Learn, in Order to Practise:
The Effect of Political Rotation on Local Comparative Advantage in China [*]

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Abstract

Using detailed data on city leaders' resumes and biographical profiles, measures of industrial policy based on a textual analysis of annual government work reports, and measures of industry-specific export performance of Chinese prefectures for the period 1997-2013, we examine the impact of political rotation on interregional knowledge diffusion. Our study yields robust evidence indicating that the appointment of a new city party secretary (PS), who serves as the leader of the local Chinese Communist Party (CCP) organization, is associated with a significant increase in the revealed comparative advantage (RCA) in industries where the PS's previous work location exhibited better performance. These results are particularly pronounced in industries that heavily rely on contract enforcement and are led by officials with higher educational attainment. Furthermore, we provide evidence that the observed productivity response in these industries can be attributed to the implementation of industrial policies favoring them. In combination, these findings offer the first evidence of knowledge diffusion resulting from political rotation in China.

Keywords: knowledge diffusion, comparative advantage, exports, industrial policy, political rotation, China
JEL Code: D73, F10, O25, O33

1   Introduction

Knowledge has been widely recognized as a crucial element of economic development, making it a central aspect of modern growth theory (Jones, 2002, 2022). A substantial portion of knowledge and know-how is tacit in nature (Polanyi, 1958, 1966), and its acquisition and dissemination occur through practical experience and direct human interaction (Senker, 1995; Howells, 1996). While previous studies have primarily focused on migration flows as the primary means of knowledge transfer between source and destination regions, resulting in increased productivity (Peri, 2012; Bahar and Rapoport, 2018; Bahar et al., 2022), this paper examines a less-explored factor in knowledge diffusion: the rotation of political leaders, using evidence from China.

In China, which accounts for approximately one-third of global manufacturing (Bradsher, 2022), sub-national government officials, particularly leaders of the Chinese Communist Party (CCP) organization, hold significant political power (Joseph, 2019) and play crucial roles in formulating and implementing local development strategies (Li and Zhou, 2005; Yao and Zhang, 2015). Their capacity for critical thinking and decision-making, which influences policy development at the local level, is closely linked to their tacit knowledge, often acquired through previous experiences, including leadership positions.[1] Therefore, the dynamics of political power at the local level in China provide an ideal context for examining the impact of political turnover on knowledge diffusion across different regions of the country.

Our empirical exercise looks at how the appointment of a new city party secretary correlates with the city's future ability to export certain products that are specialized where the incoming political leader previously served. To this end, we construct a unique and comprehensive dataset that links industry-specific export performance of Chinese cities with detailed information on the resumes of prefectural leaders and their biographic records. To address the challenge of measuring the knowledge gained through an official's previous tenure, which is often intangible and difficult to quantify, we adopt a conventional approach in a novel setting (Bahar et al., 2014; Todo et al., 2016; Bahar and Rapoport, 2018; Bahar et al., 2022) and focus on the industry-specific productivity im-

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[1]For example, studies such as Horowitz and Stam (2014) demonstrate that political executives with prior military service and combat experience tend to avoid militarized disputes and wars while in office. Additionally, Dreher et al. (2009) provide evidence that government leaders with private enterprise experience are more likely to implement market-liberalizing reforms. Conversely, mayors with ideological experiences opposing capitalism (e.g., during the Cultural Revolution) are found to be less supportive of private investments (Wang et al., 2019). Furthermore, Guo et al. (2018) find that county-level Party secretaries in China, who have experienced famines, tend to levy lower agricultural taxes and provide more agricultural subsidies in their jurisdictions.

provements through examining changes in cities' export baskets. Our key assumption is that producers of a good in a city will exhibit a stronger revealed comparative advantage (RCA) in the global market once they have become more productive. In this paper, we specifically investigate the productivity gains resulting from industry-specific learning acquired by political leaders in their prior positions. By leveraging variations in RCA and local leader rotations across cities, we provide detailed empirical evidence on the role of political rotation as a catalyst for knowledge diffusion.

We present robust empirical evidence demonstrating that political rotations can account for variations in industry-specific productivity, as measured by the RCA of cities in exporting particular goods, for products intensively exported by cities where the incoming political leader previously served. In particular, we find that the coming-in of a party secretary from a significant city exporter of a given industry is, on average, associated with up to a 3.5% annual increase in the city's comparative advantage in the same industry during her/his tenure. By exploiting biographic information of political officials, our estimates imply that—evaluated at the sample average—the marginal effects for a young and high-educated leader are nearly two times larger than for an elderly and low-educated one, respectively. Furthermore, we observe an even more pronounced effect among political leaders who pursued majors in engineering, law, and political science during their college education. This effect is particularly significant in sectors that heavily rely on contract enforcement and in developing cities with limited access to input and output markets.

We demonstrate that the observed increase in industry-specific productivity following the arrival of a new leader is associated with the implementation of industrial policies in favor of these particular products. To measure industrial policy at the local level, we utilize a unique and extensive dataset comprising the *Annual Government Work Reports*, which encompass Chinese-language descriptions of new government policies and work plans for all Chinese cities between 1997 and 2013. Specifically, we examine the extent to which the descriptions of policy reflect an intention to promote specific sectors. Applying our classification algorithm to this rich data, we quantify the practice of industrial policy at the city, sector, and year levels. Based on our estimates, the likelihood of a city implementing policies favoring sectors that are specialized in cities where the political leaders had her/his previous term is higher than for other sectors by 2.2 percentage points.[2] To the best of our knowledge, our work represents the first comprehensive analysis of local industrial policies implemented in Chinese cities.

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[2]For manufacturing sectors defined by the 2-digit China Industry Classification (CIC) code, the average probability of being mentioned with positive–tone words is 37% across cities and years.

The empirical findings we present withstand various robustness and falsification tests. First, to mitigate the influence of demand-side factors on measuring industry-specific productivity, we follow Redding and Weinstein (2017) and Hausmann and Xu (2019), examining how political rotations impact the micro-mechanisms of RCA. The observed productivity effects are likely driven by supply-side factors such as cost reduction, quality improvement, and expansion and differentiation of goods varieties. Secondly, we employ advanced econometric techniques (Borusyak et al., 2021) to demonstrate the absence of differential pre-trends in various economic outcomes across Chinese cities prior to the appointment of new officials. This analysis addresses concerns about potential biases arising from pre-existing trends. Third, to address the issue of non-random assignment of political rotations across cities, as the appointment of local leaders may be influenced by unobserved factors, we categorize the political officials based on their pre-determined characteristics and control for the detailed group fixed effects in our analysis. Furthermore, our benchmark estimates remain robust when employing alternative criteria and functional forms to measure RCA, using different margins of exports as outcome variables, and conducting a placebo experiment in which we randomly assign party secretaries to destination cities. The sizes and patterns of the estimates are remarkably similar, reinforcing our confidence in the idea that knowledge diffusion triggered by political rotations plays a significant role in shaping the local comparative advantage for Chinese cities.

Our paper contributes to several strands of literature. First and foremost, the paper aligns with the emerging body of research on the role of worker mobility in facilitating knowledge diffusion, which is crucial for comparative advantage.[3] As the natural carriers of tacit knowledge needed to induce industry-specific productivity shifts, immigrants (Kerr, 2018; Bahar and Rapoport, 2018; Casabianca et al., 2022), return migrants (Bahar et al., 2022), migrant inventors (Miguelez and Temgoua, 2020; Bahar et al., 2020) and farmers (Bazzi et al., 2016; Pellegrina and Sotelo, 2021) have been shown to play a significant role in promoting interregional knowledge diffusion.[4] We contribute to this literature by identifying political rotation as a novel mechanism through which governance experience and knowledge accumulated during a public official's prior term can be transferred or

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[3]Other than human minds, international trade (Cai et al., 2022; Akcigit and Melitz, 2022) and FDI (Lind and Ramondo, 2018; Bircan et al., 2021; Abebe et al., 2022) are also important carriers of knowledge that boost innovation and technology development.

[4]At the disaggregate level, Hausmann and Neffke (2019) provide plant-level evidence from Germany that shows labor mobility facilitates technology diffusion among plants. Additionally, personal mobility not only promotes the diffusion of knowledge but also affects other economic activities between countries, such as FDI (Mayda et al., 2022) and the demand for products from the home country (Gould, 1994; Head and Ries, 1998; Dunlevy and Hutchinson, 1999; Bailey et al., 2021).

diffused to their new assignment. To the best of our knowledge, this paper represents one of the pioneering studies investigating how political turnover influences the formation of local comparative advantage and regional manufacturing structure.

The paper closely connects to the economic impact of sub-national political turnover, which is a crucial and dynamic factor in promoting regional economic development. Previous research has primarily focused on examining the effects of political turnover on firm productivity (Earle and Gehlbach, 2015; Kong et al., 2018), investments (Piotroski and Zhang, 2014; Shi et al., 2021; Dong et al., 2022), provision of public jobs and services (Brassiolo et al., 2020; Fagernäs and Pelkonen, 2020; Akhtari et al., 2022), environmental outcomes (Deng et al., 2019; Kahsay and Medhin, 2020), and GDP growth (Li and Zhou, 2005). Our findings contribute to this literature by demonstrating that political turnover can influence the composition of a city's exports, which we interpret as evidence of knowledge diffusion.

Notably, political turnover has been identified as a significant driver of China's remarkable economic growth (Xu, 2011). This can be attributed to at least two main mechanisms. First, the seminal work of Li and Zhou (2005) and subsequent studies (e.g., Yao and Zhang, 2015; Jia et al., 2015; Xiong, 2018; Li et al., 2019) demonstrate that the promotion of local officials in China is often based on their ability to stimulate economic growth. As a result, political turnover has a positive impact on overall economic performance.[5] The second mechanism involves the influence of social ties with politicians and government officials on the allocation of economic resources and economic development (Chen and Kung, 2016; Fang et al., 2018; Chen and Kung, 2019; Cong et al., 2019; Bai et al., 2020; Jiang and Mei, 2020; Jiang and Zhang, 2020; Shi et al., 2021; Guo et al., 2021; Li et al., 2022; Fang et al., 2022; Chen et al., 2022). In comparison to this body of research, our paper stands out by highlighting the rotation of political leaders as a key mechanism linking knowledge diffusion and the formation of local comparative advantage across regions.

To understand the mechanism at play, we employ a textual analysis approach following Caldara et al. (2020) and Benguria et al. (2022) to measure industrial policy based on the content of the annual government work reports from Chinese cities. We examine the associations between industrial policy, industry-specific productivity increases, and political trajectory of CCP secretaries in the cities.[6] This paper thus contributes to the

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[5]Government officials at the same level (e.g., city leaders within a province) compete with each other on the basis of relative GDP growth, and the winners are rewarded with promotions up the administrative hierarchy.

[6]Caldara et al. (2020); Benguria et al. (2022) use textual analysis to construct firm-level trade policy uncertainty based on earnings calls reports, and analyze the effect of trade policy uncertainty on investment by listed firms in the US and China, respectively.

emerging literature on the measurement of industrial policy.[7] In a related study, Juhász et al. (2022) employ an automated classification algorithm to construct industry policy measures using government policy announcements from the Global Trade Alert database and examine global patterns.[8] In our analysis, we delve deeper into the extent to which the objectives of industrial policy can be attributed to sector-specific knowledge carried by local leaders from their previous work experiences.

Our paper is also closely related to studies on the determinants of China's export success in the past decade. Previous studies have highlighted the role of fast productivity growth, driven by the decline of trade barriers and China's accession to the World Trade Organization (WTO), in contributing to China's export expansion (Yu, 2015; Brandt et al., 2017). In addition, Tombe and Zhu (2019); Fan (2019); Ma and Tang (2020); Zi (2020); Liu and Ma (2022) examine the role of migration and changes in tariff barriers in driving export growth in China.[9] Wang (2013) studies the effects of Special Economic Zones on exports and other economic performance in China. Complementing these studies, our paper provides a new perspective on knowledge transmission in understanding the formation of China's export comparative advantage. We examine whether local leaders can contribute to the development of comparative advantage in specific industries in the cities where they currently serve, drawing on the industry-specific knowledge they acquired from their previous work experiences. By focusing on the role of political leaders and knowledge diffusion, we add to the understanding of the factors shaping China's export patterns and its economic development.

The rest of the paper is organized as follows. Section 2 introduces the institutional background relevant to this study. Section 3 presents a conceptual framework to illustrate why political rotation can influence local comparative advantage. Section 4 describes data and the empirical strategy. Section 5 presents the main empirical findings. Section 6 examines mechanisms through which political rotations affect local comparative advantage. Section 7 concludes the paper.

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[7]As discussed in Juhász et al. (2022), the lack of basic measures and facts about industrial policy is remarkable, despite its fundamental importance. Previous research on industrial policy has focused on specific case studies (Kalouptsidi, 2018; Barwick et al., 2019; Choi and Levchenko, 2021; Lane, 2022) and quantitative exercises testing theoretical motivations for industrial policy (e.g., Liu, 2019; Bartelme et al., 2019), while empirical studies on industrial policy have been limited.

[8]They find that an important feature of industrial policy is technocratic, and industrial policy is aimed at sectors usually with higher RCA within a country.

[9]Brandt and Lim (2020) provide a decomposition of China's manufacturing export growth into changes in productivity, demand, and labor and firm-entry costs.

2   Institutional Background

Levels of Administration

China has a one-party political system, and the highest decision-making authority is the Politburo Standing Committee (PSC) of the Communist Party. Under the central government, China has four levels of formal administration. The first level is made up of 34 provincial-level governments.[10] The second tier of administration includes 333 prefectural-level administrative units that include 293 prefecture-level cities, 30 autonomous prefectures, 7 prefectures and 3 leagues after 2018. The third level of administration includes nearly 3,000 counties and county-level cities. The lowest tier of official administration consists of about 40,000 townships and towns. All levels of administration have political structures that mirror the central government with the parallel party and government organizations. Each Chinese prefecture-level city has two political leaders: party secretary and mayor, where the party secretary is the head of the prefectural Communist Party Committee, and the mayor is the head of the prefectural government. Party secretaries are ranked higher than prefectural mayors, even though mayors have executive power (Yao and Zhang, 2015).[11]

We focus on the rotation of the prefectural-level party secretary in the baseline analysis and take prefectural mayors into account in robustness checks. Prefectural party secretaries have the final decision over many most important economic and political policies within their prefectures. For instance, the prefectural party secretaries play a vital role in winning industrial parks that create manufacturing jobs and attract foreign direct investment locally (Kahn et al., 2021); they also decide the spatial dimension of urbanization in their jurisdictions (Zhang et al., 2022) and the issuance of local government debt (Fan et al., 2022). Therefore, the knowledge and preferences of prefectural party secretaries often have crucial implications for the patterns of economic activities both within and between cities (Shi et al., 2021; Nian and Wang, 2019; Zu, 2022).

Routine Rotation of Local Officials

To prevent the possibility that local officials are stationed in one place and form close ties with the local elites so that they become unresponsive to central demands, the central leaders request local officials to be regularly transferred to equivalent positions in unfa-

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[10]This includes 4 direct-controlled municipalities, 5 autonomous regions, and 2 special administrative regions of Hong Kong and Macau, all of which hold provincial status.

[11]For a detailed introduction of China's political system, see Lawrence and Martin (2013).

miliar places (Zhang et al., 2022).[12] The rotation and appointment of party secretaries of prefecture-level cities are recommended by provincial leaders and approved by the Organization Department of the Central Committee of the Communist Party of China (Jiang and Zhang, 2020), and decisions are usually notified and communicated several months before the rotation begins. Rotations usually occur within the province. Figure B1 displays the share of new party secretaries whose last positions are in other provinces. Other than the phenomenal increase in 1999, the beginning of the release of the "Provisional Regulations on the Exchange of Party and Government Leading Cadres," across-province rotation of officials is rare, which often requires arrangements by the Organization Department of the Central Committee of the Communist Party of China. On average, they only accounted for 1.8% of newly appointed prefectural party secretaries and 0.4% of all prefectural party secretaries.

We claim that the time and the choice of destination for any given rotation at the city level are determined in a quasi-random fashion. First, as discussed in Jiang and Zhang (2020), the goals that rotation seeks to attain are mostly political rather than economic. Second, the destination of the rotation at the city level is heavily influenced by the availability of appropriate positions in practice, which further depends on various complicated factors beyond an individual's control, such as retirement, term limits, disciplinary investigations, or simply movements in other positions. The quasi-random nature of the rotation process can be illustrated through the example of Shaomin Lan, the former party secretary in Suqian City of Jiangsu Province before being appointed to Taizhou City of Jiangsu in 2014. On June 2014, just before his new term in Taizhou, thinking he could still work in Suqian for some time, Lan stated on his social media that "*the most romantic thing in the world is that we grow old together in Suqian*." However, the provincial party committee announced his rotation less than a month later, and the decision was out of sudden and unexpected by Lan himself.[13]

3 Why Political Rotation Affects Comparative Advantage

In this section, we formulate the possible mechanism underlying the relationship between the political rotation of local leaders and industry-specific exporting performance. We

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[12]In addition to preventing corruption and improving governance, the rotation system also serves as a means of political control, as it allows the party leadership to monitor and manage officials more closely. The rotation of officials can also help to promote loyalty to the party and ensure that officials remain committed to its goals and policies (Zeng, 2016).

[13]For detailed information on the anecdotal evidence, see http://m.thepaper.cn/kuaibao_detail.jsp?contid=1258551&from=kuaibao

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use this framework to inform our empirical investigation that follows in the next few sections. The model is purposefully simple and a close variant to those used elsewhere in the trade and knowledge diffusion literature. In particular, the framework we present below is effectively a marriage of the trade model in (Eaton and Kortum, 2002; Caliendo and Parro, 2015) and Bottazzi and Peri (2003) where local production efficiency is affected by knowledge diffused from other regions.

3.1 Model Setup

While trading some degree of generality for analytical results, we study the economy consisting of two regions that are indexed by i or $n = 1, 2$, each of which has J industries that are indexed by k or $j = 1, ..., J$. Labor is the only input in production and is immobile across regions. Final goods are freely traded across regions in a competitive market. A critical feature of the model is that it allows embodied knowledge contained in the industry j of a region to have different impacts on the production efficiency of the same industry in the other region, depending on the distance between the two locations. The rotation of a political leader increases industry-specific export performance by shortening the distance that reduces the knowledge diffusion between locations, for the industry intensively exported by the place where the political leader had her/his previous term.

Households   In each region, there is a measure of one representative household that maximizes utility by consuming final goods C_n^j. The utility function is

$$u\left(C_n\right) = \prod_{j=1}^{J} \left(C_n^j\right)^{\alpha_n^j}, \text{where} \sum_{j=1}^{J} \alpha_n^j = 1.$$

For simplicity, we assume households have symmetric demand across goods in different industries, i.e., $\alpha_n^j = \frac{1}{J}$, $\forall n, j$. Household income I_n is derived from the wage, w_n, i.e., $I_n = w_n$.

Intermediate goods   In each industry j, a continuum of intermediate goods $\omega^j \in [0, 1]$ is produced. The production of each ω^j only uses labor with a variety-specific productivity, $z_n^j\left(\omega^j\right)$. The production technology of a good ω^j in region n is

$$q_n^j\left(\omega^j\right) = z_n^j\left(\omega^j\right) l_n^j\left(\omega^j\right),$$

where $l_n^j\left(\omega^j\right)$ denotes the labor used for the production of ω^j in region n. Due to the constant returns to scale in production and the perfect competitiveness of markets, price

equals the marginal cost $w_n / z_n^j(\omega^j)$.

