On the Centralization of Policy Making in China

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Abstract

Leveraging over two decades of Chinese policy documents and government work reports, we identify more than 116,000 distinct policies and trace their complete life cycles. We document three main findings. First, the landscape of the policymaking process has been primarily shaped by local officials, who plays a central role in both originating new policies and facilitating their diffusion. Second, after 2013, the central government shifted its incentives by ceasing rewards for bottom-up policy innovation and instead promoting the diligent enforcement of centrally assigned policies, leading to significant centralization of policy making. Third, focusing on industrial policies, we highlight tradeoffs between centralization and decentralization. Top-down industrial policies tend to be less aligned with local compatibilities and are less effective at spurring industrial growth, revealing the cost of centralization. Conversely, under decentralization, strategic competition among local politicians can distort policy diffusion, reducing the fit between policies and local contexts and undermining their effectiveness. We estimate both distortions quantitatively. Our results indicate that, over the past decade, the economic costs of centralizing policy making in China have far outweighed its benefits.

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1 Introduction

A fundamental question in political economy concerns the appropriate level at which preferences should be aggregated and policy decisions made—a matter that has sparked extensive debates over the merits of centralization versus decentralization (Tiebout 1961, Rueschemeyer, Skocpol, and Evans 1985, Zabojnik 2002, Besley and Coate 2003). This tension is particularly pertinent in the governance of large societies: while top-down policy promotion can streamline adoption, internalize spillover and enhance efficiency, it often sacrifices the local customization inherent in bottom-up innovations (Alesina, Angeloni, and Etro 2001).

Despite its theoretical importance, systematically understanding and quantifying the tradeoffs between centralization and decentralization in the policy-making process remains challenging. Doing so requires tracing the entire lifecycle of each policy idea—from its inception, through its diffusion among local governments and between local and central authorities, to its eventual outcomes. For any given policy, one must assess who initiated the idea, when and how it spread, and the extent to which it is tailored to local conditions and achieves effective results.

To bring empirical clarity to these dynamics, in this project, we examine them in the context of China — a setting where the balance between centralization and decentralization is of exceptional importance. This is not only due to the vast scale of China's society and economy, but also because of its history of policy disasters resulting from decades of heavy-handed central planning (Lin 1990, Meng, Qian, and Yared 2015). Since moving away from a centrally planned system after 1979, China has experienced unprecedented economic growth—a phenomenon many social scientists attribute to the effective use of local initiatives in decentralized policy innovation (Oi 1995, Montinola, Qian, and Weingast 1995, Xu 2011).

Specifically, we document how the roles of central and local governments in China's policy-making process have evolved over the past two decades and examine the associated consequences. To this end, we have assembled a novel dataset that allows us to map out a holistic picture of policymaking in the past decades. That comprises more than 151,000 central government policies and 3.3 million local policy documents and work reports issued between 1980 and 2023. We identify over 116 thousand distinct policy ideas implemented during this period and trace their origins, diffusion, and outcomes throughout their lifecycles.

Our analysis reveals three main findings. First, we document that in the first decade of the 21st century, China's policy-making was highly decentralized, with 82% of policy ideas first introduced by local governments. By exploiting the frequent rotation of politicians across localities, we disentangle bureaucratic fixed effects from locality fixed effects in driving local policy innovation, and we find that local bureaucrats were the primary force behind the initiation of new policy ideas. Furthermore, we show that local bureaucrats also drove decentralized policy diffusion: after the innovator of a new policy departs, there is an immediate 41.6% decline in that policy's adoption rate by other localities.

Second, we document a stark change in policy-making dynamics over the past decade. We show that, prior to 2013, local politicians who pioneered new policies that diffused widely were rewarded with promotions; after 2013, however, promotions were awarded to those who led the vigorous adoption of top-down policies. In response to these reversed incentive schemes, local politicians shifted their focus from innovation to compliance, fueling a rapid trend toward policy centralization and increasing the central government's share in policy initiation by more than 10 percentage points.

Third, we investigate the tradeoffs associated with the centralization trend in policy making, by focusing on the subset of industrial policies, which are aimed at promoting industrial growth and innovation. We show that, industrial policies targeting sectors that are more compatible with local conditions, as measured by alignments with pre-existing regional supply chains and local firms' *ex ante* investment preferences, are on average significantly more effective in generating desirable outcomes for the government, such as industrial output, new patents, and export.

We then document that centralizing (industrial) policy-making has mixed impacts on the compatibility between policies and localities. On the one hand, we show that bottom-up industrial policies are better aligned with local conditions than top-down policies, which, combined with the larger treatment effects of more locally-compatible industrial policies, highlight the economic cost of policy centralization. On the other hand, centralization can help mitigate inefficiencies stemming from strategic horizontal policy diffusion. In decentralized settings, politicians with similar backgrounds often compete for the same promotion opportunities and therefore avoid adopting policies from one another—actions that could inadvertently boost a competitor's credentials. Since these politically similar leaders are frequently assigned to economically comparable localities, such strategic competition can inhibit the diffusion of potentially beneficial policies, ultimately reducing the compatibility between policies and localities and lowering economic efficiency.

Using our estimates, we conduct a back-of-the-envelope calculation to assess the potential costs and benefits associated with the policy centralization trend since 2013. Our findings suggest that over the past decade, the economic costs of centralization may have substantially outweighed its benefits. For instance, if China had maintained the 2012 share of locally initiated industrial policies in subsequent years, our estimates indicate that export growth may have risen by approximately 61.1%. While these figures rely on strong assumptions and should be interpreted with caution, the calculated costs consistently appear to exceed the benefits by an order of magnitude, lending robustness to our qualitative conclusion and serving as a cautionary tale against over-centralization.

This paper relates to three strands of literature. First and foremost, 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 (World Bank 2003; 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 (Cremer, Estache, and Seabright 1994; Seabright 1996; Besley and Case 1995). 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

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).

impact of (de)centralization on specific dimensions such as safety (Jia and Nie 2017), pollution (Lipscomb and Mobarak 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; Wang and Yang 2025; Rawski 1995; Roland 2000; Qian 2002). Through our analysis of industrial policies over the past decades, we demonstrate that even though the 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.

The remainder of this paper will be organized as follows. Section 2 describes the data sources, how we define policies, and how we trace their lifecyles. Section 3 provides a descriptive overview on what used to be a highly decentralized policymaking process in China. Section 4 documents the trend of re-centralization in the post-2013 era, and unpacks the incentives in the background. We then zoom in a subset of industrial policies to quantitatively estimate the tradeoff between centralization and decentralization in Section 5. Section 6 concludes.

2 Background and Data

2.1 What is a "policy"?

A central question in our empirical quest concerns the precise identification of "policies". Towards this end, we manually collect the universe of policy-related keywords from annual prefectural government reports (2003-2020, Renmin database).

Prefectural government reports tend to adhere to a standardized format of writing. In each of the reports for the past 20 years, section 1 always starts with a recap on policies and achievements in the past, and section 2 outlines plans for the coming year. For our purposes, we only focus on the "recap" section to get rid of policy ideas merely mentioned and never implemented. To extract keywords from the sentences, we build a library of stop words such as “enhance”, “further”, “implement” to restrict our attention to core elements that distinguishes a policy from another. We then verify them with AI, asking ChatGPT 4o-mini to verify if those keywords indeed suffices to make sense as standalone policy keywords, and then exclude from master dataset those deemed inappropriate. Once the keywords are extracted, we look for their presence in the universe of policy document texts to locate their initiation and trace their diffusion. Appendix Table A.1 provides examples of a random subset of policy keywords, along with a few key features that we constantly refer to throughout the paper.

Two key assumptions are implicitly built in this definition of policy keywords. First, any non-trivial policy agenda that is implemented by the local government must be mentioned at least once in the universe of government reports, either by themselves or by follow-up adopters. Second, the level of “aggregation” chosen by politicians in the report is appropriate insofar as it captures distinguishable features of individual policies.

While we regard both assumptions as generally valid, we develop three alternative definitions of policy keywords to understand if our results are robust. Specifically, we try (i) extracting keywords directly from the universe of policy titles; adding an additional dimension of policy *domain*; and (ii) bundling policies sufficiently close to one another, where distance is computed via comparing the vector of policy documents that contains each keyword. In Online Appendix, we describe how they are carried out. Our main results remain robust to alternative versions of aggregation.

2.2 Tracing policy lifecycles

With the keywords extracted, we map out their diffusion process in the universe of policy documents. We collect data on all documents issued by central, provincial and prefectural level government (1980-2023). We obtain data from `www.pkulaw.com`, one of the largest and most authoritative legal search engines extensively used by lawyers, judges, and academics hosted by Peking University Law School. For each policy, we compile information on its title, full content, issuing authority, effective date, area of law, and legal status as of December, 2023.

