	0.608*	0.639*	0.648*
	(1.987)	(2.165)	(2.220)	(0.332)	(0.372)	(0.353)
# of obs.	571	571	571	872	872	872
Mean of DV	0.401	0.401	0.401	0.317	0.317	0.317
Start cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Finish cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Start Age FE	No	Yes	Yes	No	Yes	Yes
Level of education FE	No	No	Yes	No	No	Yes

Notes: Standard errors clustered at the prefectural level are reported below the estimates. Each column within each panel comes from a politician-level regression. In Panel A, we regress politician promotion indicators on logged innovation and compliance index. Essentially, those indices capture both the speed of one's action and the success of the policy. In Panel B, we unpack the black box of those indices. Specifically, instead of the innovation index, we count the number of locally initiated policies that became national policies in the last three years; and instead of the compliance index, we count the number of times a locality adopted a national policy within the first three years. "Start cohort" is the year a politician takes office interacted with his or her position hierarchy, "Finish cohort" is the year a politician leaves office interacted with his or her position hierarchy, "Start age" is the age of the politician when they start their tenure, "Level of education" is a dummy variable indicating whether they obtained any post-graduate degree prior to their term in office.

Table A.7: Targeting Future Market Outcomes

VARIABLES	Average Market Value(2000-2024)	Future Market Value(2024)
	(1)	(2)
Panel A: All Local Policies		
Central initiation	46.49	88.69
	(38.25)	(72.15)
Central endorsement	28.75	63.17
	(29.36)	(59.98)
Bottom up	31.99	55.12
	(21.86)	(42.98)
# of obs.	427	427
Panel B: Equal Number of Local and Central Policies		
Central initiation	46.49	88.69
	(38.43)	(72.50)
Central endorsement	65.34*	139.9*
	(37.20)	(75.01)
Bottom up	279.7***	543.1***
	(65.08)	(111.8)
# of obs.	210	210

Notes: In this table, we compare the market size of industries targeted by industrial policies initiated or supported by either central or local governments. Average Market Value is the average global market value of a given industry. Future Market Value is the global market value of a given industry in 2024. Panel A includes all local policies, while Panel B restricts the sample to local policies targeting industries with the highest future output values, ensuring that the number of central and local policies is balanced. Central initiation refers to policies directly initiated by the central government. Central endorsement captures policies that were first initiated by local governments but later picked up by the central government. Bottom-up policies are those initiated solely by local governments without central government endorsement.

Table A.8: Targeting Strategically Important Industries

VARIABLES	% in Sanction List
Panel A: All Local Policies	
Central initiation	0.0137
	(0.0692)
Central endorsement	0.139**
	(0.0707)
Bottom up	0.00445
	(0.0533)
# of obs.	427

Notes: This table compares the likelihood that industries targeted by industrial policies—initiated or supported by either the central or local government—are included in the U.S. sanctions list against China.

Table A.9: Targeting Comparative Advantage (RCA)

VARIABLES	RCA (2000)	RCA (2024)	Δ RCA
Panel A: All Local Policies			
Central initiation	-0.412	-0.452**	-0.0395
	(0.330)	(0.222)	(0.288)
Central endorsement	-0.942***	-0.416**	0.526**
	(0.284)	(0.206)	(0.247)
Bottom up	-0.213	0.0581	0.271
	(0.288)	(0.194)	(0.241)
# of obs.	427	427	427
Panel B: Equal Number of Local and Central Policies			
Central initiation	-0.412	-0.452**	-0.0395
	(0.330)	(0.223)	(0.290)
Central endorsement	-0.544**	-0.228	0.862***
	(0.236)	(0.223)	(0.245)
Bottom up	0.144	0.879***	1.573***
	(0.224)	(0.233)	(0.257)
# of obs.	210	210	210

Notes: In this table, we compare China's Revealed Comparative Advantage (RCA), as reflected in trade data, in industries targeted by industrial policies initiated or supported by either central or local governments. Panel A includes all local policies, while Panel B restricts the sample to local policies targeting industries with the highest future RCA, ensuring that the number of central and local policies is balanced.

Table A.10: Targeting Market Distortion

VARIABLES	Market Distortion
Panel A: All Local Policies	
Central initiation	0.896***
	(0.0937)
Central endorsement	0.930***
	(0.0991)
Bottom up	0.969***
	(0.0784)
# of obs.	1,109
Panel B: Equal Number of Local and Central Policies	
Central initiation	0.896***
	(0.0938)
Central endorsement	1.302***
	(0.0882)
Bottom up	1.965***
	(0.0748)
# of obs.	747

Notes: In this table, we compare the market distortion of industries targeted by industrial policies initiated or supported by either central or local governments. Market distortion includes market frictions accumulated through backward input-output linkages. Panel A includes all local policies, while Panel B restricts the sample to local policies targeting industries with the highest Market Distortion, ensuring that the number of central and local policies is balanced.