Final goods   Produces of final goods in industry j and region n supply Q_n^j at the minimum cost by purchasing intermediate goods ω^j from the lowest cost supplier across regions. The production technology of Q_n^j is given by

$$Q_n^j = \left[\int r_n^j(\omega^j)^{1 - \frac{1}{\sigma^j}} \, d\omega^j \right]^{\frac{\sigma^j}{\sigma^j - 1}},$$

where $\sigma^j > 0$ is the elasticity of substitution across intermediate goods within industry j, and $r_n^j(\omega^j)$ is the demand for intermediate goods ω^j from the lowest cost supplier. The demand for ω^j is given by

$$r_n^j(\omega^j) = \left(\frac{p_n^j(\omega^j)}{P_n^j} \right)^{-\sigma^j} Q_n^j,$$

where P_n^j is the unit price of the final good, $P_n^j = \left[\int p_n^j(\omega^j)^{1-\sigma^j} \, d\omega^j \right]^{\frac{1}{1-\sigma^j}}$, and $p_n^j(\omega^j)$ is the lowest price of ω^j across regions. Since we assume away trade costs, the price of intermediate good ω^j in region n is given by

$$p_n^j(\omega^j) = \min \left\{ \frac{w_1}{z_1^j(\omega^j)}, \frac{w_2}{z_2^j(\omega^j)} \right\}.$$

We follow Eaton and Kortum (2002) and Caliendo and Parro (2015) to assume that the efficiency of producing a good ω^j in the region n is the realization of a Fréchet distribution with a location parameter $\lambda_n^j \geq 0$ and a shape parameter θ^j. A higher λ_n^j denotes higher average productivity in an industry in a region. The productivity draws are independent and identically distributed across goods, industries, and regions. We also require the parameters to satisfy $1 + \theta^j > \sigma^j$. Following Caliendo and Parro (2015), the price of the final good in industry j and region n is given by

$$P_n^j = C^j \left[\lambda_1^j w_1^{-\theta^j} + \lambda_2^j w_2^{-\theta^j} \right]^{-\frac{1}{\theta^j}},$$

where C^j is a constant.[14] Therefore, the overall price index of region n is derived as $P_n = \prod_{j=1}^J (P_n^j)^{\frac{1}{J}}$.

Expenditure shares   The total expenditure on goods of industry j in region n is $X_n^j = P_n^j Q_n^j$. Denote the expenditure on goods of industry j in the region n that are supplied

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[14]$C^j \equiv \Gamma\left(\frac{\theta^j + 1 - \sigma^j}{\theta^j} \right)^{\frac{1}{1-\sigma^j}}$, where $\Gamma(t) \equiv \int_0^\infty x^{t-1} e^{-x} dx$ is the Gamma function.

by region i by X_{ni}^j. We derive region n's share of expenditure on goods from i as $\pi_{ni}^j = X_{ni}^j/X_n^j$. According to Fréchet distribution, π_{ni}^j can be expressed as

$$\pi_{ni}^j = \frac{\lambda_i^j w_i^{-\theta^j}}{\lambda_i^j w_i^{-\theta^j} + \lambda_n^j w_n^{-\theta^j}}.$$

Due to symmetry at the level of micro regions, $\pi_{11}^j = \pi_{21}^j (\equiv \pi_1^j)$, and $\pi_{12}^j = \pi_{22}^j (\equiv \pi_2^j)$ for each j, where $\pi_1^j + \pi_2^j = 1$.

Trade balance   The trade balance condition can be expressed as

$$\sum_j X_1^j \pi_{12}^j = \sum_j X_2^j \pi_{21}^j.$$

Since $X_n^j = \frac{1}{J} I_n$ and $I_n = w_n$, expenditure share can be alternatively derived as the following equations:

$$\pi_1^j = \frac{\lambda_1^j}{\lambda_1^j + \lambda_2^j \left(\frac{\sum_j \pi_2^j}{\sum_j \pi_1^j}\right)^{-\theta^j}}, \quad \text{and} \quad \pi_2^j = 1 - \pi_1^j. \tag{1}$$

Above system defines a unique solution of π_1^j and π_2^j for each j, which further pins down the wage ratio $w_2/w_1 = \sum_j \pi_2^j / \sum_j \pi_1^j$. The Balassa revealed comparative advantage (RCA) of industry j in the region n can be derived as

$$RCA_n^j = \frac{1}{1 + \frac{\sum_{j'} \pi_n^{j'}}{\pi_n^j} \cdot \frac{1 - \pi_n^j}{J - \sum_{j'} \pi_n^{j'}}}. \tag{2}$$

3.2   Political Rotation and RCA across Regions

The simple model maintains many of the benefits of these earlier works. An important distinction in our case is that we allow local production efficiency to be affected by knowledge diffused from other regions. In particular, industry-specific productivity is affected by the productivity of the same industry in other regions in spatial proximity. This definition is easily derived as the reduced form of a model such as Romer (1990) and Jones (1995), whose empirical relevance has already been widely documented (e.g., Bottazzi and Peri (2003)).

In particular, we assume that the industry technology parameter of industry j in the

region n (λ_n^j) is a function of knowledge available to the region:

$$\lambda_n^j = \sum_m e_{nm}^j A_m^j,$$

where A_m^j denotes the industry-specific knowledge generated in the region m. We note that when we discuss knowledge throughout the paper, it is not restricted to productive knowledge, i.e., the knowledge that helps improve the production efficiency directly. It also involves the knowledge of governance for specific industries, as well as the experience in developing certain industries. For example, a government leader can transfer knowledge about how to provide supportive conditions (e.g., infrastructure) and address potential coordination failures for some industries, which promotes their productivity through reduced coordination and transaction costs. The marginal effect of knowledge on technology parameters is measured by $e_{nm}^j \leq 1$ with $e_{nn}^j = 1$, which is inversely related to knowledge transmission barriers between m and n. Such a specification allows embodied knowledge contained in industry j to have a different impact on the production efficiency of the same industry in other regions, depending on various barriers between region m and region n. The rotation of political leaders from m to n is modeled as a decrease (increase) in knowledge transmission barriers (efficiency) between m and n, i.e., $\mathrm{d}e_{nm}^{k(m)} > 0$ for industry $k(m)$, where $k(m)$ is an index function denoting the industry in which location m has a revealed comparative advantage.

Proposition 1 analyzes how political rotation affects the industry-specific RCA in the two-region case. Specifically, we let the rotation from region m to n lead to an increase in $e_{nm}^{k(m)}$, which induces a higher level of $\lambda_n^{k(m)}$, holding other $\lambda_n^{k(m)}$ parameters unchanged.

Proposition 1 *An increase in knowledge transmission efficiency $e_{nm}^{k(m)}$, induced by the rotation of a political leader from region m to n, leads to higher revealed comparative advantage for the industry $k(m)$ where her/his previous position location has better performance, i.e., $k(m) \in \{k | RCA_m^k \geq RCA_m^j, \forall j = 1, ..., J\}$; that is,*

$$\frac{\partial RCA_n^{k(m)}}{\partial e_{nm}^{k(m)}} > 0, \quad \forall m \neq n \in \{1, 2\} \tag{3}$$

The proof of Proposition 1 is provided in Appendix A.1, which makes use of the positive correlation between RCA_n^j and π_n^j in equation (2). More effective knowledge diffusion across regions is welfare-enhancing, which we summarize in Proposition 2.

Proposition 2 *A higher knowledge transmission efficiency caused by political rotation from m to n increases the welfare of the destination location n.*

The proof of Proposition 2 is in Appendix A.2, where the welfare of location n is expressed as $w_n/P_n = \prod_{j=1}^{J} (\lambda_n^j/\pi_n^j)^{1/2\theta^j}$. Although not the focus of the current work, it should be noted that political rotation can lead to non-trivial welfare gains, as depicted by this simple model.

4   Data and Empirical Strategy

Having explained how political rotation-induced knowledge diffusion shaped the comparative advantage across regions in a simple conceptual model, we describe our empirical strategy and data, with additional data details in Appendix G. We investigate the relationship between the political rotation and the dynamics of the export baskets of new officials' receiving cities. In particular, we study whether the coming-in of a new city party secretary can induce product-specific productivity shifts in industries where her/his previous position location has a better performance. In the analysis, we focus on prefecture cities as the geographic administrative unit that reflects *hukou* status, thus limiting the endogenous issue of internal migration, and as prefectures can be precisely identified in the available location information in China Customs Data and in the resumes of political officials.[15]

4.1   Measuring Party Secretary Transfers

We obtain information on the career records of all CCP secretaries at the prefecture-level from the Officials Dataset maintained by the China Center for Economic Research at Peking University. The data contain detailed biographical profiles of every political official from 1994 to 2017, which include the official's gender, educational background, major field of study, previous administrative ranks, job titles, jurisdictions served, and records of promotion and prosecution. With their career mobility records, we are able to capture bureaucratic transfers among party secretaries across cities. In our main analysis, we focus on prefectural party secretaries since they are the highest leaders at the city level and have the largest impact on local economies and communities. In the robustness, we expand the scope by taking the rotation of city mayors into consideration.

We define a dummy variable (i.e., $Transfer_{c' \to c,t}$) to indicate the position status of a party secretary in the city c and year t, who transferred from c'. Specifically, the indicator

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[15]There are three layers of administrative units: the first include provinces, autonomous regions, and centrally controlled municipalities. Prefecture-level divisions are the second level, mostly including prefecture-level cities. Large prefectures are subdivided into (autonomous) counties and county-level cities. Last, townships or towns are the third level. Our unit of analysis is the prefecture city.

variable takes one if year t is during the tenure of the party secretary in c, *and* her/his last position is in c' ($c' \neq c$).[16] For further clarification, we consider the following hypothetical example. Suppose a party secretary served city A from 2001 to 2003 and started a new term in city B from 2004 to 2006. The dummy variable $Transfer_{A \to B,t}$ takes value one for years $t = 2004, 2005, 2006$, and zero otherwise. We restrict attention to political rotations of prefectural party secretaries.

Figure 1 describes the pattern of prefectural PS transfers across time and space in China. Each year, our interested party secretaries—who are in their first year in office transferred from other prefectures—take about 10 percent out of all prefectural party secretaries (solid lines in panel (a)). Among all first-year party secretaries, about 30 percent worked in other prefectural governments (dashed lines in panel (a)). The two proportions keep stable during our sample period (1997-2013). Panel (b) plots the frequency of party secretary transfers by destination prefecture, where we find no systemic spatial patterns, indicating that the party secretary transfers are less likely to correlate with socioeconomic characteristics at the prefecture level.

4.2   Measuring Industry-specific Export Performance

To measure the industry-specific export performance of Chinese cities, we follow the conventional wisdom (Bahar et al., 2014; Todo et al., 2016; Bahar and Rapoport, 2018; Bahar et al., 2022) and use the concept of revealed comparative advantage of Balassa (1965), which will be used to construct export-related variables both in the dependent and independent variables of the specification.

$$RCA_{cjt} \equiv \frac{Export_{cjt}/\sum_j Export_{cjt}}{\sum_c Export_{cjt}/\sum_c \sum_j Export_{cjt}}, \tag{4}$$

where c, j, and t denote cities, industries (4-digit HS codes), and years, respectively.[17] $Export_{cjt}$ is the total exports of industry j from prefecture c to the rest of the world in year t, which we aggregated from the China Customs Database. Prefecture c is considered to have a revealed comparative advantage in the industry j and year t if $RCA_{cjt} > 1$. The dynamic pattern of RCA across space and industries are summarized by the transition matrix in Appendix Table C1. On average, through the sample period between 1997

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[16]In practice, an official's position in a given year is identified as the position where she/he took the longest during the year. In the case that one started the new term after July 1st, we consider the beginning of her/his new term as the next year.

[17]Throughout the paper, we refer to an HS 2-digit code or Chinese Industry Classification (CIC) 2-digit code as a "sector" (depending on the empirical application of interest), an HS 4-digit code as an "industry," and an HS 6-digit code as a "product," respectively.

Figure 1: Summary: Political Rotation of City Party Secretaries

(a) Share of New Party Secretaries: Time Trend
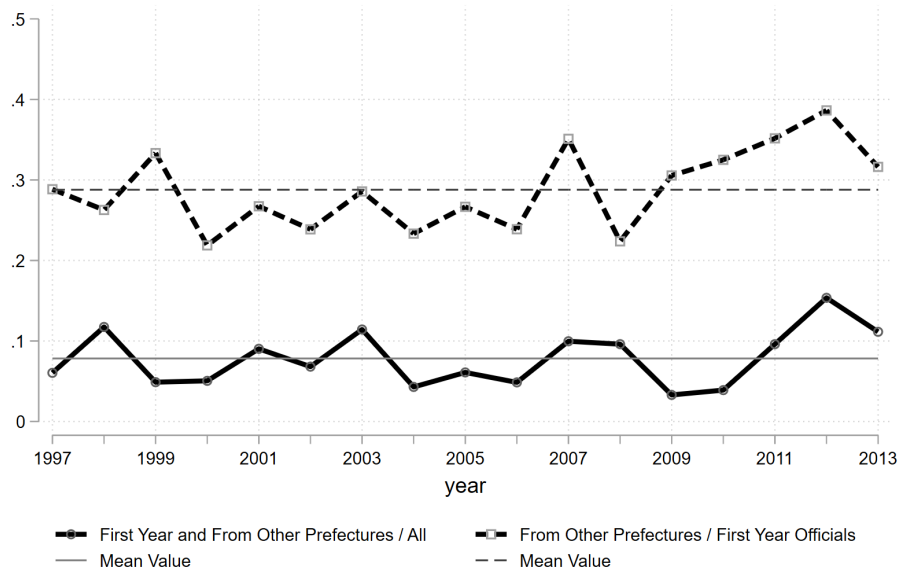
(b) Frequency of Party Secretary Transfers Across Cities
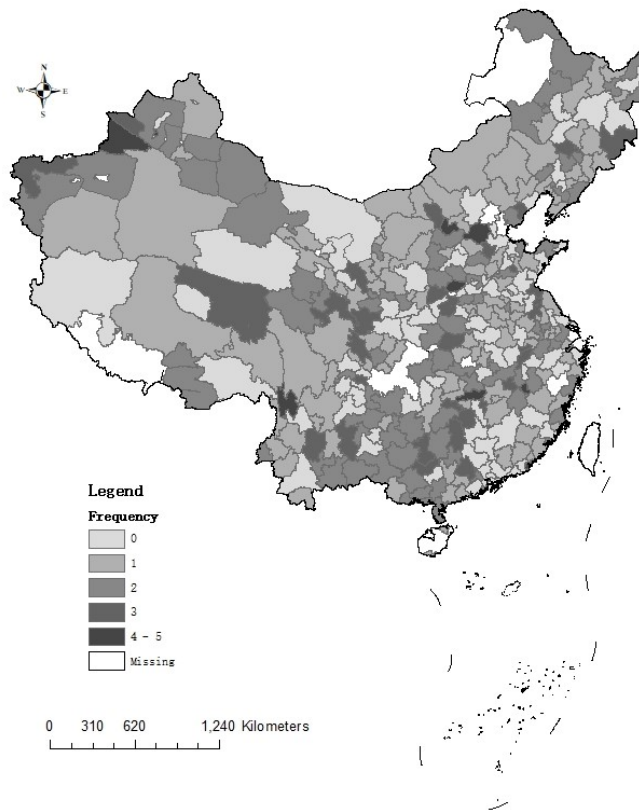
Note: In panel (a), the solid line represents the share of the new city party secretaries (who are in the first year of the prefectural party secretary position) whose last positions are in other prefectures in all prefectural party secretaries across city-year observations. The dash line represents the share of the new city party secretaries coming from other prefectures in all the new city party secretaries. Panel (b) plots for each prefecture the number of party secretaries whose last positions are in other prefectures during 1997-2013. Darker colors stand for higher frequency.

and 2013, over 75% observations have zero export, and only less than 10% observations have a comparative advantage as represented by $RCA_{cjt} > 1$. In terms of dynamics, we observe an active evolution of RCA over time, despite RCA levels being mainly time-persistent. For instance, nearly 10% city-industry pairs with zero exports in the previous year could develop some comparative advantage next year (i.e., $RCA_{cjt} > 0$); the probability of achieving RCA (i.e., $RCA_{cjt} > 1$) for industries with modest RCA levels in the local market (i.e., $RCA_{cj,t-1} \in (0,1]$) reaches to 15%.

To remove demand-side influences in measuring industry-specific productivity, we follow Redding and Weinstein (2017); Hausmann and Xu (2019) and investigate how political rotations affect the micro-mechanisms of RCA, for which we decompose RCA into the contributions of different margins displayed in (5):[18]

$$
\ln RCA_{cjt} \approx \overbrace{\underbrace{\ln\left(RCA_{cjt}^P\right)}_{\text{Average prices}} + \underbrace{\ln\left(RCA_{cjt}^{\varphi^S}\right)}_{\text{Average quality}} + \underbrace{\ln\left(RCA_{cjt}^S\right)}_{\text{Variety differentiation}} + \underbrace{\ln\left(RCA_{cjt}^N\right)}_{\text{Variety}}}^{\text{Supply-side factors}}
$$

$$
+ \underbrace{\overbrace{\ln\left(RCA_{cjt}^{\varphi^D}\right)}^{\text{Average Taste}} + \overbrace{\ln\left[RCA_{cjt}\left(\text{S, w, L}\right)\right]}^{\text{Average Market Size}}}_{\text{Demand-side factors}} + \underbrace{\ln\left[\frac{N_{cjt}^M/N_{jt}^{EM}}{N_{ct}^{MJ}/N_t^{EMJ}}\right]}_{\text{Ability of market entrance}}, \tag{5}
$$

where how good prefecture c is in exporting in industry j is represented by RCA_{cjt}, which depends on her competitiveness in average prices (RCA_{cjt}^P), product quality ($RCA_{cjt}^{\varphi^S}$), number of varieties (RCA_{cjt}^N), and product differentiation (RCA_{cjt}^S). Besides supply-side factors, factors related to the demand may also influence industry-specific productivity differences across cities and industries, such as taste differences and heterogeneity in the market size of destinations. The last term captures market entrance capability. The decomposition allows one to remove demand-side influences in measuring RCA_{cjt}.

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[18]The details of this method are presented in Appendix D.

4.3 Empirical Specification

We examine the relationship between political rotation and industry-specific productivity using the following general specification:

$$Y_{cjt} = \beta \sum_{c'} Transfer_{c' \to c,t} \times 1\{RCA_{c'jT} > 1\} + \mu_{ct} + \lambda_{jt} + \delta_{cj} + \eta_{rst} + \delta_{cj} \times t + \varepsilon_{cjt}, \quad (6)$$

where c, r, j, and t denote prefectures, provinces, industries, and years, respectively; T is the year of the PS transfer; s denotes sectors at the aggregate level (i.e., HS 2-digit). Our primary outcome variable is the logarithmic Balassa revealed comparative advantage of industry j in the city c and year t. The explanatory variable of interest is $\sum_{c'} Transfer_{c' \to c,t} \times 1\{RCA_{c'jT} > 1\}$ that captures an overall knowledge diffusion induced by political rotation of party secretaries, where $Transfer_{c' \to c,t}$ is an indicator for inter-prefectural party secretary transfers from c' to c defined in 4.1, and $1\{RCA_{c'jT} > 1\}$ is a dummy indicating that prefecture c' has a reveal comparative advantage in the industry j in year t. Hereafter, we refer to the explanatory variable as "PS transfer shock". We control for city-year (μ_{ct}), industry-year (λ_{jt}), city-industry (δ_{cj}) and province-sector-year (η_{rst}) fixed effects. We also control for the potential existence of prefecture-industry-specific time trends by adding the interaction between city-industry dummies and the time variable ($\delta_{cj} \times t$). We cluster standard errors at the prefecture level. The coefficient β in equation (6) captures the impact of a PS transfer shock on the industry-specific productivity in the destination city. The consistency of the estimate of β relies on the assumption that there is no selection of party secretaries into destinations conditional on these detailed fixed effects and the linear prefecture-industry-level trends. We provide supportive evidence for the validity of the assumption in our empirical analysis in Section 5.2 by showing no significant correlations between the PS transfer shocks and prefecture-industry-level attributes previous to the transfers.