Our final data consists of 3,454,306 policy documents, among which 151 thousand are issued by the central government. We then merge the it with the keyword list to construct our master dataset using Aho-Corasick algorithm, which allows us to trace the diffusion of each policy idea. On average, each policy idea has been mentioned by 22.92 different ministries / bureaus of the local government.

2.3 Measuring locality-industry-specific growth

Policy objectives are inherently multi-dimensional. To be able to evaluation its effectiveness, in Section 5, we zoom into a subset of industrial policies. We define each industry as a 4-digit industrial code, following China's standard coding system (national standard GB/T 4754, 2017), which is a hierarchical system for classifying economic activities managed by National Bureau of Statistics (NBS). It's similar to the NAICS in the U.S. or NACE in the EU, and the 4 digit identifier is the most granular and most widely used version.

We collect information on new investment from Business Registration Database, maintained by State Administration for Industry and Commerce. It contains more than 250 million records of business registration from 1980 to 2023, and serve as a comprehensive database capturing new investment. Each firm is classified into a 4-digit industry code upon registration.

We collect information on firm-level performance from Annual Survey of Industrial Enterprises, maintained by the National Bureau of Statistics. It contains the financial records of all manufacturing firms making more than 5 million RMB per year before 2011, and 20 million afterwards. Each firm is classified into a 4-digit industry code by the National Bureau of Statistics.

We collect information on export revenue from Detailed Records of Imports and Exports, collected 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 the HS codes into the 4-digit industrial codes used in our analysis, we first map the HS codes to the United Nations ISIC industry codes, and then convert the ISIC codes into 4-digit industrial codes using official documentation provided by the Chinese government. To improve the accuracy of the conversion, we further applied NLP methods to identify the semantically closest code pairs.

Finally, we collect information on patent from China National Intellectual Property Administration.The patent data cover approximately 11 million patents filed by Chinese companies in China between 1990 and 2020. Each patent can be linked to a related industry classified by a 4-digit code. Additionally, we gather the geographic location of the company that filed the patent by linking the patent data with company databse.

2.4 Biographical information of politicians

Following Wang and Yang (2025) and Wang, Zhang, and Zhou (2020), 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. We also estimate each politician's ex ante promotion prospect in each year, which is a flexible function of his age, his official rank in the bureaucratic system, and a vector of all observable characteristics. It can be used as a proxy for his career advancing incentives.

3 Tracing where policy ideas come from

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

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.

Furthermore, 24,322 (25.68%) of the locally initiated policies eventually evolved into national policies. 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.[2]

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, both local bureaucrats and the localities themselves significantly drive policy innovation. Notably, the impact of local bureaucrats is quantitatively more important, explaining an additional 150% of the variation in the data compared to the contribution of the localities. In addition, year fixed effect seems to be particularly important in shaping policy innovation, a fact that we will discuss in greater detail in Section

2. 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.

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 is particularly pronounced when the departing politician is *not* promoted to a higher position.

Similar patterns show up when we examine the departure of central government officials. Appendix Figure A.1 shows that the number of adopters decreases by 22.9% following the departure of the minister who initiated the policy.

These results suggest that policy diffusion relies heavily on incentivized bureaucrats actively "selling" their innovations: when the inventor of a new policy is no longer in a position to take full credit for its success, other prefectures have little incentive to adopt that policy.

Taken together, the findings in Sections 3.2 and 3.3 highlight the critical role of local bureaucrats in China's decentralized policy-making process, serving as the key driving force behind both policy innovation and policy 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 that can diffuse widely or even get picked up by the central government; and (b) be an early adopter of new policies assigned by the central government to set an example for other localities.

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? Figure 2 aims answer this question. We estimate the following cross-sectional regression within a series of overlapping 5-year windows:

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

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. Within each sliding window, we compare politicians who leaves office in adjacent years against each other, and we collect the estimates to plot the trend of relative importance of innovation (compliance). 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.5 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 an 7.8 pp 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.5 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 6, Panel A illustrates such reallocation. For each year, we compute the average ratio between the innovation index and the compliance 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, on average, 8.5 times that of the compliance index, and this ratio slowly declined to 7 times by 2012. After 2013, however, the ratio began declining sharply: by 2020, the innovation index was only twice that of the compliance index, representing a decline of more than 300% in relative magnitude within the period of seven years.

Figure 6, 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 6, 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 6 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.5, 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.[3]

That said, a (albeit milder) centralization trend appears to have existed even before 2013, and numerous other factors may have affected policymaking in the 2010s. Thus, while we document the empirical facts on promotion patterns and innovation/compliance trends, we do not insist on any specific causal mechanism for these observations.

5 Tradeoffs of policy centralization

So far, we have documented that China's policymaking process once relied substantially on bottom-up innovation (Section 3) before quickly shifting toward greater centralization after 2013 (Section 4). In light of these findings, in this section we examine the consequences associated with the centralization of policymaking over the past decade.

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

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, we restrict our analysis in this section to a subsample of industrial policies. In these 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 2024). It is worth noting that our measure of industrial policy consequence reflects policy effectiveness through the lens of the government's own goals, which may or may not align with the broader welfare of society.

Therefore, the empirical question becomes: given the government's goal of promoting industrial growth through industrial policies, what are the 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 down into several parts: in Section 5.1, we explain how we measure the compatibility between industrial policies and localities, and why this is a crucial dimension for evaluating the consequences of policy centralization; in Sections 5.2 and 5.3, we assess, respectively, the costs and benefits of centralized policymaking through the lens of policy-locality compatibility; and finally, in Section 5.4, we quantitatively compare the costs and benefits of policy centralization since 2013.

5.1 Policy compatibility with local conditions

The effectiveness of a policy in a given locality depends heavily on how well its design and implementation align with local conditions. This is especially true for industrial policies. For instance, an effort to promote the mass installation of solar panels in a rainy area may prove futile.

In this section, we first explain how we measure the compatibility between an industrial policy and a locality, and show that such compatibility is indeed an important predictor of policy effectiveness (in generating industrial growth).

5.1.1 Measurement of compatibility

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

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 industry in a specific prefecture:

$$Investment\ Compatibility_{cp} = \frac{I_{cp} \,/\, \sum_{p' \in P} I_{cp'}}{\sum_{c' \in C} I_{c'p} \,/\, \sum_{c' \in C, p' \in P} I_{c'p'}} \tag{5}$$

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 (2024), 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.

Alignment with pre-existing local supply chains Instead of inferring the revealed preferences of business investors, another 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:[4]

$$S_{cp} = \sum_{j \neq p} \alpha_{jp} \cdot I_{cj} \tag{6}$$

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.

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

$$\textit{Supply-chain compatibility}_{cp} = \frac{S_{cp} \,/\, \sum_{p' \in P} S_{cp'}}{\sum_{c' \in C} S_{c'p} \,/\, \sum_{c' \in C, p' \in P} S_{c'p'}} \tag{7}$$

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.

4. 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.

Descriptive patterns Appendix Figure A.4 plots the spatial distribution of these measures of policy-locality compatibility, using the automobile industry as an example. As shown, the compatibility measures—whether inferred from revealed preferences or defined based on supply chains—are highly correlated, which is intuitive, as firms tend to favor locations with easier access to supply networks. However, the compatibility patterns for state-owned and non-state-owned enterprises are not entirely the same, suggesting that these two types of firms may have different preferences when making investment decisions.

Another interesting pattern we observe is the self-selection into the adoption of industrial policies. Appendix Figure A.2 plots the average compatibility of localities adopting the industrial policy against the number of years after inception. We observe a striking downward-sloping trend, suggesting that localities care about policy compatibility a lot themselves, and high-compatibility localities are likely the early adopters without central intervention. On the other hand, when the central government do intervene, a crowd of not-so-compatible localities takes up the policy to signal loyalty. Appendix Table A.2 quantifies the break of trend – average policy compatibility with ex-ante investment drops by 17.8 percentage points immediately after central endorsement.

It is worth noting, however, when we measure relative strength based on cumulative equity investment, the version based on private enterprise investment and the one based on state-owned enterprise investment, while correlated with each other, do display notable differences. This is not surprising given that SOEs tend to specialize in different industries compared to private firms, and the distinction will allow us to examine whether an industrial policy is more aligned with the revealed preference of private firms, or that of SOEs.

5.1.2 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 estimate the following event study separately for industrial policies that promote industries in line with local strengths versus those that defy local strengths:

$$Y_{pct} = \sum_T \beta_T T_{ipt} + \phi_{cp} + \gamma_{pt} + \lambda_{ct} + \varepsilon_{pct} \tag{8}$$

where Y_{pct} is the outcome of interest for industry p in prefectural city c in year t, 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. 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. 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.