Table A.11: Targeting Industries with Economics of Scale

VARIABLES	Economics of Scale
Panel A: All Local Policies	
Central initiation	0.293
	(0.220)
Central endorsement	0.616***
	(0.201)
Bottom up	0.361*
	(0.189)
# of obs.	472
Panel B: Equal Number of Local and Central Policies	
Central initiation	0.293
	(0.222)
Central endorsement	1.007***
	(0.197)
Bottom up	1.349***
	(0.189)
# of obs.	195

Notes: In this table, we compare the economic of scale of industries targeted by industrial policies initiated or supported by either central or local governments. Economic of scale is the average level of economy of scale in following countries: France, Germany, Belgium, and the United Kingdom. Panel A includes all local policies, while Panel B restricts the sample to local policies targeting industries with the highest economic of scale, ensuring that the number of central and local policies is balanced.

Table A.12: Targeting Pollution-Intensive Industries

	Pollution
Panel A: All Local Policies	
Central initiation	0.00203
	(0.0395)
Central endorsement	0.202***
	(0.0516)
Bottom up	0.0426
	(0.0329)
# of obs.	646

Notes: This table compares the likelihood that industries targeted by industrial policies—initiated or supported by either the central or local government—are classified as polluting industries. Pollution is a dummy variable indicating whether an industry is identified as pollution-intensive in the 2021 Comprehensive Directory of Environmental Protection, published by the Ministry of Ecology and Environment of China.

Table A.13: Centralization and Policy Compatibility: Robustness Check

	Investment		Supply-chain	
	% compatible	compatibility	% compatible	compatibility
Central endorsement	-0.0167*	-0.0936***	-0.00188	-0.0333*
	(0.00922)	(0.0306)	(0.00879)	(0.0198)
Sanction	0.0347**	0.220***	0.0543**	0.199***
	(0.0157)	(0.0678)	(0.0243)	(0.0511)
Pollution	0.0525***	0.221***	0.0844***	0.247***
	(0.0172)	(0.0634)	(0.0298)	(0.0570)
Economics of Scale	-0.00113	0.0227	-0.0267***	-0.0353*
	(0.00763)	(0.0287)	(0.00900)	(0.0199)
# of obs.	118,104	118,104	116,333	116,333
Mean of DV	0.23	0.78	0.35	0.90
SD of DV	0.42	1.31	0.47	0.79
Prefecture $\times$ Year FE	Yes	Yes	Yes	Yes

Notes: This table reports the point estimates of differences in policy compatibility between centrally-endorsed policies and local initiated policies. Controlled for the following industry characteristics: whether the industry is a strategically important industry (included in the sanction list), whether it is a polluting industry (included in the pollution list), and the extent of its economies of scale. All specifications control for prefecture-by-year fixed effects. Standard errors clustered at the prefecture-year level are reported in parentheses.

Table A.14: Policy portfolio and proximity

	Similarity in policy portfolio		
	(1)	(2)	(3)
Panel A: Economic Proximity			
Economic proximity	0.655***	3.574***	0.187***
	(0.0264)	(0.0630)	(0.0211)
Political proximity	-0.0600***	-0.0261***	-0.0279***
	(0.00440)	(0.00447)	(0.00511)
Economic × political proximity	-0.0532***	-0.0360***	-0.0228***
	(0.00258)	(0.00564)	(0.00340)
# of obs.	1,261,316	1,113,712	1,112,192
Mean of DV	-42.33	-42.33	-42.33
Economic indicator	GDP per capita	Fiscal revenue	% tertiary sector
Year FE	Yes	Yes	Yes
Origin FE	Yes	Yes	Yes
Destination FE	Yes	Yes	Yes

Notes: We compute pairwise similarity between vectors denoting policy portfolios across all prefecture pairs from 2003-2020. Distance is computed via Euclidean norm. We measure economic proximity by the difference between city pairs of GDP per capita (fiscal revenue, and % GDP contribution from tertiary sector) in units of standard deviation. Normalizing by year eliminates the mechanical variation attributable to increasing scale. We measure political proximity by the Mahalanobis distance between all observable politician characteristics, which we describe in detail in Section 2. We also include their interaction term. Year fixed effects and origin and destination prefecture fixed effects are controlled for across columns. Standard errors clustered at the prefecture-pair level are reported below the estimates.