Appendix Table C2 displays summary statistics for the analysis sample of 326 Chinese prefecture cities and 1,059 industries, for which we measure their exposure to the "PS transfer shock" and the Balassa RCA from 1997 to 2013. We observe that the prefecture-industry level exposure to the "PS transfer shock" increases over time. Despite a small drop in the year of the Great Recession outbreak in 2008, the average Balassa RCA across prefectures and industries also exhibits an overall rising pattern during the sample period.

5 Results

This section presents our main empirical findings on the impact of the political rotation of party secretaries on the change of RCA across industries and cities. We begin by presenting the baseline specification, followed by heterogeneity analyses. Then we discuss the robustness of our findings and present validity checks for identification strategy.

5.1 Baseline Results

Table 1 reports the estimated effect of the PS transfer shock on overall RCA and various micro-mechanisms. As there are zeros in the RCA measure, we transform the outcome variable using the inverse hyperbolic sine following (Bahar and Rapoport, 2018). The linear monotonic transformation behaves similarly to a log transformation, except for values around zero. The interpretation of the estimated coefficient obtained using the inverse hyperbolic sine is similar to that obtained from a log-transformed variable.[19]

Column (1) estimates the impact of political rotation on the annual change in the RCA of a industry in the city's export basket. Notably, the dependent variables are computed using exports of industry j from city c to the rest of the world. The result suggests that the coming-in of a new city party secretary from cities that are significant exporters of the industry j (with a higher $RCA_{c'jt}$) is associated with an annual 3.5 percentage point increase in the RCA of the same industry in the city, which corresponds to a 15.8% increase relative to the sample mean of RCA across industries and cities during our sample period. In columns (2) to (4), we study the impact of political rotation on the micro mechanism of RCA. We find that the positive impact of a PS transfer shock on city-industry-specific export performance mainly arises due to the improved ability to overcome fixed costs of market entry and various supply-side factors, specifically as displayed in columns (5) to (8), where we further split the change in supply-side RCA into various channels: a fall in production costs, a rise in goods quality, and an expansion and differentiation in goods varieties.

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[19]The inverse hyperbolic sine is defined as $\sinh^{-1}(RCA) = \ln(RCA + \sqrt{1 + RCA^2})$. For values greater than zero, it equals $\sinh^{-1}(RCA) = \ln(2) + \ln(RCA)$. For more detailed information on the inverse hyperbolic transformation, see MacKinnon and Magee (1990). Our results are robust to using alternative types of log transformation.

Table 1: Political Rotation and the Change in RCA Across Regions and Sectors

Dep var:	(1) $\ln RCA_{cjt}$	Micro Mechanism		
		(2) Supply-side	(3) Demand-side	(4) Ability of market entrance
PS Transfer Shock	0.035***	0.013***	0.005	0.025***
	(0.005)	(0.003)	(0.008)	(0.005)
Outcome mean	0.221	0.236	0.314	0.301
Observations	5,326,714	5,319,764	5,044,969	5,326,714
Adjusted R-squared	0.402	0.425	0.311	0.430

Dep var:	Supply-side factors			
	(5) Variety	(6) Differentiation	(7) Marginal costs	(8) Quality
PS Transfer Shock	0.010***	0.010***	0.009***	0.012***
	(0.002)	(0.002)	(0.002)	(0.003)
Outcome mean	0.247	0.247	0.256	0.262
Observations	5,326,714	5,326,714	5,320,599	5,321,175
Adjusted R-squared	0.612	0.609	0.582	0.453

Note: The dependent variables are prefecture-industry-level revealed comparative advantage (RCA) and its different margins using the decomposition method as described in Appendix D. All dependent variables are in the function of $\sinh^{-1}(Y) = \ln(Y + \sqrt{1 + Y^2})$, where Y represents the outcomes. In all regressions, we control for prefecture-industry, prefecture-year, industry-year, and province-sector-year fixed effects, as well as prefecture-industry linear trends. Here a sector (an industry) refers to a 2-digit (4-digit) HS code. Standard errors are clustered at the prefecture-sector level. ***, **, * represent significance levels of 1%, 5%, and 10%, respectively.

5.2 Robustness Checks

We now perform a battery of robustness checks to provide support for our identification assumption and show the robustness of our baseline results.

5.2.1 Placebo and Pre-trend Tests

Our baseline identification, once controlling for the detailed fixed effects and time trends in (6), assumes no selection of party secretaries into destination cities based on any time-variant industrial attributes. To validate the identification assumption, we examine the (conditional) correlations between our constructed party secretary transfer shocks and prefectural industrial characteristics in years prior to the start of the tenure of the new party secretary. Specifically, we regress the lagged term and the change of prefecture-industry-specific RCA on the revised PS transfer shock measure that takes the value one

in the first year of the party secretary's term in prefecture c and captures the arrival of a new party secretary with industry-specific working experience. The results are reported in Appendix Table C3, Panel A, which shows that there is no correlation between historical trajectories of prefecture-industry-specific export performance and the selection of party secretaries into a destination. The finding ensures that our strategy of using PS transfer shock identifies exogenous growth in export performance.

In addition, we adopt recently advanced econometric approaches (Borusyak et al., 2021) to show an absence of differential pre-trends in a variety of economic outcomes across Chinese cities in the years preceding the time when the new officials begin their terms. The testing procedure is based on data prior to the start of the tenure of the new party secretary in a city. The robustness regression is specified as below

$$Y_{cjt} = \sum_{\tau=-6}^{-2} \beta^\tau 1\{year = \tau\}_{cjt} + \mu_{ct} + \lambda_{jt} + \delta_{cj} + \eta_{rst} + \delta_{cj} \times t + \varepsilon_{cjt}, \tag{7}$$

where $1\{year = \tau\}$ indicates $|\tau|$ years before the coming-in of a new party secretary in the city c, and we use the year $\tau = -1$ as the reference time. Other variables remain the same as in (6). The dependent variables include the overall RCA, the supply-side RCA, the demand-side RCA, the measure for market entrance ability, the extensive margin of trade, and total exports.[20] We plot the estimated coefficients β^τs in appendix Figure B2 with the 95% confidence intervals. According to these figures, none of the coefficients remains statistically significant. Further, we follow Borusyak et al. (2021) and conduct an F-test for the joint significance of the estimated coefficients β^τs presented in each figure and find that they are jointly insignificant with a p-value much larger than 0.1. Thus, these results suggest that receiving cities of new party secretaries were not already experiencing an improvement in export performance.

5.2.2 Randomization-based Tests

To rule out the possibility that our findings might be driven by some unobserved stochastic trends in city-industry-specific export performance, we randomize the sourcing places of inter-city party secretary transfers while keeping RCA_{cjt} across cities and industries intact. Specifically, for each city-year (ct) with a new party secretary coming from prefecture c', we randomly draw the prefecture of the official's previous position, c^{false}; the revised PS transfer shock is $\sum_{c^{false}} Transfer_{c^{false} \to c,t} \times 1\{RCA_{c^{false}jt} > 1\}$. As an alternative to

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[20]The extensive margin of trade for a specific industry j and city c equals one if city c exports in the industry j.

the placebo, we randomly select industries in which the previous position location of the new coming-in party secretary has a better performance.[21] We conduct the simulation 500 times. Appendix Figure B3 displays the distribution of estimates obtained from the 500 simulations. We highlight our baseline estimate with a blue vertical dashed line in the figure for comparison. As the figure shows, estimates obtained from the simulated samples are centered around zero, while the benchmark estimate is beyond the 95 percentile of the distribution.

5.2.3 Detailed Fixed Effects Based on Official Characteristics

To ensure that there is no selection of party secretaries into destinations, we conduct an analysis to control for more detailed fixed effects based on party secretaries' predetermined characteristics. In particular, we categorize party secretaries into subgroups based on gender, age (i.e., 45 or below, 46-50, 51-56, and 57 or above), attained education (i.e., below collage, college, and graduate or above), and early working experience (i.e., working experience in firms, local governments, and the central government before coming to the division-head level *Zheng Chu Ji*). Together we categorize party secretaries into 192 cells, which we controlled as the cell-industry-year fixed effects in (6). The result is reported in Appendix Table C3, Panel B, and it suggests that our baseline estimates remain robust, as adding the detailed fixed effects based on official characteristics has a negligible impact on the estimated coefficients.

5.2.4 Alternative Outcome Variables

To lend further support for our baseline results with RCA as the main outcome, we study the impact of political rotation on various direct measures of exporting performance in columns (1)-(5) in Appendix Table C4. We find that the positive PS transfer shock increases the city-industry-specific probability of exporting (column (1)), total exports (column (2)), the number of exporting firms (column (3)), the number of destinations (column (4)) and the number of HS 6-digit products (column (5)), respectively. Through all regressions, we observe that PS transfer shock increases overall sales and encourages firm entry in exporting markets, consistent with our baseline results.

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[21]Suppose there are J industries displaying revealed comparative advantage in location c' for a specific transfer from c' to c in t ($Transfer_{c' \to c,t} = 1$), we randomly draw J industries (i.e., HS 4-digit code) from the total 1,059 industries.

5.2.5 Other Robustness Checks

Alternative RCA criteria: Appendix Table C3, Panel C reports results where we use different cutoff values to tell whether an industry has a revealed comparative advantage in constructing PS transfer shock. We find positive and significant effects for all three cutoffs ranging from 0.5 to 5. Notably, a greater cutoff value is associated with a larger magnitude of the coefficient estimates, suggesting a stronger learning effect from industries with a larger comparative advantage in the location of the official's previous position.

Rotation of prefectural mayors: We show that the impact of political rotation is not only effective among party secretaries but is also efficacious amongst prefectural mayors. This set of results is presented in Panel D of Appendix Table C3 that follows the same specifications as in equation (6). We find significantly positive effects of the mayor transfer shocks on the performance of related industries, although the magnitude of the coefficient becomes smaller than that of estimates obtained focusing on party secretaries. The results are broadly consistent with the political characteristics in China that the party secretary is considered to have the most political power (Joseph, 2019) and play integral roles in planning and making local development strategies (Li and Zhou, 2005; Yao and Zhang, 2015).

Alternative functional forms for outcome variables: In columns (6) to (8) of Appendix Table C4, we report the estimates where we use alternative functional forms to transform the dependent variable. In columns (9) to (11), we use dummy variables to indicate whether city c has revealed comparative advantage in the industry j in year t, based on alternative cutoff values. The significant impact of political rotation on RCA remains robust.

Alternative sample periods and the exclusion of influential cities: To ensure our results are not driven by the specific sample period or the presence of very big cities, we replicate the baseline estimation using different sub-sample periods and exclude special groups of cities. The top panel of Appendix Table C5 reports the results obtained from using three sub-sample periods, namely: 1997-2001, 2002-2007, and 2008-2013.[22] We find that the estimated effects of party secretary transfer shock on the RCA of related industries remain significant across all three sub-periods. In the bottom panel, we exclude influential cities such as provincial capital cities, sub-province-level cities, and coastal cities,

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[22]The first sub-period are years before China joined WTO in December 2001; the other two sub-periods are divided according to the outbreak of the Great Recession in 2008.

respectively. The results stay similar to the baseline. All the evidence suggests that our baseline findings are less likely driven by some particular years and influential cities.

5.3   Heterogeneity Analysis

The granularity of the data allows us to examine the heterogeneous effects of the political rotation on industry-specific productivity increases across space. Through these exercises, we focus on the baseline specification with fixed effects as column (1) of Table 1.

First, we divide the sample into 15 sectors based on the 2-digit HS code. To summarize how the impact of political rotation on industry-specific export performance differs by sector, Figure 2(a) plots the estimated coefficients of PS transfer shock with 95% confidence intervals, where sectors are sorted according to the magnitude of the estimates. Indeed, in 10 out of the 15 cases, we observe that the PS transfer shock has a positive effect on the RCA for affected industries and cities.[23] Further, we explore industry characteristics that can help explain observed differences in knowledge diffusion efficiency. Figure 2(b) displays the correlation between the estimated coefficients of PS transfer shock and the measure of sectoral reliance on contract enforcement –the fraction of intermediate inputs that require relation-specific investments constructed by Nunn (2007). The figure displays a significantly positive correlation between the two, indicating that the productivity effect brought by the coming-in of a new city party secretary is more prominent for sectors with a higher dependence on contract enforcement.

Second, the impact of the PS transfer shock on industry-specific export performance may also differ geographically. Thus, in Table 2, we add an interaction term between the PS transfer shock and variable for city characteristics to our baseline regression. The results of the first two columns show that the productivity effect of political rotation is stronger for prefectures farther from China's coastline and the provincial capital. In columns (3) and (4), we study how market structure affects productivity through knowledge diffusion，where we use two scores from the National Economic Research Institute (NERI) Index of Marketization of China's Provinces that measure the market competitiveness for the final product and factor markets, respectively.[24] The results show that political leaders have a more substantial and far-reaching influence on markets where there is a low level of competitiveness, and the finding is consistent with Guo et al. (2017),[25]

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[23]Sectors with relatively muted knowledge diffusion mainly produce primary goods, such as vegetable products, animal & animal products, foodstuffs, and mineral products, whose production depends more on natural resources.

[24]The information of the NERI Index of Marketization of China is in Appendix G. Fan et al. (2011); Wang et al. (2017) provide a detailed introduction to the data and various measures in the database.

[25]Guo et al. (2017) examine the impact of government R&D subsidies for small and medium-sized firms

Figure 2: Heterogeneous Effects of PS Transfer Shocks by Sector

(a) Learning Effect by Sector

(b) Contract Intensity and Learning Effect
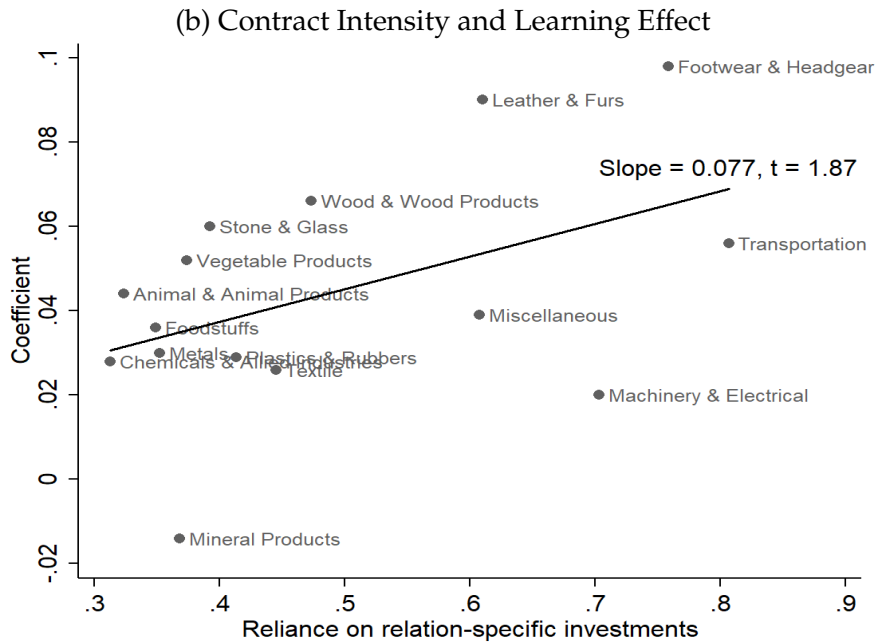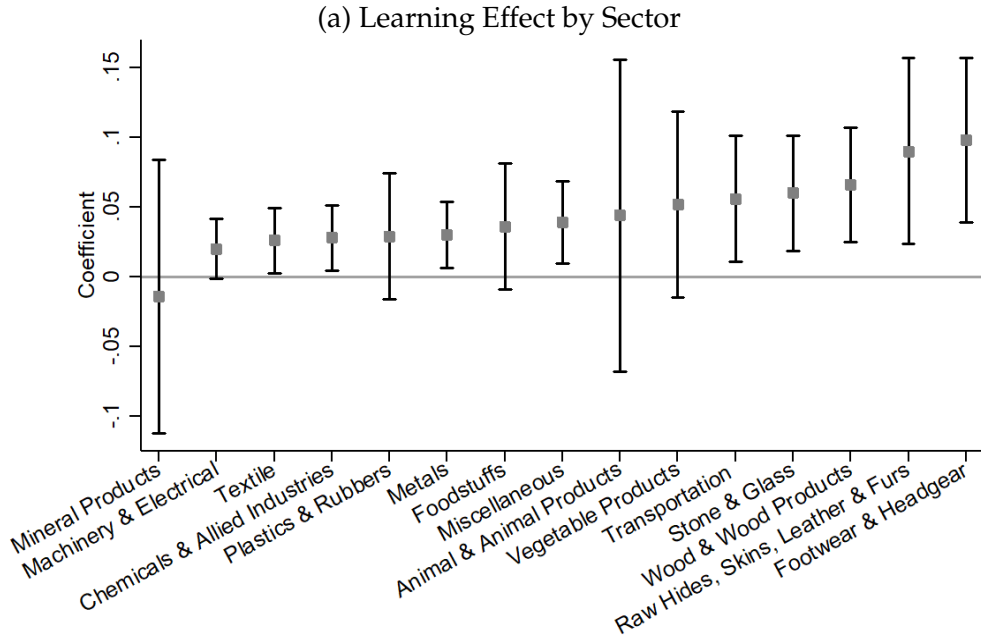
Note: Figure (a) plots the estimated coefficients with 95% confidence intervals for subsamples of 15 sectoral groups. Figure (b) plots the estimated coefficients in Figure (a) against the fraction of inputs not sold on an exchange and not reference priced in a trade publication (Nunn, 2007).

as captured by the greater knowledge diffusion brought about by the rotation of party secretaries in places with a smaller marketization score. Moreover, we find the productivity effect brought by knowledge diffusion is greater in smaller and poorer cities, as reported in columns (5) and (6). Altogether, political rotation is more effective in promoting knowledge diffusion in small and developing cities that are remote from openness and competition.

Table 2: Heterogeneous Effects of PS Transfer Shocks across Regions

Dep var: $\ln RCA_{cjt}$	(1)	(2)	(3)	(4)	(5)	(6)
PS Transfer Shock	0.044***	0.035***	0.046***	0.048***	0.041***	0.036***
	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.005)
× Distance to coastline	0.019***					
	(0.003)					
× Distance to province capital		0.007**				
		(0.003)				
× Product market score			-0.022***			
			(0.007)			
× Factor market score				-0.023***		
				(0.005)		
× Log population					-0.046***	
					(0.007)	
× Log GDP per capita						-0.009*
						(0.005)
Observations	5,305,966	5,326,714	5,310,074	5,310,074	5,190,296	5,190,296
Adjusted R-squared	0.402	0.402	0.402	0.402	0.402	0.402

Note: In the regressions, all the six regional variables are demeaned, and the product market development and factor market development scores are standardized with a standard deviation of 1. The regional variable in column (1) is the logarithm of the distance from a city's geometric center to coastline in kilometers; in column (2), it is the logarithm of one plus the distance to the provincial capital in kilometers. In all regressions, we control for prefecture-industry, prefecture-year, industry-year, province-sector-year fixed effects, and prefecture-industry-specific linear time trends. An industry refers to an HS 4-digit code, and a sector refers to an HS 2-digit code. Standard errors are clustered at the prefecture-sector level. ***, **, * represent significance levels of 1%, 5%, and 10%, respectively.