As shown in Figure 3, industrial policies that align with local strengths are significantly more effective in delivering industrial growth compared to those that are incompatible with local conditions. 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 entrepreneurs reveal a preference for a given locality-industry through their investments (i.e., when $Investment\ RCA > 1$), the corresponding industrial policy—compared an average industrial policy not necessarily aligned with local entrepreneurs' revealed preferences—will generate an additional 637% growth in industrial output, a 151% rise in exports, and additionally 901% more patent filings. Similarly, if an industrial policy is launched in a locality that has corresponding comparative advantage in terms of pre-existing supply chains (i.e., when $Supply\ RCA > 1$), it will on average generate an additional 195% growth in industrial output, a 11.6% rise in exports, and 257% more patent filings. Such robustness is with the observation that these two comparative advantage measures are highly correlated with each other.

Interestingly, however, the heterogeneity disappears when we measure policy-locality compatibility based on SOEs' revealed preferences. 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 the presence of regional supply chains—so that following private market investment patterns can potentially lead to more desirable outcomes from the government's perspective.

5.2 Costs of centralization

Appendix Figure A.3 shows that, the post-2013 centralization trend in general policy making, as documented in Section 4, also applies to the subset of industrial policies. Centralized policy making, by sacrificing useful decentralized local information, might result in lowered compatibility between localities and industrial policies, thereby undermining industrial growth.

5.2.1 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."[5]

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 best tailored to its specific conditions.

5.2.2 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, for each industrial policy, we compute the extent to which it complies with local conditions, according to the measures defined in Section 5.1.

As shown in Table 2, among all the industrial policies implemented in China over the past two decades, those assigned from top-down are significantly less compatible with local economic conditions, as measured by *ex ante* business investment flows or *pre-existing* local supply chains. On average, compared to bottom-up industrial policies, top-down ones are 12.7% less likely to be promoting an industry in a locality that has relative strength in it.

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

These findings reveal the prevalence of lowered policy-locality compatibility under centralization, which, combined with the association between policy-locality compatibility and policy effectiveness, would imply that top-down industrial policies might end up being less effective in generating industrial growth. This hypothesis is confirmed by Appendix Table A.4, which documents that top-down policies lead to 87.6% lower industrial output, 17.2% less export, and 365% fewer patent filings, as compared to their bottom-up counterparts.

Alternative policy objectives Since the government explicitly emphasizes that these industrial policies are aimed at promoting industrial growth, our findings indicate that centralization might conflict with the government's stated objectives. That said, it remains plausible that the central government pursues additional goals beyond industrial growth, 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 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. However, this does not necessarily imply that, *within* China, these industrial policies will be allocated to localities 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.6,central initiated and central endorsed industrial policies target industries that are marginally larger (by 17% for central initiated policies,4% for central endorsed policies) in the long run. However, as documented in Panel (C), weighting short-run industrial growth by this long-run potential measure does not substantively alter our results. Moreover, because the number of central policies is smaller than that of local policies, we compare an equal number of central and local policies to ensure a fair comparison. Specifically, we focus on local policies that target industries with the largest future market size. As documented in Panel (B), these local policies are more likely to target industries with strong growth potential.

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 US government and confirm that the central government is more likely to promote these industries than local governments (Panel (A) of Appendix Table A.7). That said, as shown in Panel (B) of Appendix TableTable A.7, even after excluding these national security-related industries, our main findings regarding the reduced locality–policy compatibility for top-down policies persist, suggesting that the costs of centralization cannot be attributed solely 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. To test this, we use UN Comtrade data to calculate China's revealed comparative advantage (RCA) in each industry based on export patterns, and then compare RCA values for top-down versus bottom-up industrial policies. As shown in Panels (A) and (B) of Appendix Table A.8, local,rather central governments exhibit a slightly stronger tendency to target industries in which China is expected to have a future comparative advantage. When the number of central and local policies is equalized, the industries selected by local governments align more closely with those that are competitive in 2024.This suggesting that central authorities are not inherently more forward-looking than local governments when selecting industrial policies.

5.3 Benefits of centralization

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 help mitigate such bias?

Specifically, a common issue under decentralized policy making is the strategic bias in policy diffusion across localities. Anecdotally, when local politicians compete for the same promotion opportunities, they may have incentives to avoid learning policies from one another in order not to enhance their competitors' credentials. We first discuss qualitative examples of such behavior and then quantitatively examine its prevalence using our data.

5.3.1 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).

5.3.2 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; 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.

We estimate the follow equation:

$$S_{ijt} = \alpha_2 \cdot \text{Proximity}_{ijt,m} + \lambda_t + \gamma_i + \sigma_j + \varepsilon_{ijt} \tag{9}$$

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 Figure 4, economic similarity between prefectures are strong, positive predictors of policy similarity. In other words, neighboring localities and those with similar economic conditions are more likely to adopt similar policies. This finding is intuitive since policy effectiveness depends in part on local socio-economic conditions: if a policy is proven effective in a prefecture with similar conditions, it is more likely to succeed locally.

In stark contrast, 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 3 quantifies these patterns: one standard deviation of increase in economic similarity is associated with a 1.04 (2.5%) increase in policy similarity, whereas one standard deviation of increase in political similarity is associated with a 0.08 (0.2%) *decrease* in policy similarity.

Importantly, as shown in Table 3 Panel B, for the political similarity analysis we are able to control for a stringent set of "prefecture-pair fixed effects," which holds constant the natural rate of policy diffusion between two localities and exploits only the variation in political similarity generated by bureaucratic turnovers over time. Furthermore, we can even control for a full set of "origin politician-by-destination prefecture" fixed effects (Panel B, Column 3), thereby isolating the variation created solely by political turnover at the destination prefecture. This approach enables us to examine whether changes in political competition affect a prefecture's likelihood of adopting policies issued by an origin prefecture whose political leader remains unchanged. Our findings remain under these more stringent specifications, suggesting a causal role of political competition in influencing policy diffusion.

Economic similarity and political similarity To what extent do the patterns documented in Table 3 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.5, 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.

Therefore, to quantify the extent to which strategic competition affects the overall compatibility between policies and localities, it is insufficient to focus solely on the policies that were not adopted; one must also account for the substitute policies that are chosen. Motivated by this insight, we compute, for each prefecture in each year, the share of its "economic / geographic neighbors" that are led by the prefectural leader's "political competitors." Specifically, among all other prefectures (i) who are within the same province (hierarchical neighbors); (ii) who are among the top 30 closest in distance (geographic neighbors); (iii) whose GDP per capita differs by no more than 0.43 standard deviation (50 percentile) from that of a given prefecture, 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.

Figure 5 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 A.9 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 Appendix Table A.10, 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.

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.11 and Appendix Tables A.12

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 When horizontal policy diffusion is replaced by top-down assignment, local politicians may be less concerned about inadvertently enhancing their peers' credentials and, consequently, more willing to adopt policies proven effective in peer localities with similar socio-economic conditions.

Appendix Table A.10, A.11, and A.12 verifies this hypothesis: the negative correlation between "average policy–locality compatibility" and "share of similar localities led by political competitors" is driven entirely by bottom-up industrial policies and becomes statistically insignificant for top-down industrial policies. This finding supports the interpretation that top-down policy assignment can help mitigate the biases inherent in decentralized policy diffusion.

5.4 Back of the envelope calculation: cost vs. benefit

As shown in Sections 5.2 and 5.3, the centralization of policy making has mixed impacts on policy–locality compatibility. By linking these countervailing forces to the association between policy–locality compatibility and policy effectiveness documented in Section 5.1, we conduct a back-of-the-envelope calculation to quantify the economic tradeoffs of policy centralization.

According to our estimates, under the centralization trend in the past decade, 3384 prefecture-level industrial policies that would have been bottom-up became top-down.

Based on our baseline estimates, each top-down industrial policy, compared to a bottom-up one, is 12.7% less likely to be compatible with local conditions, while simultaneously mitigating 1.59% of the loss of compatibility attributable to strategic competition. By linking these estimates to the differential effectiveness of compatible versus incompatible industrial policies in generating industrial growth, we calculate that the centralization trend since 2013 has, on net, resulted in 289 billion loss of industrial output and 31 billion loss of exports.[6]

6 Conclusion

In this paper, we map the landscape of the policymaking process in China. By tracing the full arc of of over 116 thousand policies – from inception to diffusion and adoption – we uncover distinctive features of the institutional setup that were 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 project. We point out a tension between the compatibility of local-tailored policies and the distortion that comes from horizontal differentiation in political tournaments.

These tradeoffs are not unique to China. As governments around the world grapple with challenges that increasingly demand both coordination and tailoring – from climate policy to industrial strategy – understanding the optimal hierarchical level from which decisions should be made, and the underlying costs one have to bear, becomes increasingly imperative. In illuminating the mechanics and consequences of China's re-centralization, this paper not only contributes new evidence but also invites a rethinking of how large states can design institutions that balance initiative with integration.