Table A.15: Politician competition and directed policy learning

	Policy learning		
	(1)	(2)	(3)
Panel A: Economic proximity			
Economic proximity	0.007***	0.013***	0.003***
	(0.001)	(0.001)	(0.001)
Economic indicator	GDP per capita	GDP	Fiscal exp
Origin prefecture FE	Yes	Yes	Yes
Destination prefecture FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Panel B: Political proximity			
Political proximity	-0.001***	-0.001***	-0.004***
	(0.0001)	(0.0001)	(0.0001)
Origin prefecture FE	Yes	No	No
Destination prefecture FE	Yes	No	No
Prefecture (d) $\times$ prefecture (o) FE	No	Yes	No
Prefecture (d) $\times$ politician (o) FE	No	No	Yes
Year FE	Yes	Yes	Yes

Notes: We identify instances of policy learning as an indicator variable of prefecture i adopting, at year t, a policy initiated by prefecture j. In Panel A, we measure economic proximity by the difference between city pairs of GDP per capita, GDP and fiscal expenditure, in units of standard deviation. Normalizing by year eliminates the mechanical variation attributable to increasing scale. In Panel B, we measure political proximity by the Mahalanobis distance between politician characteristics, which we describe in detail in Appendix C. Across columns, we sequentially control for origin and destination fixed effects, prefecture-pair fixed effects, as well politician $\times$ target location fixed effects, in addition to year fixed effects. Standard errors clustered at the prefecture-pair level are reported below the estimates.

Table A.16: Politician competition and policy compatibility

	% compatible		Avg. compatibility	
	(1)	(2)	(3)	(4)
Panel A: Baseline (closest 20 neighbors)				
# competitors among economic neighbors	-0.00386**	-0.00414**	-0.0197***	-0.0204***
	(0.00189)	(0.00181)	(0.00672)	(0.00644)
Panel B: Closest 30 neighbors				
# competitors among economic neighbors	-0.00252*	-0.00262*	-0.0131**	-0.0134***
	(0.00146)	(0.00141)	(0.00520)	(0.00495)
Panel D: Closest 40 neighbors				
# competitors among economic neighbors	-0.00238**	-0.00173*	-0.0106***	-0.00843**
	(0.00103)	(0.000986)	(0.00367)	(0.00360)
Panel E: Central-endorsed policies				
# competitors among economic neighbors	-0.00221	-0.00127	0.000650	0.00421
	(0.00562)	(0.00571)	(0.0210)	(0.0208)
Panel F: Geographic neighbors				
# competitors among geographic neighbors	0.00187	0.00227	0.000506	0.00181
	(0.00204)	(0.00191)	(0.00681)	(0.00626)
Panel G: Extensive margin				
# competitors among geographic neighbors	-0.0108**	-0.00352	0.164	0.674
	(0.00469)	(0.00419)	(0.692)	(0.612)
# of obs.	3,690	3,690	3,690	3,690
Mean of DV	18.912	18.912	18.912	
Prefecture FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Notes: In this table, we regress the number of policies adopted by a given prefecture at a give year on the number of geographic, hierarchical, and economic neighbors who are also political contenders. Standard errors clustered at the prefectural level are reported below the estimates.

Table A.17: Competition among geographical and provincial neighbors

	Investment Compatibility			Supply-Chain Compatibility		
	All Policy	Local Policy	Central Policy	All Policy	Local Policy	Central Policy
Panel A: Strategic competition among geographical neighbors						
Competitors	-0.0143	0.0111	-0.0196	-0.0196**	-0.0488***	-0.0107
	(0.0230)	(0.0351)	(0.0188)	(0.00827)	(0.0185)	(0.00656)
# of obs	4,012	3,101	3,987	4,010	3,079	3,985
Panel B: Strategic competition among neighbors within province						
Competitors	-0.0223	-0.0346	-0.0271	-0.0171	-0.0781***	-0.00682
	(0.0346)	(0.0537)	(0.0295)	(0.0123)	(0.0295)	(0.00974)
# of obs	4,012	3,101	3,987	4,010	3,079	3,985
Prefecture FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the effects of the number of competing prefectures on the compatibility of policies adopted by local governments, across two dimensions of policy alignment: investment compatibility (columns 1–3) and supply-chain compatibility (columns 4–6). The analysis distinguishes among three types of policies: all policies (All Policy), central policies implemented by local governments (Central Policy), and locally diffused policies (Local Policy). Panel A represents the number of competitors within a certain geographic area, while Panel B shows the number of competitors within the same province. All specifications include prefecture and year fixed effects, with robust standard errors clustered at the prefectural level.