Finally, the characteristics of new officials may also affect the efficacy of knowledge diffusion, such as age, educational attainment, major of study in education, and political connections of the new party secretaries.[26] We add the interaction between PS transfer

Table 3: Heterogeneous Effects of PS Transfer Shocks in Official Characteristics

Dep var: $\ln RCA_{cjt}$	(1)	(2)	(3)	(4)	(5)	(6)
PS Transfer Shock	0.028***	0.024***	0.024***	0.029***	0.036***	0.035***
	(0.007)	(0.007)	(0.007)	(0.006)	(0.005)	(0.007)
× Age 50 or Younger	0.019***					
	(0.007)					
× College Education		0.017**				
		(0.009)				
× Major: Economics			0.003			
			(0.013)			
× Major: Engineering			0.021*			
			(0.011)			
× Major: Pol. Sci. & Law			0.034*			
			(0.018)			
× Major: Others			0.015			
			(0.010)			
× Connection (Colleague)				0.011		
				(0.007)		
× Connection (Fellow-townsman)					-0.046	
					(0.033)	
× Connection (Almuni)						0.005
						(0.018)
Observations	5,326,714	5,326,714	5,326,714	4,981,585	4,981,585	4,981,585
Adjusted R-squared	0.402	0.402	0.402	0.398	0.398	0.398

Note: In all regressions, we control for prefecture-industry, prefecture-year, industry-year, province-sector-year fixed effects, and prefecture-industry-specific linear time trends. An industry refers to an HS 4-digit code, and a sector refers to an HS 2-digit code. The variable of city leader characteristics is an indicator for those aged 50 or younger in column (1) and an indicator for completing college education in column (2). In column (3), we interact the PS transfer shock variable with dummy indicators for four categories of college majors (economics, engineering, political science and law, and the others), and all the four indicators takes zero for those without college education completion. In columns (4)-(6), the variables to be interacted with the PS transfer shock are indicators for political connections between city party secretaries and the provincial party secretaries in forms of college, fellow-townsman, and almuni, respectively. Standard errors are clustered at the prefecture-by-sector level. ***, **, * represent significance levels of 1%, 5%, and 10%, respectively.

shock and various official characteristics measures into baseline regression (6), and results are reported in Table 3. In the first column, we divide new party secretaries by the median age level when they began new terms in the destination cities.[27] The first column indicates that the political rotation of the younger party secretaries likely triggers a stronger knowledge diffusion and a bigger productivity effect. The pattern is consistent with the human capital theory that younger and better-educated individuals have stronger learning abilities.(Rosenzweig, 1995; Heckman, 2006; Rubinstein and Weiss, 2006).[28] In column (2), we interact the PS transfer shock variable with the dummy variable for whether the party secretary has at least a college education, and nearly 65% of the party secretaries have a high school diploma in our sample.[29] The estimate suggests that a party secretary with a college degree or above brings about a 71% (i.e., 0.017/0.024=0.71) larger effect on the RCA of industries where the location of her/his previous position has a better performance than those without completing a college education. These results are broadly consistent with previous findings that highlight the role of human capital in promoting local economic development (Besley et al., 2011), and are in line with the evidence that more schooling is associated with not only more abundant knowledge but also a higher ability to learn from experience and practicing (Rosenzweig, 1995). In column (3), we divide party secretaries by their major of study in college and use those without a college degree as the reference group. We find those with engineering and political science & law backgrounds are more likely to favor knowledge diffusion. As having connections with upper-level leaders seem more helpful in attracting policy benefits that affect local economic development (Kahn et al., 2021), the last three columns of Table 3 study the role of connection to political leaders at the provincial level in influencing the productivity effect of PS transfer shock. We consider three types of connections between prefectural and provincial party secretaries, namely, the (i) connection as former colleagues, (ii) connection as fellow-townsman relationship, and (iii) connection as alumni.[30]. We find that none

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[27] The mean and median age of rotating party secretaries when they begin a new term in the destination is 51.

[28] To rule out that our baseline results are not driven by promotion incentive (Yao and Zhang, 2015), we further examine the heterogenous impact of PS transfer shock using the cutoff age 57 for those older than 50. The choice of a cutoff age of 57 is based on the fact that the average tenure of office for city leaders is three years, which suggests that those who become party secretaries at age 57 or older have little possibility for further promotion as the age of 60, i.e., the upper-bond age for prefectural leaders according to the Chinese political system. The results show an insignificant difference in the estimated effects between the 51-56 age group and those aged 57 or older, suggesting that career incentives might have played a less critical role in explaining the positive impact of political rotation on export performance.

[29] We focus on the first college degree from formal schooling and do not consider degrees from on-the-job education.

[30] A pair of prefectural and provincial party secretaries has a fellow-townsman relationship if they come from the same city of origin. Results remain similar if we define the fellow-townsman relationship by their

of the interaction terms is statistically significant, indicating that connection to upper-level political leaders does not bring more fuel in powering the knowledge diffusion and thus export performance.

6 Mechanism Analysis

In this section, we explore the explanations for why political rotation affected industry-specific export performance across regions. We examine whether the productivity gains in some industries due to political rotation is consistent with (1) the implementation of local government policies in favor of them, and/or (2) the investment flows driven by the social networks between political leaders and investors from locations where they had previously served.

6.1 The Practice of Industrial Policy

As city party secretaries have the most political power and play integral roles in planning and making local development strategies (Li and Zhou, 2005; Joseph, 2019; Yao and Zhang, 2015), it is likely the sectors with rising RCA benefit from supportive policies, likely driven by new party secretaries who have industry-specific experience from her/his previous career. When supporting certain sectors, governments often adopt a wide range of different industrial policy tools, making it challenging to measure industry policy precisely.[31] Therefore, we use textual analysis and focus on the extent to which the descriptions of policy reflect the intent to promote certain sectors.

Text Data: Annual Government Work Report

To construct a city-level sector-time-varying measure of industrial policy, we employ Caldara et al. (2020); Benguria et al. (2022)'s method of textual analysis. We use an exhaustive corpus of government reports, the Annual Government Work Reports, which tracks and collects Chinese-language descriptions of new government policy announcements and work plans for all Chinese cities from 1997 to 2017, and apply the technique to the transcripts of annual reports. The reports are scraped from *People Data* (a database platform under *The People's Daily*, the official newspaper of the Central Committee of the Chinese

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province of origin

[31]For instance, these policy tools involve tax and subsidy arrangements (Aghion et al., 2015; Guo et al., 2017), credit provision (Ru, 2018), environmental regulation (He et al., 2020), public procurement (Zu, 2022), and the supply of land (Nian and Wang, 2019).

Communist Party).[32] These annual reports summarize the government work in the past year and disclose information about plans for economic development in the coming year, which are well-suited to our application. In particular, the policies covered by the annual reports are a superset of industrial policies, which, by definition, make some targeted activities relatively more attractive.[33] As there are limited data observations of annual work reports across cities between 1997 and 2003, our measure of industrial policy and baseline regression analysis will focus on the database version for 2003 through 2013, containing approximately 0.11 million observations over 284 cities.

Our annual city-sector-level industrial policy measures are constructed using a textual analysis of the transcripts of yearly government reports in China. A government work report mainly includes summarizing the past and making plans for the future (see Appendix Figure F6 for instance), and we focus on the latter in the textual analysis. Our measure indicates whether sector-specific words are mentioned in a supportive tone in the city's plan for the following year. There are two primary challenges we seek to address in textual analysis. First, as the *Five-year Plan*, a series of social and economic development initiatives issued by the central government since 1953 in the People's Republic of China, may also be reiterated in the annual report, it could lead to measurement error in industrial policy measure since the made of the *Five-year Plan* is likely orthogonal to political rotation. In practice, we exclude the content related to *Five-year Plan* from textual analysis and focus on the plan for the following year. Second, we distinguish supportive from unsupportive industrial policies and construct the measure reflecting the intent to promote certain sectors based on the supportive phrases.[34]

Construction Method

The construction method consists of four steps. In the first step, we manually annotate the text and identify the paragraphs for "summarizing the past" and "making plans for the future" purposes, respectively. In the second step, focusing on paragraphs on the city's plan for the future, we search each line for text with supportive intent to promote certain sectors, where we exclude the paragraphs on the *Five-year Plan* and keep descriptions of the work plan for the following year. With this step, we construct the base text data, which we

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[32]The web address of the online data platform is http://data.people.com.cn/.

[33]In theory, any industrial policy is expected to be disclosed in the Annual Government Work Reports, while not all policies in the annual reports will be an industrial policy that codes the extent to which policies are aimed at particular economic activities or sectors.

[34]Appendix Figure B4 provides an example where some sectors, i.e., ceramic, calcium & magnesium, cement, and fertilizer production, are prohibited in the future development of the city.

Figure 3: Example: Industrial Policies Revealed in the Annual Government Report of Shijiazhuang City in 2014

Note: This example consists of a paragraph of the annual work report of Shijiazhuang City in 2014. Marked in blue are words associated with various sectors. Marked in green are words that reflect the supportive attitude in promoting these sectors.

use for analysis. Third, we apply a machine-learning algorithm, the TF-IDF algorithm,[35] to the base text data to segment words in sentences and extract high-frequency keywords associated with industrial production. Finally, we categorize these keywords into 2-digit China Industry Classification (CIC) sectors and generate the variable $IndPol_{ckt}$, an indicator that takes one if sector k is mentioned to be supported in the annual report of the city c and year t. The detailed information is presented in Appendix F. Figure 3 provides an example to demonstrate the procedure, which shows that the government plans to support sectors related to bio-pharmaceutical, electronic information, high-end equipment manufacturing, and new energy vehicle production, where the supportive keywords are marked in green and the sector-specific keywords are marked in blue.[36]

We provide some evidence that our industrial policy measures can capture multiple aspects of recent China's development facts. Figure 4 displays the share of cities whose industrial policies favor textile, steel, and electronics sectors from 2003 to 2017, respectively, along with the average share across all thirty CIC 2-digit sectors over time in a dashed-black line.[37] We find the aim of developing textile sectors became less of a priority since 2008 when China was losing its comparative advantage in labor-intensive manufacturing sectors (Li et al., 2012; Lin, 2012). In contrast, the electronics sector has been increasingly important for future development, as captured by the increasing probability of being supported by industrial policies. In addition, the drop in the probability of supporting the steel sector is also in line with the time break in 2013 when massive environmental regulations and policies to deal with excess production capacity and lagging demand were implemented (State Council, 2013). This descriptive analysis lends support to the validity of our newly-constructed measure of local government industrial policies based on the text data.

Evidence on Industrial Policy

To study whether industrial productivity response is associated with the practice of industrial policies developed by the administration of new leaders, we replace the dependent variable of equation (6) with $IndPol_{ckt}$, which equals one if sector k is mentioned to be supportive in the annual report of the city c in year t, where sector k is defined by

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[35]The details of this algorithm are described in Appendix F.

[36]The document mentions that "*to set up strategic industry development fund is needed to provide support for sectors related to bio-pharmaceuticals, electronic information, high-end equipment manufacturing, and new energy vehicles.*"

[37]These three sectors account for a significant share of regional economies in China and are frequently mentioned by local governments' annual work reports. In particular, the three sectors experienced different development trends during our analytic period, which are informative of the consequential validity of our text-based measure of industrial policies.

Figure 4: Probability of Being Supported by Industrial Policies
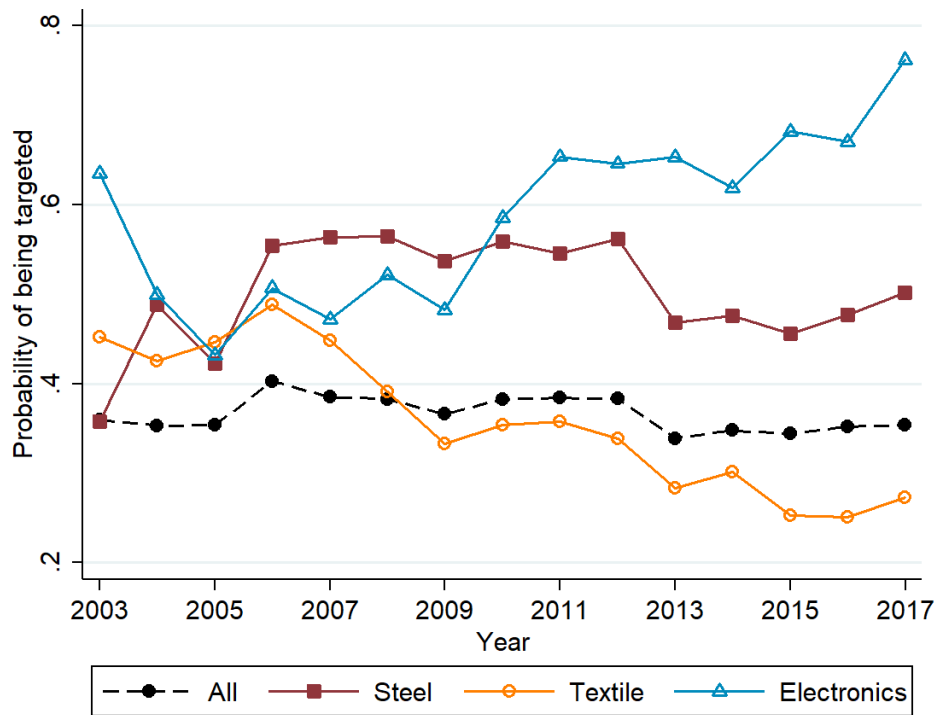
Note: This figure presents, for each of the three 2-digit CIC sectors, the share of prefectures that list the sector as a targeted sector to support in the government work report in each year. The three sectors are textile (CIC code 17), ferrous metal smelting and rolling ("Steel", CIC code 31), and communication equipment, electronics and computers ("Electronics", CIC code 39). We also report the mean across all 30 manufacturing sectors ("All", in black dashed line. The time period is 2003-2017.)

the 2-digit CIC code in this exercise.[38] Robust standard errors are clustered at the prefecture level. We focus on the sample from 2003 to 2013 due to limited data observations of annual work reports across cities before 2003. This set of results is reported in Table 4. The first three columns report results based on different fixed effects. According to column (3), the coming-in of a new city party secretary from cities that are significant exporters of the sector k (with a higher $RCA_{c'kt}$) leads to a 2.2% higher probability of making industrial policies in favor sector k by the new administration. Columns (4) – (6) are the robustness checks where we regress the one-year PS transfer shock on previous industrial policy measures. The insignificant results indicate that results are not driven by pre-existing trends in industrial policies. More robustness results are provided in the Appendix, which validate the identification assumption and ensure that the results are unlikely driven by influential observations.[39] Although suggestive, these results indicate that political rotation affects sector-specific productivity because new leaders are more likely to make sector-biased industrial policies based on the practical acquisition of knowledge learned from their experience.

6.2 Social Network

Investment flows generated by the moving social connections between political leaders and investors where they had previously served could also generate the observed change in RCA across locations. Lacking familiarity with local markets knowledge and social networks, the new leaders may lean on their personal connections and work with investors with whom the mutual trust had been built in the leaders' previous jurisdictions (Shi et al., 2021). As a result, the business and investments could flow along with the rotation of political leaders for the "protective umbrella".[40] We explore the likelihood of these scenarios.

We examine whether the political rotation leads to a possible rise and decline of in-

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[38]Different from the baseline regression in equation (6), we use the 2-digit CIC code as the analytic unit of sectors due to data limitation. We control for prefecture-year, sector-year, prefecture-sector, and province-sector-year fixed effects.

[39]Results of additional test for the parallel trend assumption based on the method of Borusyak et al. (2021) are provided in the appendix Figure B5. Appendix Table C6 provides other robustness checks: (i) expanding the sample period to include 1997-2002, during which time only limited observations of annual work reports across cities are available, (ii) excluding the years (i.e., 2003, 2008, and 2013) when major center government turnover took place, (iii) excluding the years when *Five-year Plan* was made (i.e., 2005 and 2010), (iv) dropping remote and less population-dense provinces, (v) dropping the 15 sub-provincial-level cities, and lastly (vi) expanding the sample to include mining sectors which we do not include in baseline regression.

[40]"Protective umbrella" is a metaphor referring to government officials who become a patron for private firms and investors.

Table 4: Party Secretary Transfers and Local Industrial Policies

Dep var:	Current year: $IndPol_{ckt}$			$IndPol_{ckt-1}$	$IndPol_{ckt-2}$	$IndPol_{ckt-3}$
	(1)	(2)	(3)	(4)	(5)	(6)
PS Transfer Shock	0.028**	0.018**	0.022**	-0.009	-0.016	-0.009
	(0.012)	(0.009)	(0.010)	(0.015)	(0.017)	(0.017)
Outcome mean	0.374	0.374	0.374	0.378	0.377	0.375
Sector-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Prefecture-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Prefecture-sector FE	-	Yes	Yes	Yes	Yes	Yes
Province-sector-year FE	-	-	Yes	Yes	Yes	Yes
Observations	77,500	77,500	77,500	62,248	55,034	48,298
Adjusted R-squared	0.432	0.655	0.693	0.711	0.721	0.728

Note: The sample period is from 2003 to 2013. The dependent variable is an indicator for a sector to be listed as a targeted sector in the government work report in a prefecture in a year. A sector refers to a 2-digit CIC code. We restrict the estimation sample to manufacturing industries. In columns (4) to (6), the independent variable "PS Transfer Shock" takes one only in the first year of the tenure of the party secretary in the current prefecture, and the dependent variables are the one-, two-, and three-year lagged indicator for a sector to be listed as a targeted one in the government work report in a prefecture, respectively. Standard errors are clustered at the prefecture level. ***, **, * represent significance levels of 1%, 5%, and 10%, respectively.

vestments in the destination and origin city, respectively, for sectors in which the origin city has a revealed comparative advantage. The outcome variable counts the total number and aggregate paid-in capital of newly registered firms at the city-sector-year level, where a sector is defined by a CIC 2-digit code.[41] We first estimate the equation (6) with the number and total paid-in capital of newly registered firms as the dependent variables, both of which are log-transformed using the inverse hyperbolic sine function to deal with zero values. The results are reported in Appendix Table C7. Columns (1) and (2) report a muted effect of PS transfer shock on firm entry and capital creation for sectors with improved RCA in the destination cities. We further investigate whether the transfer of political leaders from an origin city leads to the decline of firm entry and investments in the same place. We estimate a modified baseline regression model specified as follows:

$$Y_{c'jt} = \gamma \, Transfer_{c'\to,t} \times 1\left\{RCA_{c'jT} > 1\right\} + \mu_{c't} + \lambda_{jt} + \delta_{c'j} + \eta_{rjt} + \epsilon_{c'jt}, \qquad (8)$$

where $Transfer_{c'\to,t}$ is the event dummy variable indicating the transfer of any political leader out of the origin city c' who was appointed as party secretary in a different loca-

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[41]The number and paid-in equity of newly registered firms are from the Firm Administrative Registration Database, where the industry classification uses a CIC 2-digit code. See Appendix G for more detailed descriptions.

tion. This set of results is reported in columns (3) and (4) of Appendix Table C7 — the estimated impact of the out-rotation of local leaders does not see a significant drop in local investments. Notably, our city-sector level evidence is not against the finding of Shi et al. (2021), who focus on the aggregate investment flows across city pairs, as we highlight the industry-specific productivity effect induced by political rotation.