On a higher level, our paper alludes to the fact that there is widespread "misallocation" of policies. Such misallocation is driven by a combination of institutional constraints and incentive structures. What we refrain from taking a stance on is the determinants of the policy space. While we find that the quantity of policy innovations can be explained by politician incentives, we don't have much to say about the *quality* of the policies that could have been adopted, but was strangled in the cradle, as we only observe the policies that eventually appeared on paper. Understanding how institutional changes would affect the direction and quality of policy *innovation* is a fascinating project that we leave for future work.

6. Details of these calculations, as well as robustness checks based on alternative estimates, can be found in Appendix B.

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Figures

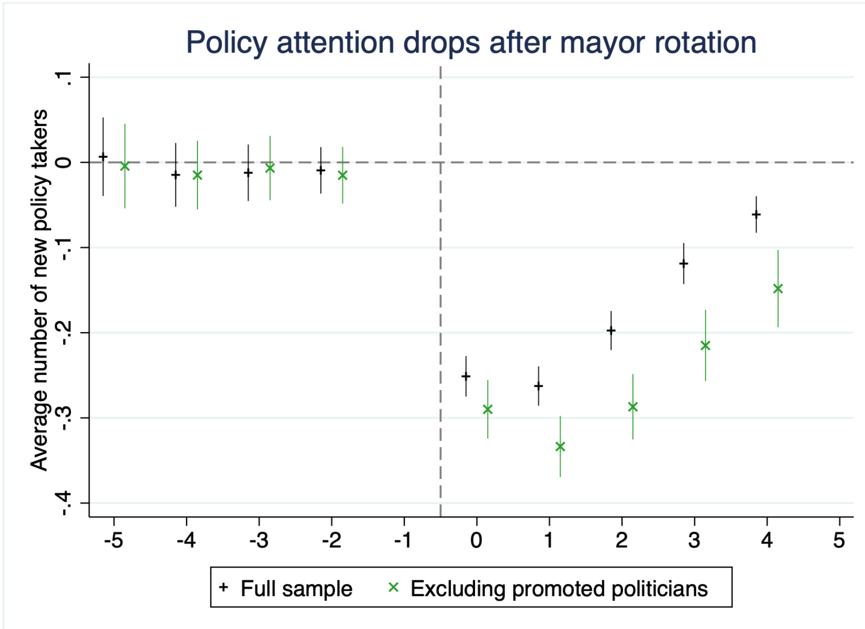
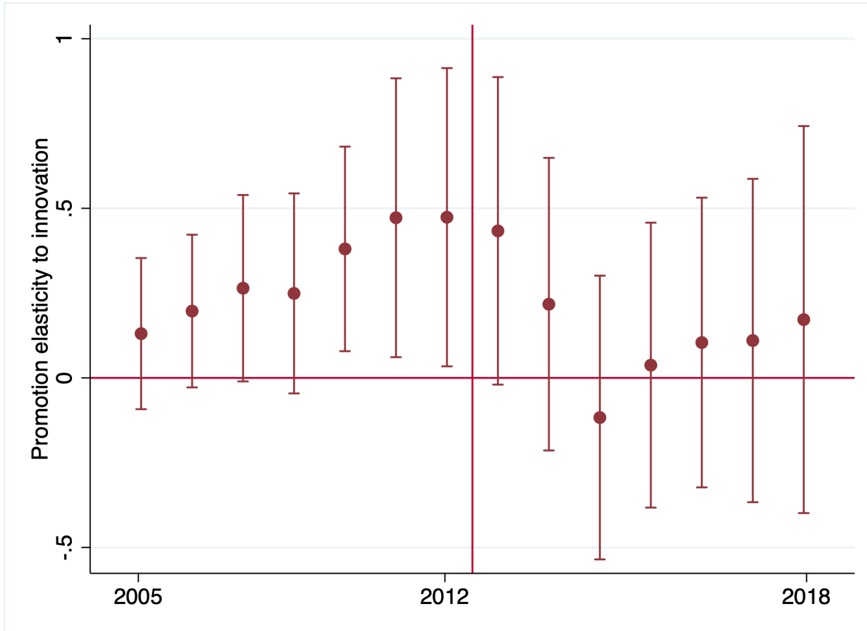
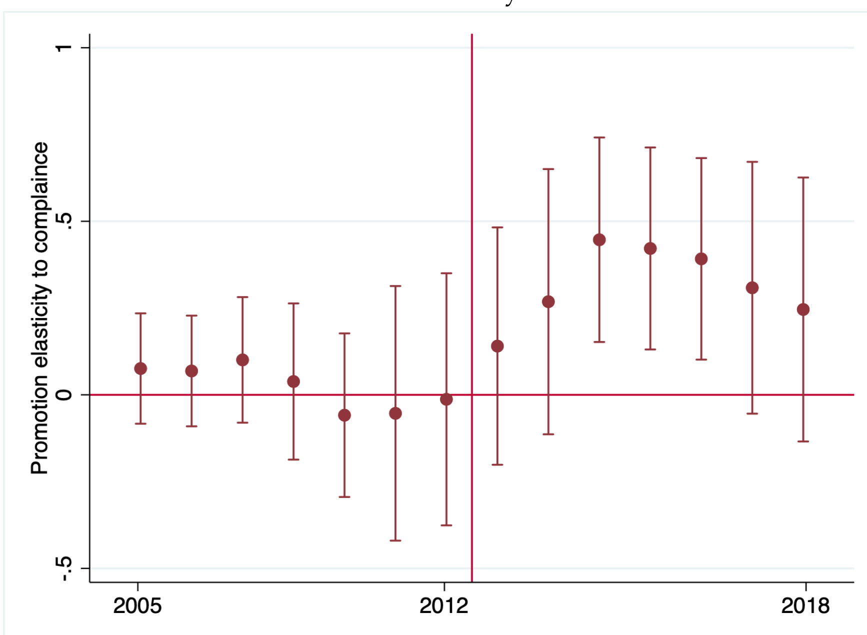


Figure 1: This figure plots the event study estimates illustrating the decrease in number of policy adoption after prefectural party secretary departure. We cluster standard errors at prefectural level, and compare baseline estimates with a "stronger" treatment where only departing politicians who were not promoted are counted as leaving.

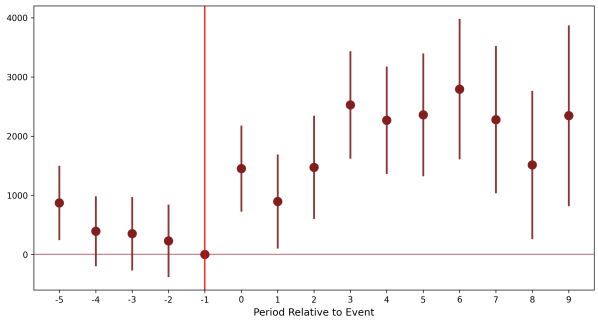


Panel A: Promotion elasticity wrt. innovation

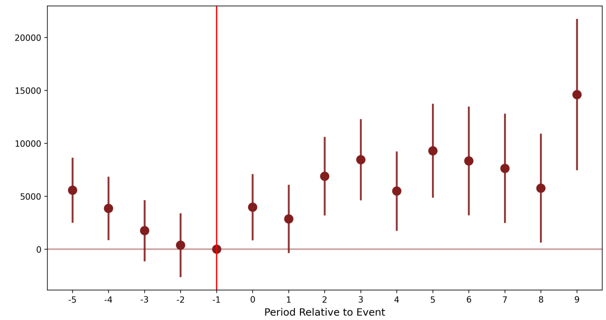


Panel B: Promotion elasticity wrt. compliance

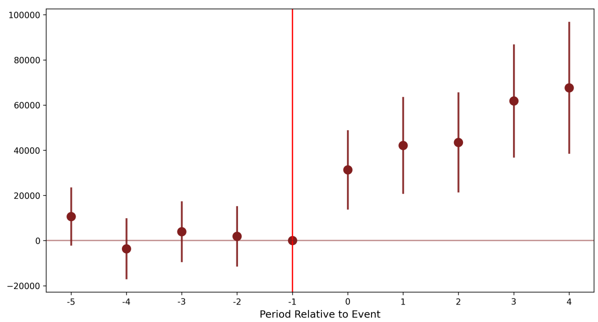
Figure 2: The two figures above plot the point estimates and confidence intervals of a series of cross-sectional regressions. In each regression, we focus on a sliding-window of politicians who depart from office during $[t-2, t+2]$. We regress their job outcome (promotion$\in \{0, 1\}$) on both an index for innovation and another for complaince. Both indices are scaled by its mean 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.