Appendix B Quantifying tradeoffs of centralization

Having documented the negative (Table X) and positive (Table Y) impacts of centralization on policy–locality compatibility, as well as the association between policy–locality compatibility and policy effectiveness (Table Z), we quantify the impacts of centralization by projecting these effects onto the number of policies that shifted from bottom-up to top-down under this centralization trend. Specifically, we use the following formulas:

$$\text{Cost}_y = \Delta N_{topdown} \times \alpha_{cost} \times \beta_y$$

$$\text{Benefit}_y = N_{localpolicy} \times \alpha_{benefit} \times \beta_y$$

where $\Delta N_{topdown}$ is the excess number of top-down policies introduced by post-2013 centralization, and $N_{localpolicy}$ is the number of policies adopted via horizontal diffusion among local governments. The coefficient α_{cost} captures how much more top-down policies violate local compatibility relative to bottom-up policies, while $\alpha_{benefit}$ measures the improved fit of locally diffused policies when the central government stops rewarding bottom-up innovation. Finally, β_y is the marginal effect of a unit change in compatibility on outcome y (export, industrial output, or patent filings).

To calculate $\Delta N_{topdown}$, we construct a counterfactual in which the share of top-down industrial policies after 2013 remains at its 2012 level, with total annual policy counts held constant. Under this scenario, 2,562 policies implemented as top-down since 2013 would instead have been bottom-up. Meanwhile, we calculate the total number of decentralized industrial policies that local governments adopted from each other through diffusion between 2013 and 2022, yielding $N_{localpolicy} = 9{,}376$.

Empirically, within a local government's policy portfolio, the average top-down industrial policy's compatibility with local conditions is lower than that of the average bottom-up policy by 0.127 (0.054) according to the investment-based (supply-chain-based) compatibility measure. Such a policy–locality mismatch quantifies one cost of centralization.

At the same time, decentralized competition among peer cities also induces policy–locality misalignments: for a given prefecture in a given year, having one additional economic neighbor governed by a political competitor lowers average compatibility by 0.0054 (0.0108 under the supply-chain measure). This competitive penalty disappears after 2013, when the central government stopped rewarding bottom-up policy innovation. Given an average of 4.096 political competitors per city, top-down design therefore mitigates competition-induced misalignment by approximately 0.022 points for investment compatibility and 0.044 points for supply-chain compatibility.

Since Section 5.2 estimated the impact of local compatibility on sales, exports, and patents, we can now translate compatibility changes into economic impacts. Leveraging our investment-compatibility estimates, we calculate that the *yearly* cost of post-2013 centralization is RMB 197 billion in industrial output loss, RMB 15 billion in export loss, and 1,090 fewer patent filings, while the *yearly* benefit is RMB 129 billion in output gain, RMB 10 billion in export gain, and 715 additional patent filings.[1] Under both measures, the benefits of centralization exceed the costs by roughly 50%.

1. According to supply-chain compatibility measures, the annual costs are . . . , and the benefits are . . .

Over the 13-year period 2013–2025, the net cost of centralization amounts to a RMB 884 billion reduction in output, a RMB 65 billion reduction in exports, and 4,875 fewer patent filings. By comparison, across the promoted industries annual export growth averages RMB 535 billion, annual sales growth RMB 2,490 billion, and annual patent filings increase by 126,939. Benchmarking our net-cost figures against these baselines shows that centralization has led to a 12% decline in annual export growth, a 36% reduction in annual output growth, and a 4% reduction in patent growth.

Panel A: Investment Compatibility				
	N	α	β	Yearly Cost/Benefit
Export				
Cost	2,562	0.134	34,156	15.442
Benefit	9,376	0.031	34,156	10.126
Sales				
Cost	2,562	0.134	435,890	197.066
Benefit	9,376	0.031	435,890	129.232
Patents				
Cost	2,562	0.134	2.412	1,090
Benefit	9,376	0.031	2.412	715
Panel B: Supply Chain Compatibility				
	N	α	β	Yearly Cost/Benefit
Export				
Cost	2,562	0.139	8,719	4.147
Benefit	9,376	0.026	8,719	2.221
Sales				
Cost	2,562	0.1394	76,140	35.917
Benefit	9,376	0.026	76,140	19.240
Patents				
Cost	2,562	0.1394	1.466	691
Benefit	9,376	0.026	1.466	370

Appendix C Measuring politicians' career incentive

We collect detailed biographical information on the universe of Chinese central ministers and local (provincial and prefectural) leaders during our four-decade sample period. For each politician in our sample, we have information on his hometown, date of birth, level of education, current job title, past work history, etc. Our data documents observations across 4,980 terms of office, in 333 prefectural cities in China from 1985 to 2017.

Following Wang, Zhang, and Zhou (2020), we estimate each politician's *ex ante* promotion prospect in each year, which is a flexible function of all the observable characteristics that we can observe, that include his age, ethnicity, gender, highest degree, major, birth province, central experience, past experience as vice prefectural party leader, past experience as mayor, past experience as secretary and official rank in the bureaucratic system, which can be used as a proxy for his career advancing incentives.

Note that the observational level is prefecture by term, so the career incentive index we constructed will be a fixed value throughout a given term of office.