In general, it appears unlikely that investment flows driven by the social connection of political leaders play a large role. In addition, even if moving social networks led by political rotation could affect export performance via investment flows, Shi et al. (2021) show that such an impact is phenomenal in sectors with strong rent-seeking incentives (e.g., finance and real estate sectors). In contrast, our study documents that the impact of political rotations on RCA is more influential in many labor-intensive manufacturing sectors (e.g., textile, footwear & headgear, and leather & furs processing), which have low levels of rent-seeking as measured by the low profit-to-asset ratio (Shi et al., 2021).

7 Conclusion

In this paper, we investigate the impact of political rotations on industry-specific productivity across Chinese cities. Our analysis is based on the unique and comprehensive dataset that links the city-industry-specific export performance, a novel measure of industrial policy constructed from a textual analysis of the statements of Annual Government Work Reports, and the detailed information on the resume of city secretaries of the CCP. We document robust evidence that political rotations can explain variation in industry-specific productivity, as measured by the RCA of cities in exporting those goods, for products that are intensively exported by cities where the political leaders had her/his previous term.

The first contribution of the paper is to uncover the political rotation of government officials, serving as intra-national drivers of productive knowledge, can shape the comparative advantage of regions in China, a relationship that has not been documented in the literature thus far. Our study indicates a sizable impact on industry-specific productivity: the coming-in of a party secretary from a significant city exporter of a given product is associated with about a 3.5% annual increase in the comparative advantage in the same product during her/his tenure of service in the new place.

The second contribution of our paper is to demonstrate that industrial policies are important ways of applying knowledge into practice for political officials. Our analysis uncovers that the industry-specific productivity increase, since the arrival of a new leader from a significant city exporter of a given product, is associated with the practice of in-

dustrial policies in favor of it. In the analysis, we make novel use of an exhaustive corpus of government reports and employ a text-based approach to measuring industrial policy. Thus, we complement the emerging literature on industrial policy practice, by providing, to the best of our knowledge, the first descriptive cross-city, cross-sector analysis of the practice of industrial policy in China. Notably, this dataset will be continuously updated and provide a live measure database on industrial policy specific to China, allowing future analysis on the determinants and consequences of Chinese industrial policies in a timely manner.

Finally, our findings have encouraging practical implications for the design and implementation of policies for appointing local government leaders in countries with centralized political systems such as China. The heterogeneity pattern in the industrial productivity response to political rotation suggests that enough dynamism and initiative to get those who are better educated and with specific technocratic specialization to the decision-making table is needed. This is not only because knowledge and skill diffusion stands at the center of overall productivity growth (Jones, 2002, 2022), but knowledge sharing and conversion are also the key instruments to reducing regional inequality within a country (Piketty, 2017).

Overall, our work highlights the economic importance of political rotation in understanding the means through which knowledge diffuses around Chinese regions. The paper also illustrates the benefits of new measures of industrial policies based on textual analysis of statements of government annual work plans. The stylized facts established by industrial productivity responses to political rations will be useful for shaping future models in which economic growth responds endogenously to local official appointments.

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A Model Appendix

A.1 Proof of Proposition 1

Without loss of generality, consider an increase in $e_{12}^{k(2)}$, i.e., a political leader transfer from location 2 to location 1, and the same logic applies to a change in $e_{21}^{k(1)}$.

Summing up the equation (1) across industries derives:

$$\sum_j \pi_1^j = \sum_j \frac{\lambda_1^j}{\lambda_1^j + \lambda_2^j \left(\frac{J - \Sigma_j \pi_1^j}{\Sigma_j \pi_1^j} \right)^{-\theta^j}}. \tag{9}$$

The left-hand side (LHS) increases in $\sum_j \pi_1^j$, and the right-hand side (RHS) decreases in $\sum_j \pi_1^j$, as plotted in Figure A1. Holding other parameters constant, an increase in $e_{12}^{k(2)}$ induces higher $\lambda_1^{k(2)}$, and the RHS becomes larger for each given $\sum_j \pi_1^j$. This leads to an increase in $\sum_j \pi_1^j$ in equilibrium. As shown in Figure A1, when the RHS line moves from RHS_0 to RHS_1, the equilibrium level of $\sum_j \pi_1^j$ increases from point A to B. In addition, following equation (1), when $\sum_j \pi_1^j$ increases, π_1^j ($j \neq k(2)$) decreases, which indicates that $\pi_1^{k(2)}$ increases.

Figure A1: Equilibrium Condition Based on Equation (9)

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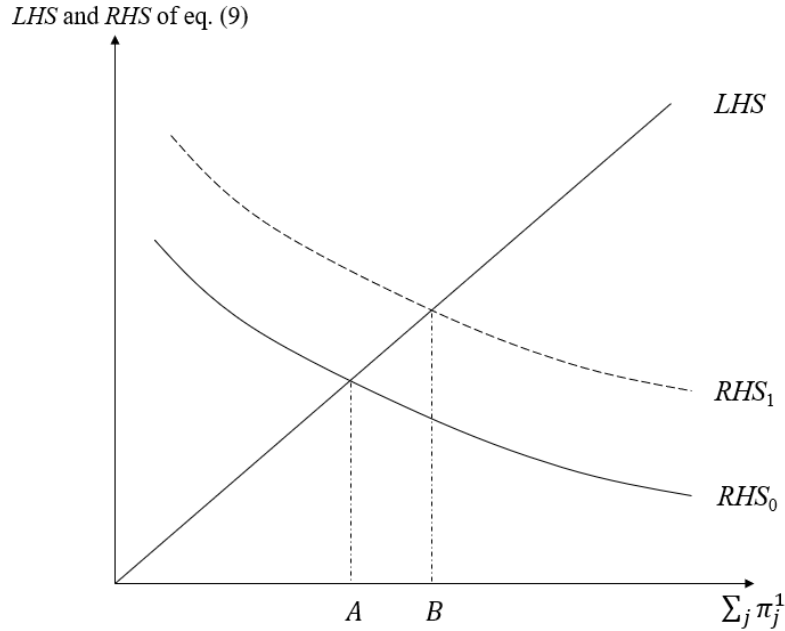
We then show the change in RCA. The RCA of region 1 in industry $k(2)$ is defined as

$$RCA_1^{k(2)} = \frac{EX_1^{k(2)}/\sum_j EX_1^j}{\left(EX_1^{k(2)} + EX_2^{k(2)}\right) / \left(\sum_j EX_1^j + \sum_j EX_2^j\right)},$$

where $EX_1^j = X_2^j \pi_{21}^j$ ($EX_2^j = X_1^j \pi_{12}^j$) denotes exports from region 1 (region 2) in industry j. The RCA can be further expressed as

$$RCA_1^{k(2)} = \frac{1}{1 + \frac{\sum_j \pi_1^j}{\pi_1^{k(2)}} \cdot \frac{1-\pi_1^{k(2)}}{J-\sum_j \pi_1^j}}.$$

As shown above, an increase in $e_{12}^{k(2)}$ induces higher $\pi_1^k(2)$ and lower $\sum_{j\neq k(2)} \pi_1^j$. Thus, we have $d\frac{\sum_j \pi_1^j}{\pi_1^{k(2)}} < 0$ and $d\frac{1-\pi_1^{k(2)}}{J-\sum_j \pi_1^j} < 0$, which indicates that $\frac{\partial RCA_1^{k(2)}}{\partial e_{12}^{k(2)}} > 0$. Following the same logic, we have $\frac{\partial RCA_2^{k(1)}}{\partial e_{21}^{k(1)}} > 0$.

A.2 Proof of Proposition 2

Following equation (1), we have

$$\frac{\lambda_1^j}{\pi_1^j} = \lambda_1^j + \lambda_2^j \left(\frac{J - \sum_j \pi_1^j}{\sum_j \pi_1^j}\right)^{-\theta^j}.$$

We have shown in Section A.1 that $\partial \left(\sum_j \pi_1^j\right) / \partial e_{12}^{k(2)} > 0$, and thus,

$$\frac{\partial \left(\lambda_1^{k(2)}/\pi_1^{k(2)}\right)}{\partial e_{12}^{k(2)}} > 0,$$

since $\lambda_1^{k(2)}$ increases and $\lambda_2^{k(2)}$ keeps unchanged with an increase in $e_{12}^{k(2)}$. In addition, for industries j other than $k(2)$, λ_1^j remains unchanged, and π_1^j ($j \neq k(2)$) decreases (as shown in equation (1)). Therefore, following the welfare formula,

$$\frac{w_1}{P_1} = \prod_{j=1}^J \left(\frac{\lambda_1^j}{\pi_1^j}\right)^{\frac{1}{2\theta^j}},$$

we have $\frac{\partial (w_1/P_1)}{\partial e_{12}^{k(2)}} > 0$. Following the same logic, we have $\frac{\partial (w_2/P_2)}{\partial e_{21}^{k(1)}} > 0$.

B Figures

Figure B1: Share of New Party Secretaries from Other Provinces
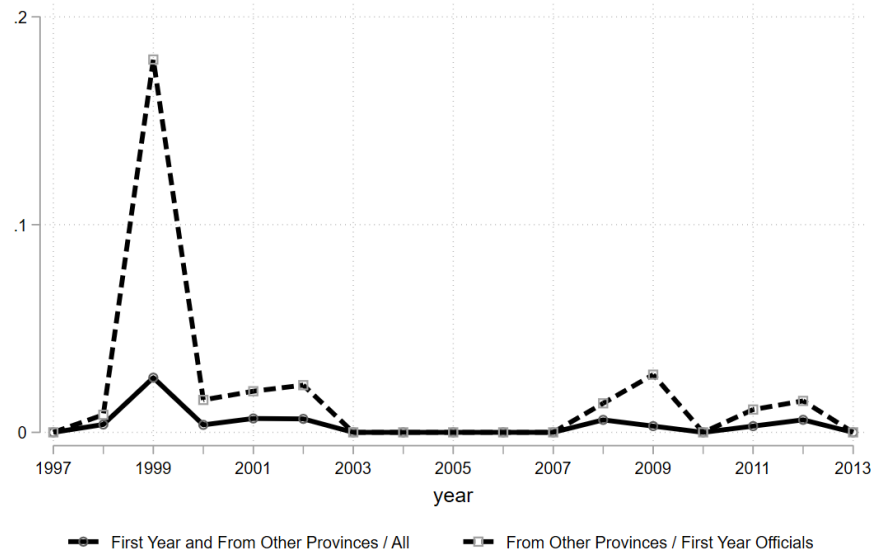
Note: The solid line represents the share of the new city party secretaries (who are in the first year of the city PS position) whose last positions are in other provinces in all city PS's in each year. The dashed line presents the share of the new city PS's coming from other provinces in all the new city PS's.

Figure B2: Pre-trend Tests

(a) RCA

F = 0.61, p–value = 0.689

(b) Supply-side RCA

F = 0.19, p–value = 0.965

(c) Demand-side RCA

F = 0.60, p–value = 0.702

(d) Number of "customers"

F = 0.62, p–value = 0.688

(e) Indicator for positive exports

F = 0.65, p–value = 0.665

(f) Total exports

F = 0.74, p–value = 0.596
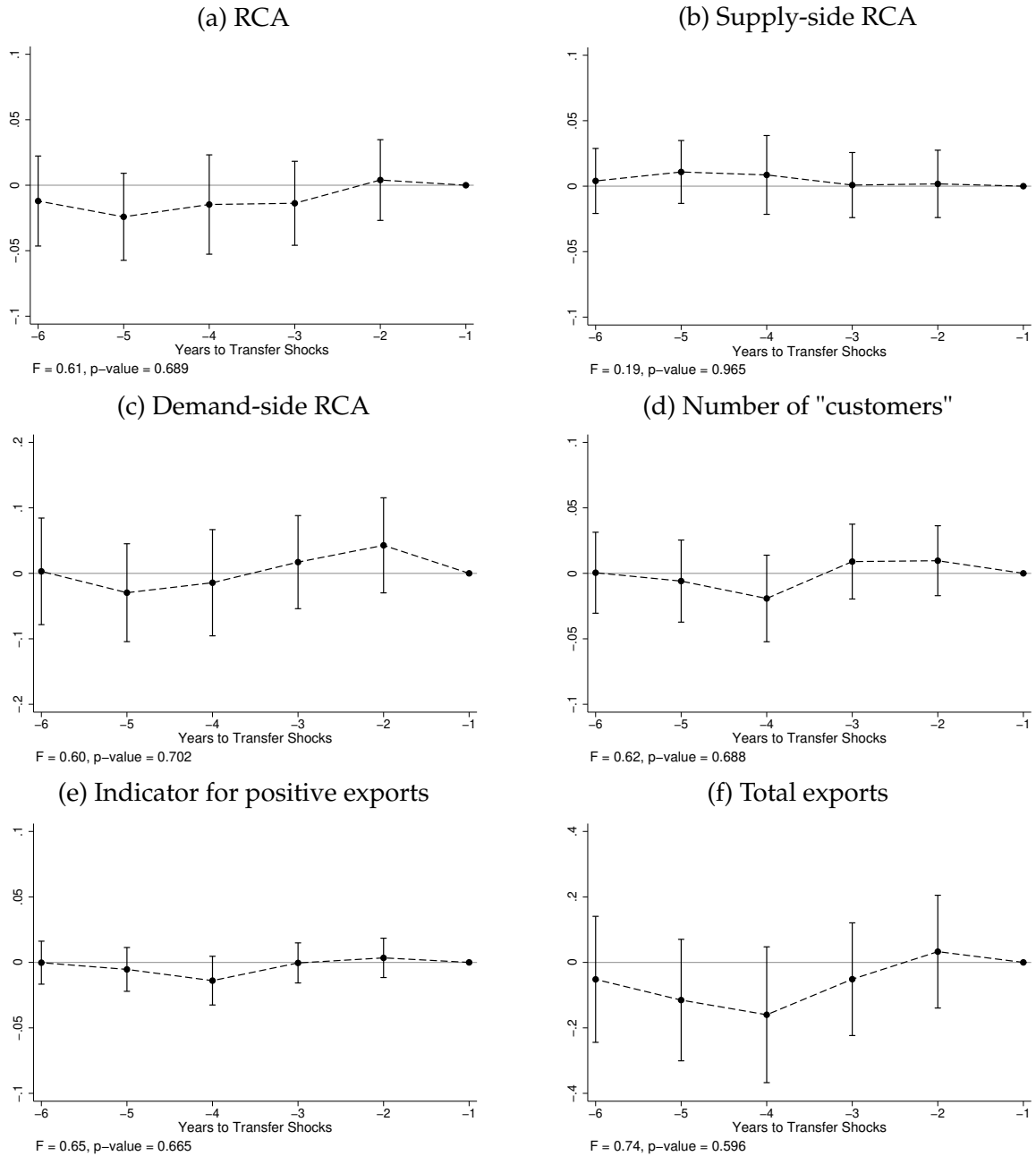
Note: The figures plot estimated coefficients β^τ of equation (7) with 95% confidence intervals. The dependent variables in (a)-(d) are the same as those in Table 1 (Columns (1)-(4)) in terms of variable definitions and the functional form. The dependent variable in (e) is a dummy indicator for positive exports, and that in (f) is total exports in the functional form of inverse hyperbolic sine transformation. The horizontal axis is the number of years to the first party secretary transfer shock at the prefecture-industry level in our sample period. We report the F-value and p-value in the F-test for the joint significance of the five coefficients.

Figure B3: Randomization-based Tests

(a) Randomly Drawing Party Secretaries' Prefectures of Last Positions

Baseline estimate = 0.035

Mean = -0.001
Std. dev. = 0.006

PS Transfer Effect Estimate
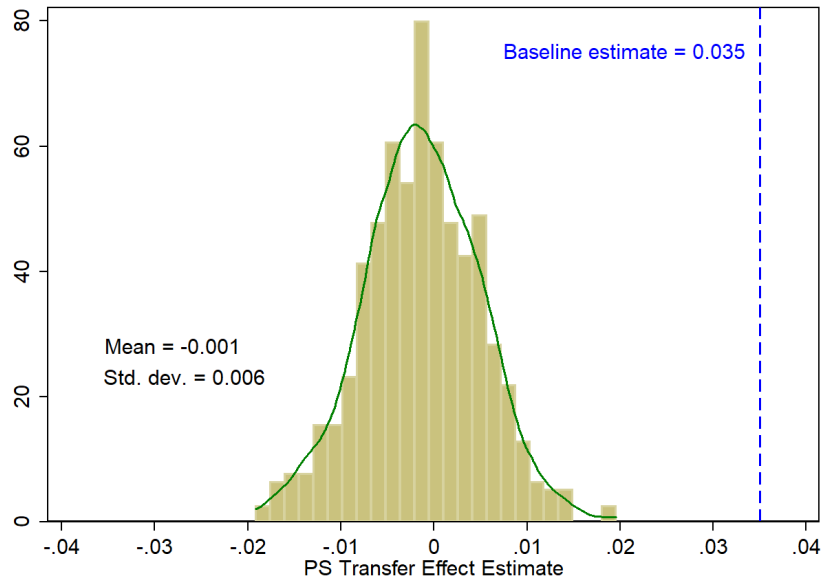
(b) Randomly Drawing Treated Industries

Baseline estimate = 0.035

Mean = 0.000
Std. dev. = 0.003

PS Transfer Effect Estimate
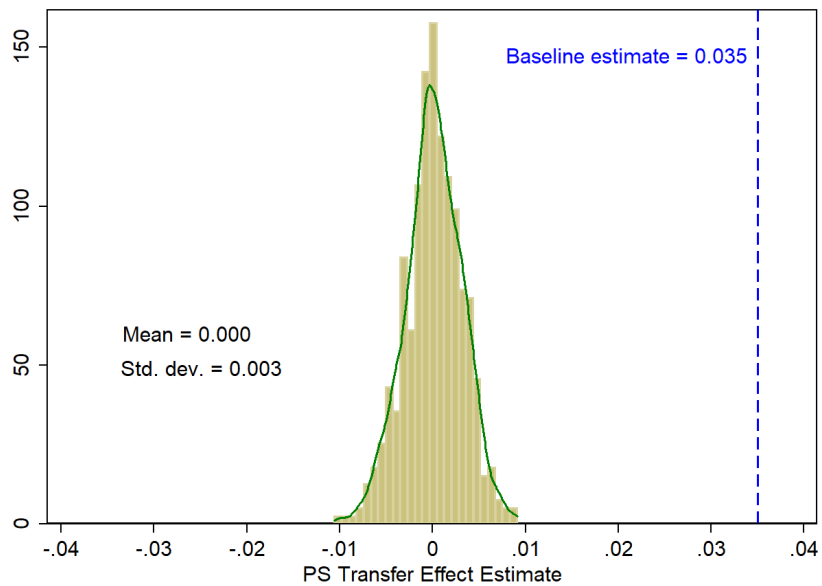
Note: In each figure, we use histograms with the kernel density function to plot the distribution of 500 coefficient estimates from the randomization of 500 times. We report the mean and standard deviation of the 500 estimates in each figure, and we show the baseline estimate of 0.035 using the blue dashed line.