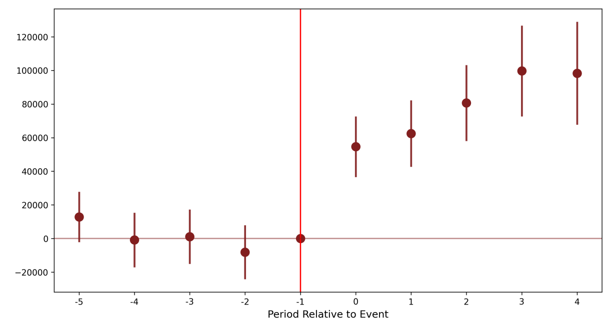
Panel A.1: Export value (1 thousand yuan), Supply-chain compatibility



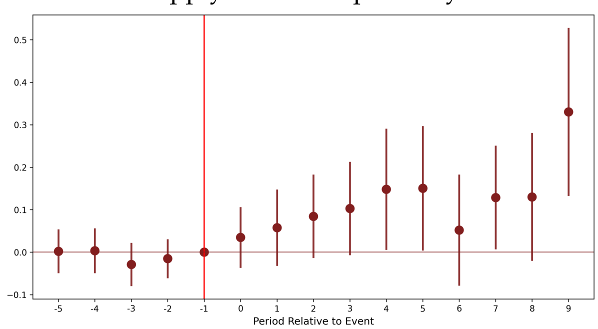
Panel B.1: Export value (1 thousand yuan), Investment compatibility



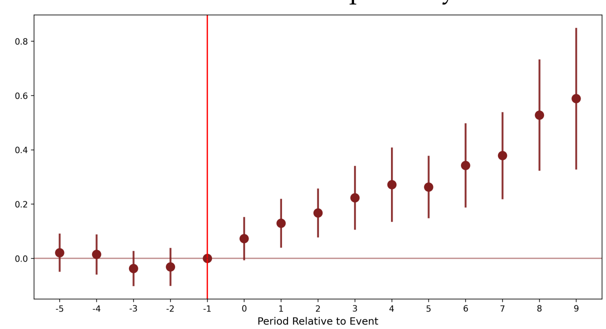
Panel A.2: Total revenue (1 thousand yuan), Supply-chain compatibility



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

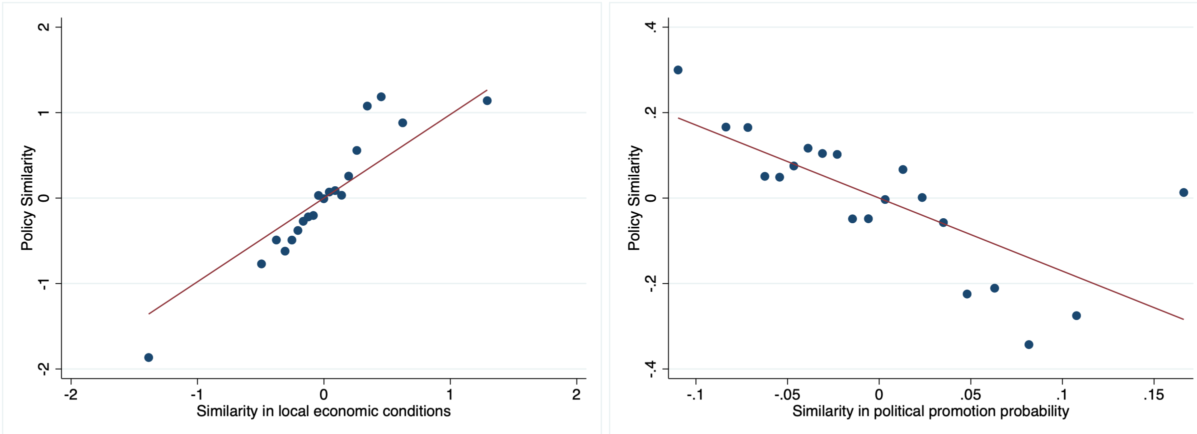


Panel A.3: Patent (counts), Supply-chain compatibility



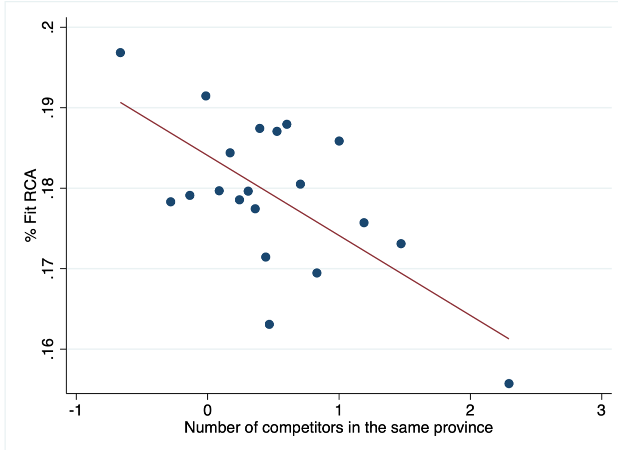
Panel B.3: Patent (counts), Investment compatibility

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.

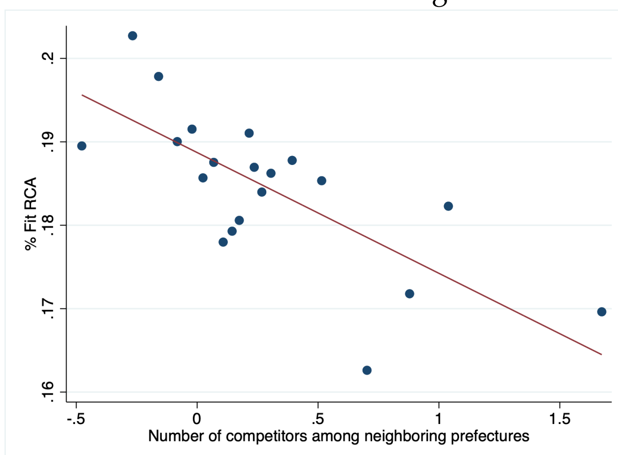


Panel A: Policy portfolio and economic proximity Panel B: Policy portfolio and political proximity

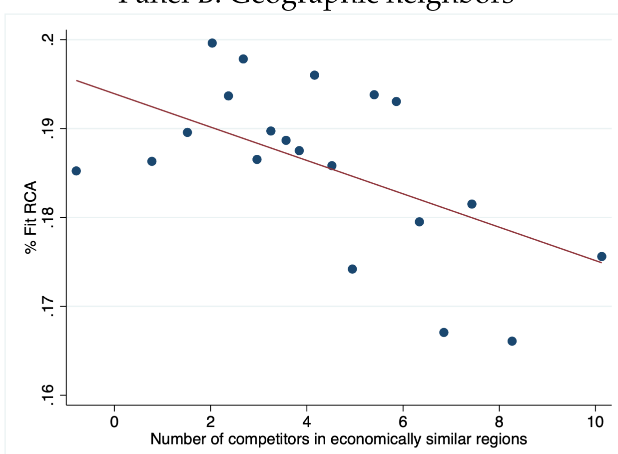
Figure 4: This figure illustrates the similarity of policy space between city-pairs with respect to their economic / political proximity. The dependent variable, policy similarity, is the euclidean distance between the two vectors of dummy variables v_{pct} indicating whether a document about policy 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.