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Figure B4: Example of Prohibited Sectors in Government Plan (Shijiazhuang City in 2014)

生态环境治理取得初步成效。大气污染防治攻坚行动全面展开，关停热电一厂和西柏坡钢铁等 3 家钢铁企业的 6 座高炉，拆除市区分散燃煤锅炉 274 台，对陶瓷、钙镁、水泥、化肥、焦化等行业实行限产停产，全市削减燃煤 310 万吨；城郊 3.4 万农户改烧型煤，取缔关停洗煤厂、储煤场 1244 家；水泥企业脱硝工程全部完成，7 台火电机组完成脱硝，市区及周边 14 台燃煤火电机组、17 台燃煤锅炉完成烟尘治理。对 592 个在建工地实施扬尘治理，主城区渣土车实行密闭运输；集中爆破拆除西北区域 18 家水泥企业，削减水泥产能 940 万吨；购置天然气公交车 450 辆，淘汰黄标车 9.8 万辆；油气回收任务提前一年完成；气象分析和预报预警工作进一步加强，构建起覆盖全市域的空气自动监测网络体系，主城区细颗粒物（PM2.5）平均浓度较上半年下降 8.7%，成功列入"国家节能减排财政政策示范城市"。洨河综合整治取得决定性成果，水质稳定达标。大力开展植树绿化和环省会经济林建设，共造林 60 万亩，全市森林覆盖率达到 34%。

Limit or prohibit

ceramics, calcium magnesium, cement, fertilizer, coking and other industries

Note: This example consists of a paragraph of the government annual work report of Shijiazhuang City in 2014. Marked in blue are words associated with sectors. Marked in red are words that reveal the negative attitude of the government.

Figure B5: Pre-trend Test: Party Secretary Transfers and Local Industrial Policies

F = 1.09, p–value = 0.311
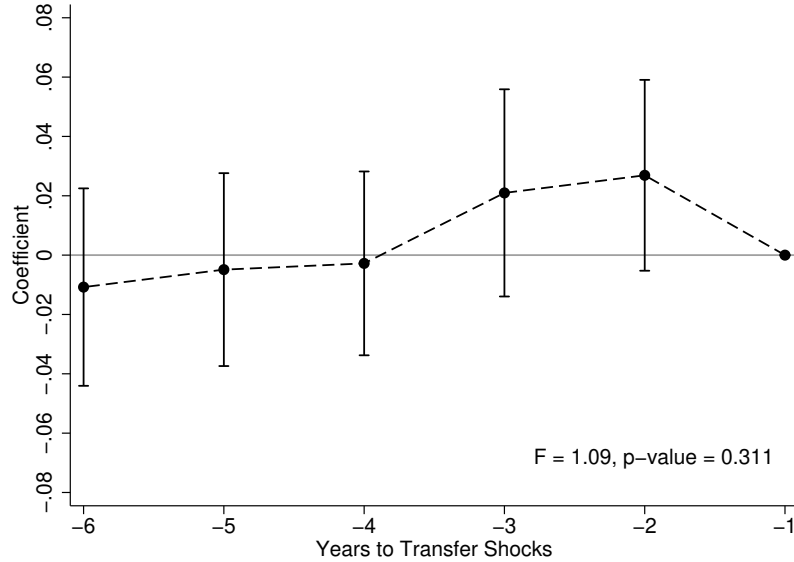
Note: This figure plots estimated coefficients β^{τ} with 95% confidence intervals of the following regression equation:

$$Report_{ckt} = \sum_{\tau=-6}^{-2} \beta^{\tau} 1\{yeardiff = \tau\}_{ckt} + \mu_{ct} + \lambda_{kt} + \delta_{ck} + \eta_{rst} + \epsilon_{cjt},$$

where the dependent variable is defined in the same way as in Section 6.1; $1\{yeardiff = \tau\}$ denotes indicators for $|\tau|$ years before the treatment at the prefecture-industry level, using the year $\tau = -1$ as the omitted group. The regression is based on untreated observations only, which corresponds to the prefecture-industry-year observations before the first PS transfer shock for a prefecture-industry pair in our sample period (2003-2013). We keep observations up to 6 years before the treatment and exclude earlier observations. After the estimation, we further conduct an *F*-test for the joint significance of the estimated coefficients β^{τ} presented in the figure. The *F* statistics and *p*-value are reported.

C Tables

Table C1: One-period Transition Matrix of RCA

	State of $RCA(t)$		
	0	$(0, 1]$	$(1, +\infty]$
Share of total (%)	76.8	15.0	8.2
State of $RCA(t-1)$:			
0	92.1	5.2	2.7
$(0, 1]$	22.2	63.1	14.7
$(1, +\infty]$	21.8	30.8	47.4

Note: The table contains the proportion (%) of the observations with current-period RCA in three ranges given the range of the last-period RCA. The calculations are based on the sample of manufacturing sectors.

Table C2: Summary Statistics on Party Secretary Transfer Shocks and Balassa RCA

Year	PS Transfer Shock			Balassa RCA		
	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.
1997	345,234	0.002	0.043	327,188	0.440	2.296
1998	345,234	0.005	0.069	326,874	0.436	2.284
1999	345,234	0.006	0.075	327,915	0.445	2.311
2000	345,234	0.007	0.083	310,814	0.470	2.365
2001	345,234	0.010	0.098	310,516	0.472	2.367
2002	345,234	0.011	0.103	309,616	0.495	2.436
2003	345,234	0.017	0.130	310,504	0.518	2.499
2004	345,234	0.017	0.131	310,662	0.527	2.517
2005	345,234	0.021	0.144	312,006	0.544	2.553
2006	345,234	0.022	0.146	313,053	0.555	2.577
2007	345,234	0.031	0.173	309,729	0.597	2.234
2008	345,234	0.034	0.182	304,128	0.549	2.151
2009	345,234	0.036	0.187	308,525	0.552	2.154
2010	345,234	0.038	0.191	309,550	0.584	2.186
2011	345,234	0.044	0.204	307,923	0.592	2.150
2012	345,234	0.048	0.215	313,845	0.679	2.640
2013	345,234	0.052	0.222	313,956	0.712	2.641

Note: This table presents by year the number of observations, mean, and standard deviation for the dummy indicator "PS Transfer Shock" and the Balassa RCA (1% winsorized) as defined in Section 4.

Panel A. Placebo Test Using Pre-existing RCA			
Dep var: $\ln RCA$	(1) $Y(t-1)$	(2) $Y(t-2)$	(3) $\Delta Y(t-1)$
First-year PS Transfer Shock	-0.003	0.001	-0.005
	(0.005)	(0.004)	(0.006)
Observations	5,008,793	4,697,911	4,626,099
Adjusted R-squared	0.398	0.412	-0.106

Panel B. Detailed Fixed Effects Based on Official Characteristics			
Dep var: $\ln RCA$	(1)		
PS Transfer Shock	0.033***		
	(0.005)		
Cell-industry-year FE	Yes		
Observations	4,601,800		
Adjusted R-squared	0.402		

Panel C. Different Cutoffs for the Last-position RCA			
Dep var: $\ln RCA$	(1)	(2)	(3)
$\sum_{c'} Transfer_{c' \to c,t} \times 1\left\{RCA_{c'jt} > 0.5\right\}$	0.029***		
	(0.004)		
$\sum_{c'} Transfer_{c' \to c,t} \times 1\left\{RCA_{c'jt} > 2\right\}$		0.041***	
		(0.006)	
$\sum_{c'} Transfer_{c' \to c,t} \times 1\left\{RCA_{c'jt} > 5\right\}$			0.048***
			(0.008)
Observations	5,326,714	5,326,714	5,326,714
Adjusted R-squared	0.402	0.402	0.402

Panel D. Effects of Mayor Transfer Shocks			
Dep var: $\ln RCA$	(1)	(2)	(3)
Mayor Transfer Shock	0.019***	0.009***	0.015***
	(0.003)	(0.003)	(0.004)
Prefecture-sector-year FE	-	Yes	Yes
Prefecture-industry trends	-	-	Yes
Observations	5,326,714	5,326,714	5,326,714
Adjusted R-squared	0.402	0.402	0.402

Note: In Panel A, the explanatory variable "first-year PS transfer shock" is the PS transfer shock which takes one only in the first year of the tenure of the party secretary in the current prefecture. In Panels A to C, we control for prefecture-industry, prefecture-year, industry-year, and province-sector-year fixed effects, and prefecture-industry linear time trends. In Panel B, we additionally control for the cell-industry-year FE as described in Section 5.2. In Panel D, we control for prefecture-industry, prefecture-year, and industry-year fixed effects in all three regressions. The standard errors are clustered at the city-by-sector level. The regressions are based on the sample of manufacturing sectors. ***, **, * represent significance levels of 1%, 5%, and 10%, respectively.

Table C4: Robustness: Alternative Exporting Performance and Functional Forms of RCA

Dep var:	(1) Indicator for exporting	(2) Export value	(3) # Exporting firms	(4) # Destination	(5) # Products	
PS Transfer Shock	0.010***	0.178***	0.051***	0.045***	0.019***	
	(0.002)	(0.026)	(0.005)	(0.005)	(0.003)	
Outcome mean	0.257	3.184	0.520	0.559	0.364	
Observations	5,868,978	5,868,978	5,868,978	5,868,978	5,868,978	
Adjusted R^2	0.655	0.740	0.860	0.855	0.801	

Dep var:	(6) RCA	(7) $\ln(1+RCA)$	(8) $\ln(RCA)$	(9) $1\{RCA>1\}$	(10) $1\{RCA>2\}$	(11) $1\{RCA>5\}$
PS Transfer Shock	0.113***	0.028***	0.064***	0.013***	0.011***	0.007***
	(0.019)	(0.004)	(0.015)	(0.002)	(0.002)	(0.001)
Outcome mean	0.539	0.177	-0.084	0.087	0.054	0.027
Observations	5,326,714	5,326,714	1,467,311	5,326,714	5,326,714	5,326,714
Adjusted R^2	0.336	0.403	0.475	0.322	0.281	0.269

Note: An industry refers to a 4-digit HS code, and a sector refers to a 2-digit HS code. The regression sample are restricted to manufacturing industries. The dependent variable in Column (1) is an indicator for positive exports at the prefecture-industry-year level. The dependent variables are the export value, the number of exporting firms, the number of destination countries, and the number of products (6-digit HS codes) at the prefecture-industry-year level in the form of inverse hyperbolic sine in Columns (2) – (5), respectively. The dependent variables in Columns (9)-(11) are indicators for RCA being larger than 1, 2, and 5, respectively. In all regressions, we control for prefecture-industry, prefecture-year, industry-year, and province-sector-year fixed effects, and prefecture-industry linear time trends. Standard errors are clustered at the prefecture-by-sector level. ***, **, * represent significance levels of 1%, 5%, and 10%, respectively.

Table C5: Robustness: Alternative Sample Periods and Geographic Locations

Dep var: $\ln RCA_{cjt}$	Panel A. Alternative time periods		
	(1) 97-01	(2) 02-07	(3) 08-13
PS Transfer Shock	0.030***	0.034***	0.047***
	(0.015)	(0.011)	(0.008)
Outcome mean	0.164	0.207	0.283
Observations	1,600,895	1,859,233	1,855,514
Adjusted R-squared	0.695	0.602	0.310
	Panel B. Excluding special groups of cities		
	(4) Provincial capitals	(5) Sub-provincial cities	(6) Coastal cities
PS Transfer Shock	0.038***	0.037***	0.038***
	(0.005)	(0.005)	(0.006)
Outcome mean	0.200	0.204	0.198
Observations	4,850,771	5,079,964	4,576,159
Adjusted R-squared	0.386	0.388	0.384

Note: A product refers to a 4-digit HS code, and a sector refers to a 2-digit HS code. The standard errors are clustered at the city-by-sector level. The regressions are based on the sample of manufacturing sectors. In Columns (4)–(6), we exclude provincial capital cities, sub-provincial cities, and coastal cities from our regression sample, respectively. In all regressions, we control for prefecture-industry, prefecture-year, industry-year, and province-sector-year fixed effects, as well as prefecture-industry linear trends. Standard errors are clustered at the prefecture-by-sector level. ***, **, * represent significance levels of 1%, 5%, and 10%, respectively.

Table C6: Robustness Checks on Party Secretary Transfers and Local Industrial Policies

	(1)	(2)	(3)	(4)	(5)	(6)
		Dependent variable: Indicator for being a targeted industry				
	Period: 1997-2013	Excluding 2003, 2008 and 2013	Excluding 2005 and 2010	Excluding northwestern provinces	Excluding sub-provincial cities	Including mining industries
PS Transfer Shock	0.030**	0.028**	0.023**	0.022**	0.023**	0.019**
	(0.012)	(0.011)	(0.011)	(0.011)	(0.011)	(0.010)
Outcome mean	0.378	0.374	0.371	0.375	0.377	0.354
Prefecture-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Sector-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Prefecture-sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Province-sector-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	57,753	63,054	81,902	70,680	73,036	97,500
R-squared	0.710	0.702	0.692	0.687	0.697	0.695

Note: This table reports estimates of the regression for industrial policy, with different adjustments to the estimation sample. In Column (1), we change the sample period from 2003-2013 to 1997-2013, which is our sample period for the estimation of effects on local RCA as in equation (6). In Column (2), from the sample period of 2003-2013, we exclude years 2003, 2008, and 2013, which are years of central government turnover. In Column (3), we exclude years 2005 and 2010, which are years to make five-year development plans. In Column (4), we exclude provinces to the northwest of the Heihe-Tengchong Line. The six provinces are Inner Mongolia, Tibet, Gansu, Qinghai, Ningxia, and Xinjiang.[a] In Column (5), we exclude the 15 sub-provincial level cities. In Column (6), we include both manufacturing industries and mining industries. The sample period used in Columns (4)-(6) is 2003-2013. We restrict the estimation sample to manufacturing industries in Columns (1)-(5). The dependent variable is an indicator for an industry to be listed as a targeted industry in the government work report in a prefecture. An industry refers to a 2-digit CIC code. Standard errors are clustered at the prefecture level. ***, **, * represent significance levels of 1%, 5%, and 10%, respectively.

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[a]These provinces sit to the northwest of the Heihe-Tengchong Line that divides the area of China into two parts with contrasting population densities. These regions account for 57.1% of China's total area but only about 5.6% of the population.

Table C7: City Leader Rotations and Firm Entry

Dep var:	# New firms	Paid-in capital	# New firms	Paid-in capital
	(1)	(2)	(3)	(4)
PS Transfer Shock	0.017	0.048		
	(0.011)	(0.047)		
Out-rotation			0.020	0.063
			(0.022)	(0.095)
Outcome mean	1.537	1.878	1.559	1.860
Sector-year FE	Yes	Yes	Yes	Yes
Prefecture-year FE	Yes	Yes	Yes	Yes
Prefecture-sector FE	Yes	Yes	Yes	Yes
Province-sector-year FE	Yes	Yes	Yes	Yes
Observations	155,176	155,176	30,352	30,352
Adjusted R-squared	0.888	0.605	0.882	0.569

Note: Columns (1) to (2) reports estimated effect of PS transfer shocks on firm entry, as described in Section 6.2. The sample period is from 1997 to 2013. The dependent variable is the number of new firms in columns (1) and (3), and paid-in capital in columns (2) and (4), both of which are log-transformed using the inverse hyperbolic sine function. A sector refers to a 2-digit CIC code. We restrict the estimation sample to manufacturing sectors. In columns (1) and (2), the key independent variable, "PS Transfer Shock" is defined as in the baseline regression (6). In columns (3) and (4), the "leader out-rotation" refers to $Transfer_{c' \to c,t} \times 1\{RCA_{c'kT} > 1\}$ in equation (8), and the time period is three years before and three years since the out-rotation event, where $Transfer_{c' \to c,t}$ takes zero and one, respectively. Standard errors are clustered at the prefecture level. ***, **, * represent significance levels of 1%, 5%, and 10%, respectively.

D   Decomposing Revealed Comparative Advantage

This section describes the method to decomposing revealed comparative advantage measure into supply and demand factors, which takes placed in three steps. The method follows Hausmann and Xu (2019).

Step 1: Approximation of RCA

We consider the revealed comparative advantage measure proposed by Balassa (1965). Through the section, we index an exporting city as c, an importer country as d, and an HS 4-digit industry as j. The revealed comparative advantage of city c in industry j and year t is denoted by RCA_{cjt}:

$$RCA_{cjt} = \frac{\mathbb{M}_{cjt}^{M}\left(X_{dcjt}\right)/\mathbb{M}_{jt}^{EM}\left(X_{dcjt}\right)}{\mathbb{M}_{ct}^{MJ}\left(X_{dcjt}\right)/\mathbb{M}_{t}^{EMJ}\left(X_{dcjt}\right)} \times \frac{N_{cjt}^{M}/N_{jt}^{EM}}{N_{ct}^{MJ}/N_{t}^{EMJ}}, \tag{10}$$

where $X_{dcjt} > 0$ is trade flow of industry j from city c to country d at time t; Ω_{cjt}^{M} is the collection of importers buying goods from city c in industry j at t with $N_{cjt}^{M} \equiv \left\|\Omega_{cjt}^{M}\right\|$ as its measure; Ω_{jt}^{EM} is the set of trading pairs in industry j at t with measure $N_{jt}^{EM} \equiv \left\|\Omega_{jt}^{EM}\right\|$; Ω_{ct}^{MJ} is the set of importer-industry pairs for exporter c at t with measure $N_{ct}^{MJ} \equiv \left\|\Omega_{ct}^{MJ}\right\|$; Ω_{t}^{EMJ} denotes set of all importer-exporter-industry combinations with measure $N_{t}^{EMJ} \equiv \left\|\Omega_{t}^{EMJ}\right\|$. Given these definitions, we express the arithmetic mean of imports (across all foreign importers) faced by exporting city c in industry j as $\mathbb{M}_{cjt}^{M}\left(X_{dcjt}\right) = \left(\sum_{d\in\Omega_{cjt}^{M}} X_{dcjt}\right)/N_{cjt}^{M}$. Similarly, we can derive the arithmetic mean of the transactions (across all exporter-importer) in industry j at time t, i.e., $\mathbb{M}_{jt}^{EM}\left(X_{dcjt}\right) \equiv \left(\sum\sum_{c,d\in\Omega_{jt}^{EM}} X_{dcjt}\right)/N_{jt}^{EM}$, the arithmetic mean of the trade flows (across all importer-industry) faced by exporter c, i.e., $\mathbb{M}_{ct}^{MJ}\left(X_{dcjt}\right) \equiv \left(\sum\sum_{d,s\in\Omega_{ct}^{MJ}} X_{dcjt}\right)/N_{ct}^{MJ}$, and the arithmetic mean of all transactions in t, i.e., $\mathbb{M}_{t}^{EMJ}\left(X_{dcjt}\right) \equiv \left(\sum\sum\sum_{c,d,j\in\Omega_{t}^{EMJ}} X_{dcjt}\right)/N_{t}^{EMJ}$.

$$RCA_{cjt} \approx \frac{\tilde{\mathbb{M}}_{cjt}^{M}\left(X_{dcjt}\right)/\tilde{\mathbb{M}}_{jt}^{EM}\left(X_{dcjt}\right)}{\tilde{\mathbb{M}}_{ct}^{MJ}\left(X_{dcjt}\right)/\tilde{\mathbb{M}}_{t}^{EMJ}\left(X_{dcjt}\right)} \times \frac{N_{cjt}^{M}/N_{jt}^{EM}}{N_{ct}^{MJ}/N_{t}^{EMJ}} \tag{11}$$

Next, we use the geometric average of trade flows in (10), instead of the arithmetic average, hence modifying the Balassa RCA to a new formula provided in (11). The approximation allows us to decompose RCA into the contributions of different margins in a sequence of steps. The new formula (11) remains similar to (10), except that the geometric mean is used to average trade flows across all foreign importers faced by exporter

city c in industry j, i.e., $\tilde{\mathbb{M}}_{cjt}^{M}\left(X_{dcjt}\right) = \left(\prod_{d\in\Omega_{cjt}^{M}} X_{dcjt}\right)^{1/N_{cjt}^{M}}$, across all importer-industry faced by city c, i.e., $\tilde{\mathbb{M}}_{ct}^{MJ}\left(X_{dcjt}\right) \equiv \left(\prod\prod_{d,j\in\Omega_{ct}^{MJ}} X_{dcjt}\right)^{1/N_{ct}^{MJ}}$, across all exporter-importer in industry j, i.e., $\tilde{\mathbb{M}}_{jt}^{EM}\left(X_{dcjt}\right) \equiv \left(\prod\prod_{c,d\in\Omega_{jt}^{EM}} X_{dcjt}\right)^{1/N_{jt}^{EM}}$, and finally across all exporter-importer in sector s, i.e., $\tilde{\mathbb{M}}_{t}^{EMJ}\left(X_{dcjt}\right) \equiv \left(\prod\prod\prod_{c,d,j\in\Omega_{t}^{EMJ}} X_{dcjt}\right)^{1/N_{t}^{EMJ}}$.