Panel A: Hierarchical neighbors

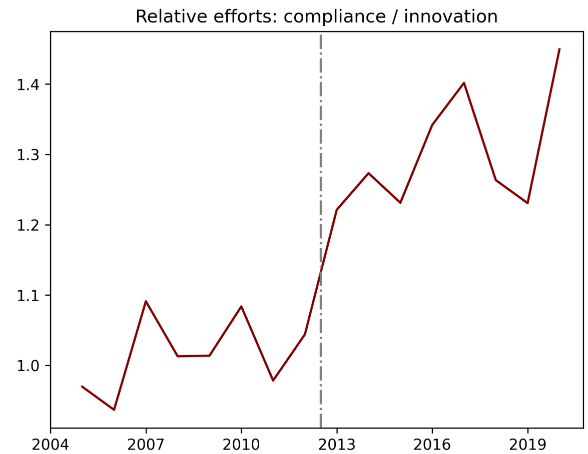


Panel B: Geographic neighbors

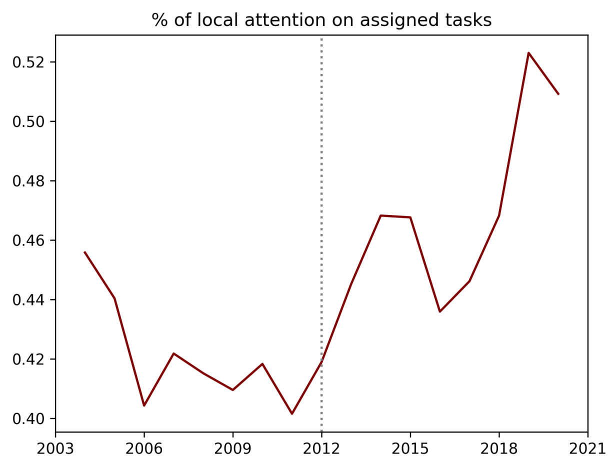


Panel C: Economic neighbors

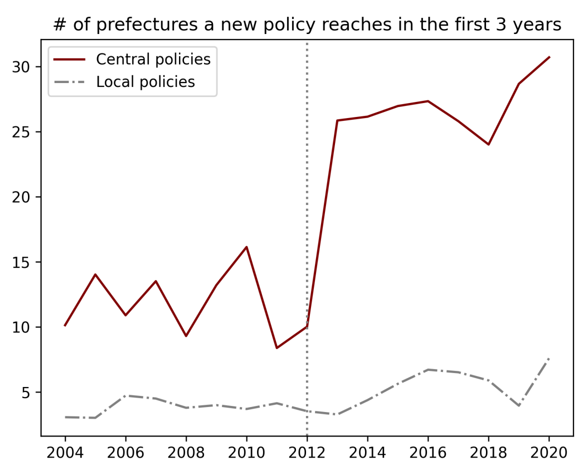
Figure 5: This figure plots the reduced-form relationship between policy compatibility and political competition. We present three binned scatter plots where we plot the percentage of industries policies implemented by a prefecture that are compatible with ex-ante entrepreneurial investment against the number of their hierarchical, geographic and economic neighbors who are also political competitors (those within $\pm$ 5 percentile of ex-ante promotion probability) among geographic, hierarchical, and economic neighbors. For each prefecture, geographic neighbors include the 30 closest cities. Hierarchical neighbors include those within the same province, and economic neighbors include those within $\pm$ 50 percentile of GDP per capita last year.



Panel A



Panel B



Panel C

Figure 6: This figure illustrates the increasing centralization of policymaking post-2013. Panel A plots the ratio of innovation index vs. compliance index by year. Those indices are defined in Section 3.2. Panel B 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 C, 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 all three cases, we see a sharp increase in the degree of centralization.

Table 1: Decomposition of innovation between bureaucrats and locality

Decomposing innovation			
	$\tau_{\text{politician}}$	$\tau_{\text{prefecture}}$	τ_{year}
Variation of Y explained	0.221	0.089	0.470

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.

Table 2: Centralization and policy compatibility

	Investment		Supply-chain	
	% compatible		% compatible	
	(1)	(2)	(3)	(4)
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
Prefecture $\times$ Year FE	No	Yes	No	Yes

Notes: This table presents the point estimates of the differential of locality compatibility between centrally-endorsed policy and local initiative. 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 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	2.226***	0.979***	0.884***
	(0.0379)	(0.0256)	(0.0254)
Year FE	No	Yes	Yes
Origin FE	Yes	Yes	Yes
Destination FE	Yes	Yes	Yes
Politician(o) $\times$ prefecture(d) FE	No	No	Yes
Politician(d) $\times$ prefecture(o) FE	No	No	Yes
Panel B: Political Incentive Proximity			
- Δ ex-ante promotion probability	-3.867***	-1.709***	-1.044***
	(0.292)	(0.125)	(0.117)
Year FE	No	Yes	Yes
Origin FE	Yes	Yes	Yes
Destination FE	Yes	Yes	Yes
Politician(o) $\times$ prefecture(d) FE	No	No	Yes
Politician(d) $\times$ prefecture(o) FE	No	No	Yes

Note: 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, we sequentially control for origin and destination fixed effects, calendar year fixed effects, as well politician $\times$ target location fixed effects. Standard errors clustered at prefecture-pair level are reported below the estimates.

Online Appendix

Appendix A Additional figures and tables

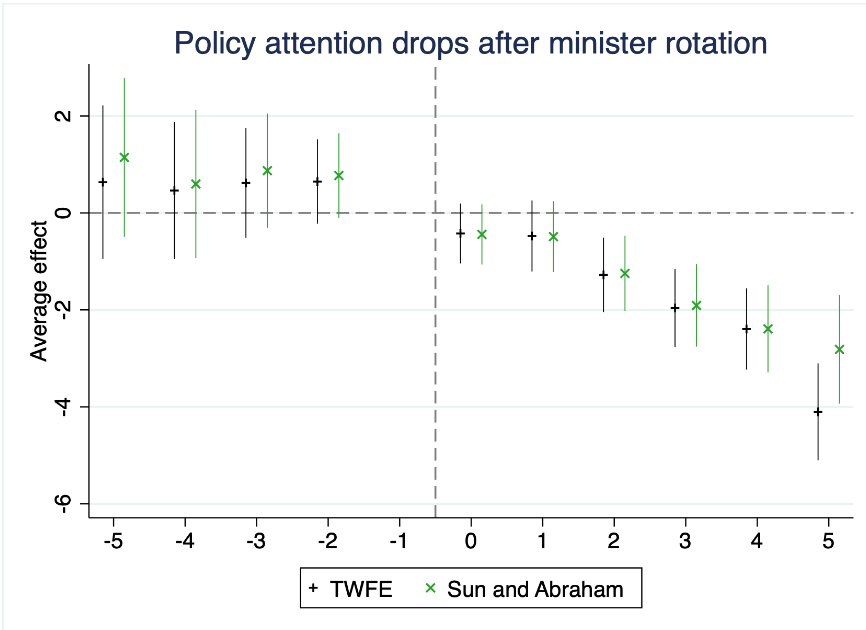
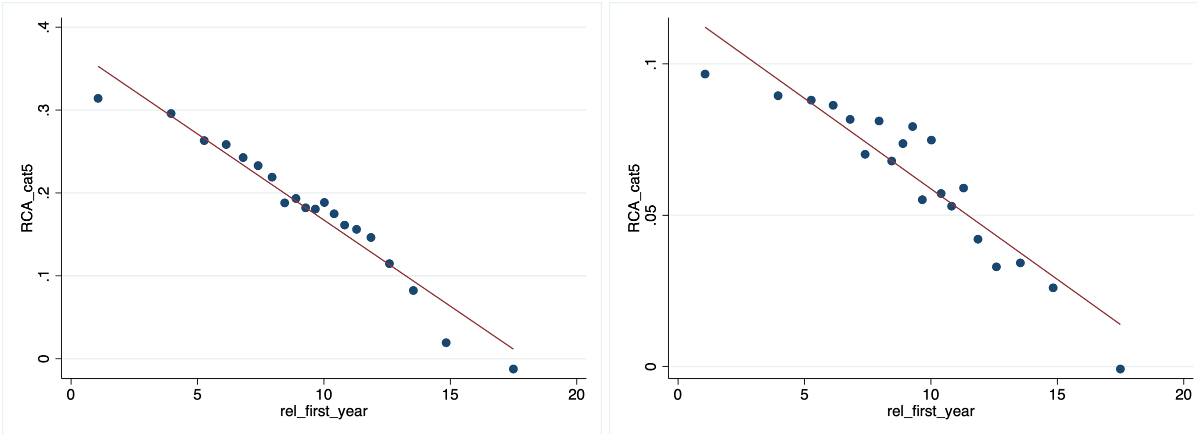


Figure A.1: This figure plots the event study estimates illustrating the decrease in number of policy adoption after central government ministerial departure. We cluster standard errors at prefectural level, and present an alternative specification where we following Sun and Abraham (2021)to account for heterogeneous treatment effects in staggered event study designs.



Panel A Panel B

Figure A.2: This figure illustrates the decline of ex-ante industry suitability along policy diffusion. For each year t relative to the initial adoption, we plot the average "compatibility" among localities adopting the industrial policy. We parse out prefectural fixed effects and industry fixed effects. In Panel A, we measure compatibility by the whether the policy complies with entrepreneurial preference. In Panel B, we measure compatibility by alignment with pre-existing local supply chains.

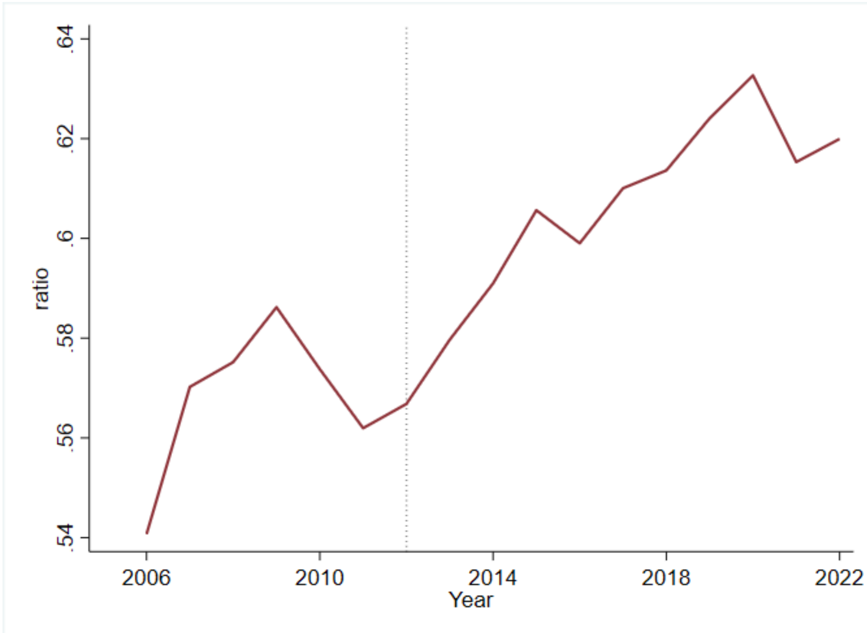


Figure A.3: This figure plots the percentage of industrial policies each prefecture implement at each year that are "endorsed" by the central government.

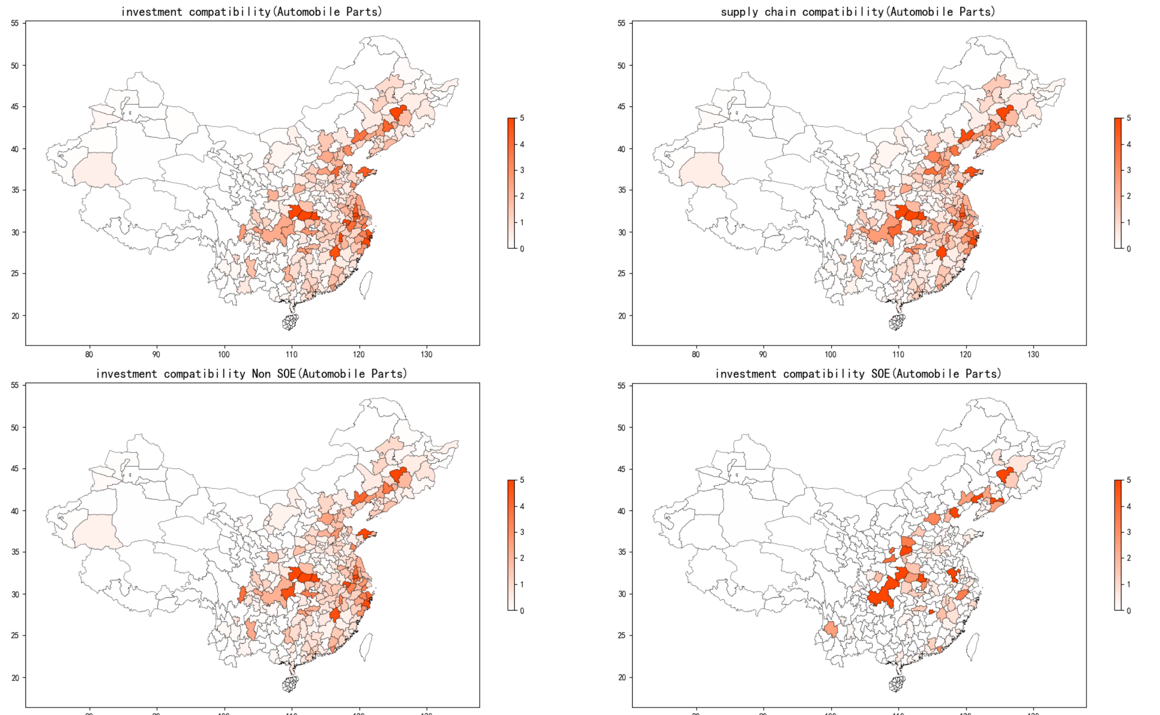


Figure A.4: This figure plots the spatial distribution of the compatibility of automobile industry across China. In the left panel, we construct the measure using new investment from private firms, while on the right, we focus on state-owned enterprises.

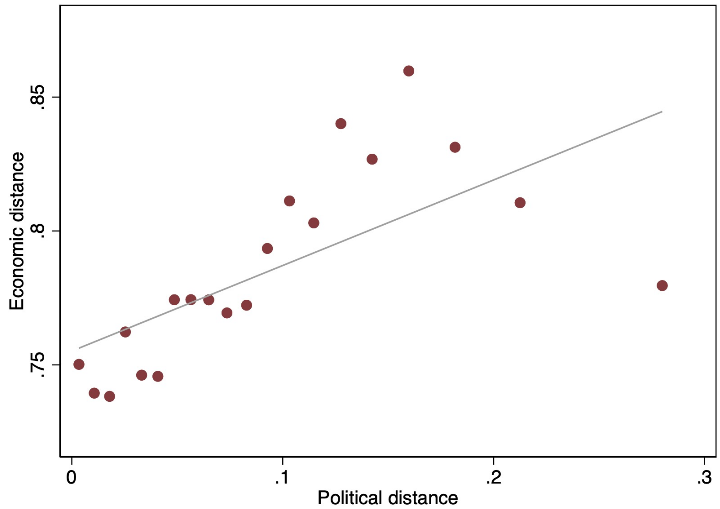


Figure A.5: This figure illustrates the sorting between economic conditions and politician characteristics. We draw a bin-scatter plot of economic distance (measured by GDP per capita dispersion) against political distance (measured by ex-ante projected promotion probability differentials). We observe 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 prefecture level.

Table A.3: Divergence in industrial policy effectiveness

	Export	Sales	Patents
	(1)	(2)	(3)
Panel A: Fit investment compatibility			
Treat × Post	64,393***	756,505***	1.688***
	(12,410)	(94,996)	(0.211)
# of obs.	2,129,252	2,525,124	1,755,811
Panel B: Defy investment compatibility			
Treat × Post	-18,125**	-14,535	-0.0705
	(7,306)	(41,202)	(0.0742)
# of obs.	2,223,234	2,654,162	1,841,780
Panel C: Fit supply-chain compatibility			
Treat × Post	2,224***	192,436***	0.702***
	(760.2)	(21,254)	(0.126)
# of obs.	2,170,866	2,355,054	1,770,958
Panel D: Defy investment compatibility			
Treat × Post	-4,104***	43,768**	0.199*
	(857.3)	(17,004)	(0.108)
# of obs.	2,222,359	2,454,283	1,826,633
Mean of DV	54,309	120,991	0.195
Prefecture × Year FE	Yes	Yes	Yes
Prefecture × Industry FE	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes

Notes: Standard errors clustered at prefecture level are reported within in parentheses.

Table A.4: Effect of Policy Type on Export and Innovation Outcomes

	Export	Sale	Patents
	(1)	(2)	(3)
Panel A: Top-down policy			
Treat × Post	-4,977	11,050	-0.0111
	(3,660)	(6,834)	(0.0868)
# of obs.	2,194,598	2,378,844	1,747,787
Panel B: Bottom-up policy			
Treat × Post	4,391	117,105**	0.702***
	(3,779)	(49,160)	(0.127)
# of obs.	2,211,326	2,430,493	1,779,441
Mean of DV	54,309	120,991	0.195
Prefecture × Year FE	Yes	Yes	Yes
Prefecture × Industry FE	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes

Notes: Standard errors clustered at prefecture-by-industry level are reported within the parenthesis.

Table A.5: Innovation, compliance and promotion likelihood

	Promotion					
	Before 2012			After 2012		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Innovation / compliance index						
log(Innovation index)	0.116**	0.116**	0.112**	0.054	0.057	0.057
	(0.051)	(0.052)	(0.052)	(0.075)	(0.076)	(0.076)
log(Compliance index)	0.004	0.011	0.003	0.140***	0.143***	0.143***
	(0.035)	(0.037)	(0.037)	(0.044)	(0.045)	(0.045)
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)
# of obs.	571	571	571	872	872	872
Mean of DV	0.401	0.401	0.401	0.317	0.317	0.317
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Hierarchy FE	Yes	Yes	Yes	Yes	Yes	Yes
Start Age FE	Yes	No	Yes	Yes	No	Yes
Level of education FE	No	No	Yes	No	No	Yes

Note: Standard errors clustered at prefecture 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. "Cohort" is the year a politician takes office, "hierarchy" is the relative rank within the bureaucratic system, "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.6: Targeting Future Market Outcomes

VARIABLES	Average Market Value	Future Market Value
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
Panel C: Robustness Check		
VARIABLES	% compatible(investment)	%compatible(supply chain)
central endorsement	-0.0421**	-0.0897***
Prefecture $\times$ Year FE	Yes	Yes
2024 industry size weight	Yes	Yes
# of obs.	16,224	18,251

Note:In this table we compare the 2024 industry output values targeted by industrial policies initiated or supported by either central or local governments. 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. 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. Panel C presents a robustness check in which the original specification is re-estimated with 2024 industry output used as a weighting factor. This regression is limited to tradable industries only.Robust standard errors are presented below the estimate.