Step 2: Decomposing RCA in CES Structure

To decompose (11), we consider the model of multi-country economy in the international framework. The preference of the representative consumer in each country is nested constant elasticity of substitution (CES). The first level CES determines the demand for each sector that consists of both tradable and non-tradable ones. Within each sector, second level CES nesting determines the demand for differentiated varieties that can be sourced from domestic or from international markets. In practice, we impose Armington assumption, defining a variety as a pair of exporter–HS 6-digit code. The aggregate unit expenditure for country d in year t is defined over the industrial price index P_{djt}^{J} for each industry $j \in \Omega^{J}$:

$$P_{dt} = \left[\sum_{j\in\Omega^{J}} \left(P_{djt}^{J}\right)^{1-\sigma^{J}}\right]^{\frac{1}{1-\sigma^{J}}}, \ \sigma^{J} > 0, \tag{12}$$

where Ω^{J} denotes the set of all industries, and σ^{J} is the elasticity of substitution across industries. Within each industry there are varieties of different kinds, which are produced by different countries. The unit expenditure (P_{djt}^{J}) for industry j depends on the prices (P_{vt}^{V}) and demand parameters (φ_{vt}^{V}) for each variety $v \in \Omega_{dcjt}^{V}$, and $\forall c \in \Omega_{djt}^{C}$:

$$P_{djt}^{J} = \left[\sum_{c\in\Omega_{djt}^{C}} \sum_{v\in\Omega_{dcjt}^{V}} \left(P_{vt}^{V}/\varphi_{vt}^{V}\right)^{1-\sigma_{j}^{V}}\right]^{\frac{1}{1-\sigma_{j}^{V}}}, \ \sigma_{j}^{V} > 1, \ \varphi_{vt}^{V} > 0, \tag{13}$$

where Ω_{djt}^{C} denotes collection of cities and countries (including d self) selling in country d, industry j in year t; Ω_{dcjt}^{V} denotes the available variety set in industry j of country d that are supplied by city c; σ_{j}^{V} is the elasticity of substitution across varieties for industry j, and φ_{vt}^{V} captures the relative demand for each variety v. One advantage of the framework is that it allows some industries to be non-traded, and allow the existence of both domestic and foreign varieties within tradable industries.

Denote the expenditure share of tradable sectors as μ_{dt}^{T}, the expenditure share of the

imported varieties within tradable sectors as μ^J_{djt}, the aggregate price indexes of the tradable sectors and of the imported varieties within tradable sectors as $\mathbb{P}^T_{dt}$ and $\mathbb{P}^S_{djt}$, respectively. We rewrite (12) and (13) as:

$$P_{dt} = \left(\mu^T_{dt}\right)^{\frac{1}{\sigma^J-1}} \mathbb{P}^T_{dt}, \quad \mu^T_{dt} = \frac{\sum_{j\in\Omega^T} \left(P^J_{djt}\right)^{1-\sigma^J}}{\sum_{j\in\Omega^J} \left(P^J_{djt}\right)^{1-\sigma^J}}, \quad \mathbb{P}^T_{jt} = \left[\sum_{j\in\Omega^T} \left(P^J_{djt}\right)^{1-\sigma^J}\right]^{\frac{1}{1-\sigma^J}} \tag{14}$$

$$P^J_{djt} = \left(\mu^J_{djt}\right)^{\frac{1}{\sigma^V-1}} \mathbb{P}^J_{djt}, \quad \mu^J_{djt} = \frac{\sum_{c\in\Omega^E_{djt}} \sum_{v\in\Omega^V_{dcjt}} \left(P^V_{vt}/\varphi^V_{vt}\right)^{1-\sigma^V_j}}{\sum_{c\in\Omega^C_{djt}} \sum_{v\in\Omega^V_{dcjt}} \left(P^V_{vt}/\varphi^V_{vt}\right)^{1-\sigma^V_j}}, \quad \mathbb{P}^J_{djt} = \left[\sum_{c\in\Omega^E_{djt}} \sum_{v\in\Omega^V_{dcjt}} \left(P^V_{vt}/\varphi^V_{vt}\right)^{1-\sigma^V_j}\right]^{\frac{1}{1-\sigma^V_j}} \tag{15}$$

where $\Omega^T \subset \Omega^J \left(\mu^T_{dt}\right)$ denotes the set of tradable industries, and $\Omega^E_{djt} \equiv \left\{\Omega^C_{djt} : c \neq d\right\}$ is the subset of foreign countries and Chinese cities supplying importer d within industry j in year t.

It is convenient to rewrite the industrial import price index ($\mathbb{P}^J_{djt}$) appearing in (15) in terms of price indexes of each exporting city within that industry ($\mathbb{P}^E_{dcjt}$):

$$\mathbb{P}^J_{djt} = \left[\sum_{c\in\Omega^E_{djt}} \left(\mathbb{P}^E_{cdjt}\right)^{1-\sigma^V_j}\right]^{\frac{1}{1-\sigma^V_j}}, \quad \mathbb{P}^E_{dcjt} = \left[\sum_{v\in\Omega^V_{dcjt}} \left(P^V_{vt}/\varphi^V_{vt}\right)^{1-\sigma^V_j}\right]^{\frac{1}{1-\sigma^V_j}} \tag{16}$$

Using the properties of the CES demand and apply them to (16), the share of variety v in the expenditure on each exporting city s^V_{vt} is given by:

$$s^V_{vt} = \frac{\left(P^V_{vt}/\varphi^V_{vt}\right)^{1-\sigma^V_j}}{\sum_{v\in\Omega^V_{dcjt}} \left(P^V_{vt}/\varphi^V_{vt}\right)^{1-\sigma^V_j}} \tag{17}$$

where exporter city and sector expenditure shares are defined analogously. We can rearrange the share term of (17) using the country price index as (16) to obtain:

$$\mathbb{P}^E_{dcjt} = \frac{P^V_{vt}}{\varphi^V_{vt}} \left(s^V_{vt}\right)^{\frac{1}{\sigma^V_j-1}}, \quad \forall v \in \Omega^V_{dcjt} \tag{18}$$

Taking logarithms on both sides, averaging across varieties within city and industry, and adding and subtracting (17), we obtain the following exact log-linear decomposition of the CES price index into four terms ($\forall v \in \Omega^V_{dcjt}$):

$$\ln \mathbb{P}^E_{dcjt} = \underbrace{\mathbb{E}^V_{dcjt} \left[\ln P^V_{vt} \right]}_{\text{Average prices}} - \underbrace{\mathbb{E}^V_{dcjt} \left[\ln \varphi^V_{vt} \right]}_{\text{Average quality \& Taste}} + \underbrace{\frac{1}{\sigma^V_j - 1} \left(\mathbb{E}^V_{dcjt} \left[\ln s^V_{vt} \right] - \ln \frac{1}{N^V_{dcjt}} \right)}_{\text{Dispersion of quality-adjusted prices}} - \underbrace{\frac{1}{\sigma^V_j - 1} \ln N^V_{dcjt}}_{\text{Variety}}$$

$$(19)$$

where $\mathbb{E}^V_{dcjt}$ denotes arithmetic operator so that $\mathbb{E}^V_{dcjt} \left[\ln P^V_{vt} \right] = \frac{1}{N^V_{dcjt}} \sum_{v \in \Omega^V_{dcjt}} \ln P^V_{vt}$; and the superscript V in $\mathbb{E}^V_{dcjt}$ indicates the mean is taken across varieties; and subscript $dcjt$ indicates the averaging operator is applied to varieties within importer d, exporter c, industry j and year t. The industrial export price index in (18) depends on the number of varieties ($\ln N^V_{dcjt}$) and dispersion of quality-adjusted prices ($\mathbb{E}^V_{dcjt} \left[\ln s^V_{vt} \right] - \ln 1/N^V_{dcjt}$) in addition to the product price ($\mathbb{E}^V_{dcjt} \left[\ln P^V_{vt} \right]$) and quality ($\mathbb{E}^V_{dcjt} \left[\ln \varphi^V_{vt} \right]$).

To relate model to RCA measure, for convenience, we introduce the operator $\xi_{cjt} \left(y_{dcjt} \right)$ as $\xi_{cjt} \left(y_{dcjt} \right) \equiv \frac{\tilde{\mathbb{M}}^M_{cjt} \left(y_{dcjt} \right) / \tilde{\mathbb{M}}^{EM}_{jt} \left(y_{dcjt} \right)}{\tilde{\mathbb{M}}^{MJ}_{ct} \left(y_{dcjt} \right) / \tilde{\mathbb{M}}^{EMJ}_{t} \left(y_{dcjt} \right)}$, where $y_{dcjt} > 0$ can be any variable that is c, d, s and t specific. Importer d's expenditure on exporter city c as a share of its expenditure on all export from China within industry j in year t as:

$$\mathbb{S}^E_{dcjt} = \frac{\sum_{v \in \Omega^V_{dcjt}} \left(P^V_{vt} / \varphi^V_{vt} \right)^{1-\sigma^V_j}}{\sum_{c \in \Omega^E_{djt}} \sum_{v \in \Omega^V_{dcjt}} \left(P^V_{vt} / \varphi^V_{vt} \right)^{1-\sigma^V_j}} = \frac{\left(\mathbb{P}^E_{dcjt} \right)^{1-\sigma^V_j}}{\left(\mathbb{P}^S_{djt} \right)^{1-\sigma^V_j}} = \frac{X_{dcjt}}{\sum_{c \in \Omega^E_{djt}} X_{dcjt}}, \quad (20)$$

where the numerator denotes importer d's price index for exporting city c in industry j at time t ($\mathbb{P}^E_{dcjt}$); the denominator captures importer d's overall import price index from China in industry j at time t ($\mathbb{P}^S_{djt}$). Then we use $\mathbb{S}^E_{dcjt}$ and country d's total import from China in industry j (i.e., $\mathbb{X}^E_{djt} = \sum_{c \in \Omega^E_{djt}} X_{dcjt}$) to substitute for the trade flow from city c to country d in industry j (i.e., X_{dcjt}) in the adjusted RCA_{cjt} appearing in equation (11):

$$RCA_{cjt} = \xi_{cjt} \left(\mathbb{S}^E_{dcjt} \right) \times \xi_{cjt} \left(\mathbb{X}^E_{djt} \right) \times \frac{N^M_{cjt} / N^{EM}_{jt}}{N^{MJ}_{ct} / N^{EMJ}_t}, \quad (21)$$

where N^M_{cjt} is the number of destinations importing goods j from c; N^{EM}_{jt} is the number of country pairs with positive trade flow in industry j; N^{MS}_{ct} is the number of destination-industry pairs with positive trade flow sourcing from country c; N^{EMJ}_t denotes the number of importer-exporter-industry pairs with positive trade flow. Using (20) and (21), we derive the decomposition of a city's RCA as:

$$RCA_{cjt} = \xi_{cjt} \left(\left[\mathbb{P}^E_{dcjt} \right]^{1-\sigma^V_j} \right) \times \xi_{cjt} \left(\text{S, w, L} \right) \times \frac{N^M_{cjt} / N^{EM}_{jt}}{N^{MJ}_{ct} / N^{EMJ}_t}, \quad (22)$$

and

$$\xi_{cjt}\left(\mathrm{S},\mathrm{w},\mathrm{L}\right) \equiv \xi_{cjt}\left([S_{djt}]^{\frac{\sigma_j^V - \sigma^J}{1-\sigma^J}}\right) \times \xi_{cjt}\left([w_{dt}/P_{dt}]^{1-\sigma_j^V}\right) \times \xi_{cjt}\left(w_{dt}^{\sigma_j^V} L_{dt}\right), \qquad (23)$$

where S, w and L denote the vector of industry shares, real income, and population. Specifically, $\xi_{cjt}\left([S_{djt}]^{\frac{\sigma_j^V - \sigma^J}{1-\sigma^J}}\right)$ captures the average expenditure share on industry j across the global markets; $\xi_{cjt}\left([w_{dt}/P_{dt}]^{1-\sigma_j^V}\right)$ capture the average real income across destination markets depending on the nominal average income and price level, and $\xi_{cjt}\left(w_{dt}^{\sigma_j^V} L_{dt}\right)$ reflects the total market size adjusted by the elasticity of substitution. All the variables appearing in (23), i.e., industry shares S_{cjt}, real incomes w_{dt}/P_{dt}, nominal per capita GDP w_{dt} and population L_{dt} are observables in the data. The last component in (22) captures the relative number of "customers" a country is trading with. To breakdown the price index $\mathbb{P}_{dcjt}^E$ in (22), we take logs on both sides of the equation (22) and substitute $\ln\left(\mathbb{P}_{dcjt}^E\right)$ using equation (19), which yields the exact log-linear decomposition of RCA as:

$$\ln RCA_{cjt} \approx \underbrace{\underbrace{\ln\left(RCA_{cjt}^P\right) + \ln\left(RCA_{cjt}^{\varphi^S}\right)}_{\text{Average prices}} + \underbrace{\ln\left(RCA_{cjt}^S\right)}_{\text{Dispersion quality-adjusted prices}} + \underbrace{\ln\left(RCA_{cjt}^N\right)}_{\text{Variety}}}^{\text{Supply-side factors}}$$

$$+ \underbrace{\underbrace{\ln\left(RCA_{cjt}^{\varphi^D}\right)}_{\text{Average Taste}} + \underbrace{\ln\left[RCA_{cjt}\left(\mathrm{S},\mathrm{w},\mathrm{L}\right)\right]}_{\text{Average Market Size}} + \ln\left[\overbrace{\frac{N_{cjt}^M/N_{jt}^{EM}}{N_{ct}^{MJ}/N_t^{EMJ}}}^{\text{Number of "Customers"}}\right]}_{\text{Demand-side factors}}, \qquad (24)$$

where each margin is defined in the following. The decomposition in (24) provides a close link between theory and data. Using the decomposition equation, we can decompose RCA change into supply and demand related factors.

$$\ln\left(RCA_{cjt}^N\right) = \left\{ \begin{array}{l} \left[\frac{1}{N_{cjt}^M}\sum_{d\in\Omega_{cjt}^M}\ln N_{dcjt}^V - \frac{1}{N_{jt}^{EM}}\sum\sum_{d,c\in\Omega_{jt}^{EM}}\ln N_{dcjt}^V\right] \\ -\left[\frac{1}{N_{ct}^{MJ}}\sum\sum_{d,j\in\Omega_{ct}^{MJ}}\ln N_{dcjt}^V - \frac{1}{N_t^{EMJ}}\sum\sum\sum_{d,c,j\in\Omega_t^{EMJ}}\ln N_{dcjt}^V\right] \end{array} \right\}$$

$$\ln\left(RCA_{cjt}^P\right) = \left\{ \begin{array}{l} \left(1-\sigma_j^V\right)\left[\frac{1}{N_{cjt}^M}\sum_{d\in\Omega_{cjt}^M}\mathbb{E}_{dcjt}^V\left[\ln P_{vt}^V\right] - \frac{1}{N_{jt}^{EM}}\sum\sum_{d,c\in\Omega_{jt}^{EM}}\mathbb{E}_{dcjt}^V\left[\ln P_{vt}^V\right]\right] \\ -\left[\frac{1}{N_{ct}^{MJ}}\sum\sum_{d,j\in\Omega_{ct}^{MJ}}\left(1-\sigma_j^V\right)\mathbb{E}_{dcjt}^V\left[\ln P_{vt}^V\right] - \frac{1}{N_t^{EMJ}}\sum\sum\sum_{d,c,j\in\Omega_t^{EMJ}}\left(1-\sigma_j^V\right)\mathbb{E}_{dcjt}^V\left[\ln P_{vt}^V\right]\right] \end{array} \right\}$$

$$\ln\left(RCA_{cjt}^{\varphi^S}\right) = \left\{ \begin{array}{l} \left(\sigma_j^V-1\right)\left[\frac{1}{N_{cjt}^M}\sum_{d\in\Omega_{cjt}^M}\mathbb{E}_{dcjt}^V\left[\ln\varphi_{cvt}^V\right] - \frac{1}{N_{jt}^{EM}}\sum\sum_{d,c\in\Omega_{jt}^{EM}}\mathbb{E}_{dcjt}^V\left[\ln\varphi_{cvt}^V\right]\right] \\ -\left[\frac{1}{N_{ct}^{MJ}}\sum\sum_{d,j\in\Omega_{ct}^{MJ}}\left(\sigma_j^V-1\right)\mathbb{E}_{dcjt}^V\left[\ln\varphi_{cvt}^V\right] - \frac{1}{N_t^{EMJ}}\sum\sum\sum_{d,c,j\in\Omega_t^{EMJ}}\left(\sigma_j^V-1\right)\mathbb{E}_{dcjt}^V\left[\ln\varphi_{cvt}^V\right]\right] \end{array} \right\}$$

$$\ln\left(RCA_{cjt}^{\varphi^D}\right) = \left\{ \begin{array}{l} \left(\sigma_j^V-1\right)\left[\frac{1}{N_{cjt}^M}\sum_{d\in\Omega_{cjt}^M}\mathbb{E}_{dcjt}^V\left[\ln\varphi_{dvt}^V\right] - \frac{1}{N_{jt}^{EM}}\sum\sum_{d,c\in\Omega_{jt}^{EM}}\mathbb{E}_{dcjt}^V\left[\ln\varphi_{dvt}^V\right]\right] \\ -\left[\frac{1}{N_{ct}^{MJ}}\sum\sum_{d,j\in\Omega_{ct}^{MJ}}\left(\sigma_j^V-1\right)\mathbb{E}_{dcjt}^V\left[\ln\varphi_{dvt}^V\right] - \frac{1}{N_t^{EMJ}}\sum\sum\sum_{d,c,j\in\Omega_t^{EMJ}}\left(\sigma_j^V-1\right)\mathbb{E}_{dcjt}^V\left[\ln\varphi_{dvt}^V\right]\right] \end{array} \right\}$$

$$\ln\left(RCA^S_{cjt}\right) = -\left\{ \begin{array}{l} \left[\frac{1}{N^M_{cjt}}\sum_{d\in\Omega^M_{cjt}}\left(\mathbb{E}^V_{dcjt}\left[\ln s^V_{vt}\right] - \ln\frac{1}{N^V_{dcjt}}\right) - \frac{1}{N^{EM}_{jt}}\sum\sum_{d,c\in\Omega^{EM}_{jt}}\left(\mathbb{E}^V_{dcjt}\left[\ln s^V_{vt}\right] - \ln\frac{1}{N^V_{dcjt}}\right)\right] \\ -\left[\frac{1}{N^{MJ}_{ct}}\sum\sum_{d,j\in\Omega^{MJ}_{ct}}\left(\mathbb{E}^V_{dcjt}\left[\ln s^V_{vt}\right] - \ln\frac{1}{N^V_{dcjt}}\right) - \frac{1}{N^{EMJ}_{t}}\sum\sum\sum_{d,c,j\in\Omega^{EMJ}_{t}}\left(\mathbb{E}^V_{hlkt}\left[\ln s^V_{vt}\right] - \ln\frac{1}{N^V_{dcjt}}\right)\right] \end{array}\right\}$$

$$\ln RCA_{cjt}\left(\mathrm{S},\mathrm{w},\mathrm{L}\right) \equiv \ln\left[\xi_{cjt}\left([S_{jst}]^{\frac{\sigma^V_j-\sigma^J}{1-\sigma^J}}\right)\times\xi_{cjt}\left([w_{jt}/P_{jt}]^{1-\sigma^V_j}\right)\times\xi_{cjt}\left(w^{\sigma^V_j}_{jt}L_{jt}\right)\right]$$

Step 3: Parameter Calibration

Parameters of Lowest-tier of Demand

To apply the decomposition equation, we need estimate the elasticities of substitution (σ^J, σ^V_j), and recover consumer perceived quality for varieties (φ^V_{vt}).