Table A.7: Targeting Critical Industries

Panel A: Targeting Critical Industry		
	% in sanction list	% in sanction list
central initiation	0.0137	-0.0300
	(0.0692)	(0.0884)
central endorsement	0.139**	0.180**
	(0.0707)	(0.0861)
bottom up	0.00445	0.0460
	(0.0533)	(0.0709)
# of obs.	427	427
Panel B: Robustness Check		
	% compatible(investment)	% compatible(supply chain)
Central endorsement	-0.0154*	-0.0190**
	(0.00910)	(0.00946)
Non critical industry only	Yes	Yes
# of obs.	111,209	112,925

Note: Panel A reports the association between policy origin and whether targeted industries lie above the median/mean in future value distribution. Panel B provides robustness checks using binary indicators of revealed advantage. Robust standard errors are presented below the estimate.

Table A.8: Targeting Future Competitive Industries

	Future RCA	Average RCA
	(1)	(2)
Panel A: All Local Policies		
central initiation	-0.836**	-0.931**
	(0.398)	(0.449)
central endorsement	-0.918***	-1.160***
	(0.327)	(0.373)
bottom up	-0.674**	-0.867**
	(0.299)	(0.354)
Top local policy only	No	No
# of bservations	427	427
Panel B: Equal Number of Local and Central Policies		
central initiation	-0.836**	-0.931**
	(0.400)	(0.451)
central endorsement	-0.559*	-0.817**
	(0.316)	(0.363)
bottom up	1.169***	1.125***
	(0.310)	(0.343)
Top local policy only	Yes	Yes
# of observations	210	210

Note: Panel A includes all local policies. Panel B restricts to top local policies (matched in number with central policies).Dependent variables are RCA and future RCA, weighted by industry size.Robust standard errors are presented below the estimate.

Table A.9: Politician competition and policy compatibility

	Number of policies		
	(1)	(2)	(3)
Panel A: Extensive margin effects			
# competitors among geographic neighbors	0.0770		
	(0.433)		
# competitors among hierarchical neighbors		0.320	
		(0.518)	
# competitors among economic neighbors			0.0748
			(0.135)
# of obs.	4,500	3,648	4,242
Mean of DV	18.912	18.912	18.912
Prefecture FE	Yes	Yes	Yes
Year FE	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 prefecture level are reported below the estimates.

Table A.10: Policy portfolio and proximity

	Investment suitability		Supply-chain suitability	
	% Fit	Avg.	% Fit	Avg.
	(1)	(2)	(3)	(5)
Panel A: Central policies				
Competitors among econ-neighbors	-0.00190**	0.00375	0.000212	-0.00462
	(0.000751)	(0.0168)	(0.000999)	(0.00362)
Observations	3,987	3,987	3,985	3,985
R-squared	0.449	0.368	0.385	0.254
Panel B: Local policies				
Competitors among econ-neighbors	-0.00578***	-0.0914*	-0.00144**	-0.0288**
	(0.00152)	(0.0507)	(0.000628)	(0.0141)
Observations	3,101	3,101	3,064	3,064
R-squared	0.233	0.152	0.219	0.294
Prefecture FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
	Comparison between central & local policies			
t-value	-2.288	-1.781	-2.47	-1.666
p-value	0.024**	0.078*	0.015**	0.099*

Note: In this table we present reduced-form estimates of the efficiency lost induced by politician competition. In particular, we count the number of political competitors (those within ± 5 percentile of ex-ante promotion probability) among economic neighbors. For each prefecture, economic neighbors include those within ± 50 percentile of GDP per capita last year. Standard errors clustered at prefecture level are presented below the estimate

Table A.11: Competitors in Province Neighbors

	Investment suitability		Supply-chain suitability	
	% Fit	Avg.	% Fit	Avg.
	(1)	(2)	(3)	(4)
Panel A: Central policies				
Competitors among province-neighbors	-0.00453	-0.0735	0.00205	-0.0101
	(0.00286)	(0.0545)	(0.00341)	(0.0121)
Observations	3,987	3,987	3,985	3,985
R-squared	0.448	0.369	0.385	0.254
Panel B: Local policies				
Competitors among province-neighbors	-0.0112*	-0.0648	-0.00407**	-0.110*
	(0.00676)	(0.174)	(0.00207)	(0.0656)
Observations	3,101	3,101	3,064	3,064
R-squared	0.230	0.151	0.218	0.294
Prefecture FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
	Comparison between central & local policies			
t-value	-0.909	0.047	-2.08	-1.499
p-value	0.366	0.962	0.040**	0.137

Note: In this table we present reduced-form estimates of the efficiency lost induced by politician competition. In particular, we count the number of political competitors (those within $\pm$ 5 percentile of ex-ante promotion probability) among hierarchical neighbors. For each prefecture, Hierarchical neighbors include those within the same province, Standard errors clustered at prefecture level are presented below the estimate

Table A.12: Competitors in Distance Neighbors

	Investment suitability		supply chain suitability	
	% Fit	Avg.	% Fit	Avg.
	(1)	(2)	(3)	(4)
Panel A: Central policies				
Competitors among geographic neighbors	-0.00163	-0.0503	-0.00138	-0.0181**
	(0.00140)	(0.0328)	(0.00241)	(0.00881)
Observations	3,987	3,987	3,985	3,985
R-squared	0.448	0.369	0.385	0.254
Panel B: Local policies				
Competitors among geographic neighbors	-0.00389	-0.00620	-0.00286**	-0.0645**
	(0.00385)	(0.102)	(0.00137)	(0.0312)
Observations	3,101	3,101	3,064	3,064
R-squared	0.239	0.151	0.218	0.294
Prefecture FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Comparison between central & local policies				
t-value	-0.551	0.411	-1.85	-1.431
p-value	0.583	0.682	0.067*	0.155

Note: In this table we present reduced-form estimates of the efficiency lost induced by politician competition. In particular, we count the number of political competitors (those within $\pm$ 5 percentile of ex-ante promotion probability) among geographic neighbors. For each prefecture, geographic neighbors include the 30 closest cities. Standard errors clustered at prefecture level are presented below the estimate

Appendix B Quantifying efficiency loss from (de)centralization

For each top-down policy, compared to bottom-up policies, there is a 12.7% higher likelihood that it is misaligned with investment compatibility and a 5.42% higher likelihood of being misaligned with supply chain compatibility.

Moreover, for each top-down policy, if one additional competing city is present, the probability that it becomes incompatible with investment compatibility due to competition is 0.38% lower compared to a bottom-up policy. Similarly, the probability of incompatibility with supply chain compatibility is 0.12% lower. Given that a city faces, on average, 4.096 competitors, top-down policies can reduce the negative impact of competition and thus improve compatibility by approximately 1.5% (based on investment compatibility) or 0.5% (based on supply chain compatibility).

As a counterfactual, suppose that the proportion of top-down policies after 2013 had remained the same as in 2012 (that is, 48%), while the total number of policies each year remained constant. In this scenario, 3,384 policies that were implemented as a top-down would instead have been bottom-up.

Finally, since we estimate the impact of local compatibility on sales, exports, and patent in the previous section, we can therefore calculate the cost and benefit using the following formula. In this formula, ΔN refers to the number of top-down policies reduced in the counterfactual scenario. α captures the likelihood that top-down policies, due to two different channels, are more incompatible/compatible with local priorities, and β reflects the extent to which such incompatibility leads to changes in economic performance such as exports, sales, or patents.

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

Our calculations show that regardless of whether we measure compatibility using the supply chain or investment suitability, the cost induced by increasing top-down policies consistently exceeds the benefit by an order of magnitude.

Table A.13: investment compatibility

	N	α	β	Result
Panel A: Export				
Cost	3,384	0.127	82,518	35,463,595
Benefit	3,384	0.0158	82,518	4,437,830
Panel B: Sales				
Cost	3,384	0.127	771,040	331,368,318
Benefit	3,384	0.0158	771,040	41,466,648
Panel C: Patents				
Cost	3,384	0.127	1.7585	755
Benefit	3,384	0.0158	1.7585	94

Table A.14: supply chain compatibility

	N	α	β	Result
Panel A: Export				
Cost	3,384	0.0542	6,328	1,160,636
Benefit	3,384	0.0050	6,328	107,709
Panel B: Sales				
Cost	3,384	0.0542	236,204	43,322,837
Benefit	3,384	0.0050	236,204	4,020,461
Panel C: Patents				
Cost	3,384	0.0542	0.5	92
Benefit	3,384	0.0050	0.5	8.56