Estimation of σ^V_j in the lowest-tier of demand follows the standard approach proposed by Feenstra (1994), which are later improved and applied by various studies such as Broda and Weinstein (2006); Hottman et al. (2016); Redding and Weinstein (2017); Feenstra et al. (2020). Starting from equation (17) that characterizes the share of variety v in the expenditure on each exporter city, we take the time difference and the difference relative to another variety (i.e., reference variety) consumed in the same industry and by the same importer. The double-differencing yields:

$$\Delta^{k,t}\ln j^V_{vt} = \left(1 - \sigma^V_j\right)\Delta^{k,t}\ln p^V_{vt} + \omega_{vt} \tag{25}$$

where k indicates the reference variety consumed by the same importer in industry j. The unobserved error term $\omega_{vt} \equiv \left(1 - \sigma^V_j\right)\left[\Delta^t\ln\varphi^V_{kt} - \Delta^t\ln\varphi^V_{vt}\right]$ captures the idiosyncratic double-differenced demand shocks. Next, we assume the total variable costs for exporter city c to supply importer d with variety v is

$$V_{dcvt}\left(Q_{dcvt}\right) = z_{dcvt}Q^{1+\delta_j}_{dcvt} \tag{26}$$

where Q_{dcvt} denotes the total quantity of variety v supplied by exporter city c in importing country d; parameter δ_j determines the convexity of marginal cost with respect to output for varieties in industry j; z_{dcjt} is an importer-exporter-variety specific shifter of the cost function. Costs are paid in terms of a composite factor input that is chosen the numeraire. We require δ_j to be greater than zero, which will be estimated. We consider the global market structure is perfect competition so that price equals marginal cost, i.e., $p^V_{vt} = \tau_{dcjt}\left(1 + \delta_j\right)z_{vt}Q^{\delta_j}_{vt}$. Given that $Q_{vt} = S^V_{vt}X_{dcjt}/p^V_{vt}$ where X_{dcjt} denotes the total purchase by importer d from exporter city c in industry j, the pricing equation can be written

in the double-differenced form as:

$$\Delta^{k,t} \ln P_{vt}^V = \frac{\delta_j}{1 + \delta_j} \Delta^{k,t} \ln s_{vt}^V + \kappa_{vt} \tag{27}$$

where the unobserved error term $\kappa_{vt} \equiv \frac{1}{1+\delta_j} [\Delta^t \ln z_{vt} - \Delta^t \ln z_{kt}]$ captures the idiosyncratic double differenced supply shocks. The orthogonality condition for each variety is then defineds as:

$$G\left(\boldsymbol{\beta}_j\right) = \mathbb{E}_T \left[\omega_{vt}\left(\boldsymbol{\beta}_j\right) \kappa_{vt}\left(\boldsymbol{\beta}_j\right) \right] = 0 \tag{28}$$

where $\boldsymbol{\beta}_j = \begin{pmatrix} \sigma_j^V \\ \delta_j \end{pmatrix}$. The condition provided by (28) assumes that the idiosyncratic demand and supply shocks at the variety level are independent, since the variety and variety-year fixed effects have been differenced out. For each industry j, we stack the orthogonality conditions to form the GMM objective function:

$$\hat{\boldsymbol{\beta}}_j = argmax_{\boldsymbol{\beta}_j} \left\{ G^*\left(\boldsymbol{\beta}_j\right)' W G^*\left(\boldsymbol{\beta}_j\right) \right\} \tag{29}$$

where $G^*\left(\boldsymbol{\beta}_j\right)$ denotes counterpart of $G\left(\boldsymbol{\beta}_j\right)$ in the data that are stacked over all varieties in industry j, and W is a positive definite weighting matrix. We give more weight to varieties which has bigger quantity in the data.

Product Quality and Taste Parameters

After we obtain the elasticities, we then recover the taste parameters. We express the taste parameters relative to the variety whose sales is at the median level, and we recover the taste parameters from the relationship characterized below:

$$\ln\left(s_{dcvt}/s_{dvt}^{med}\right) = \left(1 - \sigma_j^V\right) \ln \left[P_{dcvt}^V/P_{dvt}^{V,med} \right] + \left(\sigma_j^V - 1\right) \ln \left(\varphi_{dcvt}^V/\varphi_{dvt}^{V,med} \right) \tag{30}$$

where s_{dvt}^{med} and $P_{dvt}^{V,med}$ denote the sales share and price for the variety whose sales is at the median level in industry j and country d. We recover variety quality using (30) and normalize quality relative to that of the median-sales variety, i.e, $\ln \varphi_{dvt}^{V,med} = 0$ by normalization. We further split variety v's consumer perceived quality into two components as provided below:

$$\ln\left(\varphi_{dcvt}^V\right) = \ln\left(\varphi_{dvt}^V\right) + \ln\left(\varphi_{cvt}^V\right) + \epsilon_{dcvt} \tag{31}$$

where $\ln\left(\varphi_{dvt}^V\right)$ denotes the importer-specific component in quality which we interpret as *consumer taste*, and $\ln\left(\varphi_{cvt}^V\right)$ stands for the exporter-specific component in quality which we interpret as *product quality*. The residual term ϵ_{dcvt} denotes any other idiosyncratic reasons affecting importer d's perceived quality of variety v produced by city c. Computationally, importer-specific component $\ln\left(\varphi_{dvt}^V\right)$ is calculated by averaging $\ln\left(\varphi_{dcvt}^V\right)$ across all varieties purchased by country d in industry j; exporter-specific component $\ln\left(\varphi_{cvt}^V\right)$ is calculated by averaging $\ln\left(\varphi_{dcvt}^V\right)$ across all varieties sold by exporting city c in industry j; the idiosyncratic taste shocks ϵ_{dcvt} is what's left after subtracting the importer and exporter-specific components from the recovered variety quality.

Parameters of Upper-tier of Demand

With the estimates of σ_j^V and taste parameters, we could calculate the import price index $\mathbb{P}_{djt}^S = \left[\sum_{c\in\Omega_{djt}^E}\sum_{v\in\Omega_{dcjt}^V}\left(P_{vt}^V/\varphi_{vt}^V\right)^{1-\sigma_j^V}\right]^{\frac{1}{1-\sigma_j^V}}$, and we now turn to estimate the elasticities across industries σ^J. Recall that the expenditure share of industry j in country d as $S_{djt} = \left(P_{djt}^G\right)^{1-\sigma^J}\left(P_{dt}\right)^{1-\sigma^S}$, and the import share of industry s as $\mu_{djt}^J = \left(\mathbb{P}_{djt}^S\right)^{1-\sigma^V}\left(P_{djt}^J\right)^{1-\sigma^V}$, one could rewrite the industry share as:

$$S_{djt} = \left(\mu_{djt}^J\right)^{\frac{1-\sigma^J}{1-\sigma_j^V}}\left(\mathbb{P}_{djt}^G\right)^{1-\sigma^J}\left(P_{jt}\right)^{\sigma^J-1} \tag{32}$$

We take the time difference and the difference relative to another industry (let it be h) in country d. The double-differencing of (32) yields:

$$\Delta^{h,t}\ln S_{djt} = \left(\frac{1-\sigma^J}{1-\sigma_j^V}\right)\Delta^{h,t}\ln\mu_{djt}^G + \left(1-\sigma^J\right)\Delta^{h,t}\ln\mathbb{P}_{djt}^J \tag{33}$$

Instead of directly estimating σ^J by running an OLS on (33), one can also use an instrumental variables approach. Noting that import price index $\mathbb{P}_{djt}^J$ can be written as:

$$\Delta^{h,t}\ln\mathbb{P}_{djt}^J = \underbrace{\left(\frac{1}{1-\sigma_j^V}\right)\Delta^{h,t}\ln\overline{s_{vt}} + \Delta^{h,t}\ln\overline{P_{vt}^V}}_{\text{Instrument}} - \Delta^{h,t}\ln\overline{\varphi_{vt}^V}$$

where $\overline{s_{vt}}$ and $\overline{P_{vt}^V}$ stand for the geometric average of variety shares and prices across all varieties within the import basket of importer d in industry j. We use the first two terms as the instrument to $\Delta^{h,t}\ln\mathbb{P}_{djt}^S$. To apply the decomposition method, we require two share terms that are not available in data, namely, country d's expenditure share for industry j (HS 4-digit), S_{djt}, and import share in industry j, μ_{djt}^S. Alternatively, we infer these statistics by combining United Nations Comtrade Database (UN Comtrade), and

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the National Accounts Main Aggregate Database (NAMAD).

E   A Comparison with the Effect of FDI on Local Revealed Comparative Advantage

To evaluate the economic significance of the estimated effect of political rotation on local RCA, we compare our estimates with the effect of foreign direct investment (FDI). To this end, we follow Lu et al. (2017) and exploit the relaxation of FDI regulations in China upon China's accession to WTO at the end of 2001 to identify the effect of FDI on local RCA.

We base our analysis on the Annual Survey of Industrial Firms (ASIF) database during the 1998-2007 period. The dataset covers all state-owned enterprises (SOEs) and also covers non-SOEs with annual sales over 5 million RMB in China. The dataset contains information of ownership structure for each firm, which is used to construct city-industry level FDI shares.

We estimate the following equation:

$$Y_{cjt} = \alpha_{cj} + \gamma_{ct} + \delta FDIshare_{cjt} + \varepsilon_{cjt}, \tag{34}$$

where c, j, and t denote cities, CIC 4-digit industries, and years, respectively. Y_{cjt} is the outcome variable, and we focus on local RCA in the functional form of inverse hyperbolic sine. α_{cj} and γ_{ct} are city-industry and city-year fixed effects, respectively. $FDIshare_{cjt}$ is the key explanatory variable, i.e., the output share of FDI at the city-industry level. We do not control for industry-year fixed effects because we want to use the plausibly exogenous variation in FDI regulations across industries and time as instruments for the identification. ε_{cjt} is the error term. We cluster standard errors at the city level, as in our baseline specification for the effect of political rotation.

Our regressor of interest, $FDIshare_{cjt}$, is defined as in the literature:

$$FDIshare_{cjt} = \frac{\sum_{f \in \Omega_{cjt}} FDI\_Firm_{fcjt} \times Output_{fcjt}}{\sum_{f \in \Omega_{cjt}} Output_{fcjt}},$$

where $Output_{fcjt}$ measures the output of firm f of industry j in city c in year t; FDI_Firm fit measures the foreign equity share of firm f of industry j in city c in year t; and Ω_{cjt} is the set of firms in industry j of city c in year t.

To identify the effect of FDI on local RCA, we use variations in the changes in FDI regulations at the end of 2001 across industries as an instrument for the variable $FDIshare_{cjt}$

to identify the effect of FDI on local RCA. Following Lu et al. (2017), we define the treatment group as the encouraged industries and use the no-change industries as the control group.[42] The first stage regression is specified as

$$FDIshare_{cjt} = \alpha_{cj} + \gamma_{ct} + \eta Treatment_j \times Post02_t + \zeta_{cjt},$$

where $Treatment_j$ is an indicator for whether industry j belongs to the treatment group; and $Post02_t$ is a variable indicating the post-WTO period, i.e., $Post02_t = 1$ if $t > 2002$, $3/4$ if $t = 2002$, and 0 if $t < 2002$.

The 2SLS estimate of δ in Eq. (34) is 3.890, which is statistically significant at the 5% level. This indicates that 1-percentage-point increase in the FDI output share is associated with a 3.9 percent increase in local RCA. Our baseline results for the effect of political rotation reveal that a party secretary transfer shock increases local RCA annually by 3.5 percent, which corresponds to the effect of an increase in local FDI share by 0.9 percentage points. This is equivalent to a 7.5 percent increase relative to the average FDI share across cities and industries (12 percentage points). Additionally, using the output value across cities and industries, we can calculate that an 0.9-percentage-point increase in the FDI share corresponds to a 3.4 percent increase in the FDI value at the city-industry level.

F Measuring Industrial Policy

We present the details of how we construct industrial policy measures based on the annual work report announced by the city-level government, which consists of four main steps.

Step 1: Tagging the Annual Report

The city-level government work report is usually made at the beginning of the year. Our first step is distinguishing between the content related to "summarizing the past" and those about "planning for the future." We only focus on the latter in textual analysis. We distinguish them according to the subtitles of the government work report. A standard structure of government work report includes summarizing last year's work, planning for this coming year, and the disclosure of how to strengthen the government's self-improvement, as displayed in Figure F6 where we mark paragraphs associated with each purpose, respectively.

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[42]We exclude 7 discouraged industries and 5 mixed industries as classified in Lu et al. (2017).

Figure F6: Structure of Government Annual Work Reports (Shijiazhuang City in 2014)

一、2013 年主要工作回顾 **Review of Main Work in 2013**

刚刚过去的一年，我们在省委、省政府和市委的正确领导下，紧紧围绕转型升级、跨越赶超、建设幸福石家庄的总目标，着力稳增长、调结构、抓改革、惠民生，较好地完成了市十三届人大一次会议确定的目标任务。

二、2014 年主要工作任务 **Main Tasks in 2014**

今年是贯彻落实党的十八届三中全会精神、全面深化改革的第一年，是加快建设大省省会、实现跨越赶超、绿色崛起的重要一年，是完成"十二五"规划目标、率先全面建成小康社会的关键一年。做好今年工作意义重大，挑战与机遇并存。从面临挑战看，国际经济仍将延续缓慢复苏态势，不确定因素依然很多；我国经济发展进入由速度规模型向质量效益型转变时期，经济增长内生动力不足，下行压力依然较大；我市正处于转型发展的攻坚时期，面临着调整

三、切实加强政府自身建设 **Strengthen the government's self-improvement**

改革发展的繁重任务，对政府工作提出了新的更高要求。必须加快转变政府职能，努力创新管理方式，以更加饱满的热情、更加务实的举措，提振精气神，汇聚正能量，加快建设人民满意的服务型政府。

Step 2: Extracting Information Revealing Industrial Policies

Next, in paragraphs related to "planning for the future", we extract sentences containing the intent of promoting sectors. Particularly, we focus on sentence that reveals a supportive attitude toward various industrial activities, which include three main types of information related with:

1. supporting the development of industrial activities: This information delivers the direct intent of promoting specific sectors. For instance, the annual report of Putian City in 2006 clearly states that the local government plans to "formulate and improve the development plan of ten major industrial clusters, and cultivate emerging sectors such as arts and crafts, antique furniture, forest products processing, medical and medical supplies. In addition, the plan further aims to expand traditional sectors such as electronic information, shoe making, textile and clothing, food processing, and support growth sectors such as energy, chemical, and machinery manufacturing." (Putian, 2006). The Chinese version is provided below:

"制定和完善十大产业集群发展规划，培育工艺美术与仿古家具、林产加工、医药医疗用品等新兴产业，壮大电子信息、制鞋、纺织服装、食品加工等传统产业，扶持能源、化工、机械制造等成长产业。"（莆田市，*2006*）

2. promoting technological upgrading: Although not explicitly stated as a positive intent to develop certain sectors, some policies are described as promoting technology upgrading. For instance, the annual report of Fuzhou City in 2002 states that the government plans to "drive industrialization with informatization, and actively use high- and advanced-applicable technology to transform traditional sectors such as machinery, light textile, chemical industry, and building materials, and improve the competitiveness of our traditional sectors." (Fuzhou, 2002). The Chinese version is provided below:

"以信息化带动工业化，积极运用高新技术、先进适用技术改造机械、轻纺、化工、建材等传统产业，提高我市传统工业的竞争力。"（福州，*2002*）

3. establishing industrial parks: We also consider establishing industrial parks as location-specific industrial policy instruments. For instance, the annual report of Fuzhou City in 2008 states that the government plans "to accelerate the upgrading, expansion and functional transformation of Fuzhou and Rongqiao Economic & Technological Development Zones, along with industrial concentration areas such as Qingkou, Jiangyin, Luoyuan Bay, Binhai, Yuanhong; in addition, the government would promote the construction of industrial parks for deep aluminum processing, stainless steel, and photoelectric industrial

parks, as well build the electromechanical industrial park for Japan and Taiwan."(Fuzhou, 2008). The Chinese version is provided below:

"加快福州、融侨经济技术开发区和青口、江阴、罗源湾、滨海、元洪等工业集中区的提升扩容、功能转型，推进铝深加工产业园、不锈钢产业园、光电科技园、日本工业园、台湾机电工业园等园区建设。"（福州，*2008*）

All the above content is identified and extracted manually by 22 research assistants through all 0.11 million documents. Further, to minimize the measurement error resulting from the manual collection, we formulate a unified extract description and set up a cross-check and quality control mechanism. The average time of information extraction in each city exceeds 2.5 hours.

F.1 Step 3: Segmenting Sector-specific Keywords

Based on the sentences we extracted from the last step, we segment the corpus and identify sector-specific keywords using the Term Frequency-Inverse Document Frequency (TF-IDF) algorithm. First, we use the Jieba package in Python with Paddle Mode to segment the corpus into words, each containing 1-3 Chinese characters. We then re-combine these words into phrases that are in the form of "noun", "noun+noun", "noun+verb", or "adj.+noun". The procedures are well demonstrated by panel A of Table F8. For instance, the phrase "培育工艺美术" (i.e., cultivate arts and crafts) in the first row is divided into three words "培育" (verb: cultivate), "工艺" (noun: arts), and "美术" (noun: crafts), where the latter two words have a similar meaning in Chinese. The three words are further re-combined so that only the phrase "工艺美术" (noun: arts and crafts) is kept as it is a phrase in the form of "noun+noun". Likewise, "机械制造" (i.e., the phrase in the form of "noun+verb" and meaning machinery manufacturing), "纺织服装" (i.e., the phrase in the form of "noun+noun" and meaning textile clothing), and "能源" (i.e., the phrase in the form of "noun" and meaning energy) are extracted for the second, third, and fourth row of Table F8, respectively.

After the word segmentation, the original corpus is divided into phrases. For each phrase, we compute the measure capturing its relative importance in the document using the TF-IDF algorithm. The method uses the frequency of words to determine how relevant those words are to a given document, which is a relatively simple but intuitive approach to weighting words. The formula is as shown below:

Table F8: Examples of segmentation process

Panel A: Examples of segmentation process in Chinese				
Original text	Segmented words			Remaining phrase
"培育工艺美术"	"培育" (verb)	"工艺" (noun)	"美术" (noun)	"工艺美术"
"机械制造"	"机械" (noun)	"制造" (verb)		"机械制造"
"纺织服装"	"纺织" (noun)	"服装" (noun)		"纺织服装"
"扶持能源"	"扶持" (verb)	"能源" (noun)		"能源"
Panel B: Corresponding English translation				
Original text	Segmented words			Remaining phrase
"cultivate industrial art"	"cultivate"	"craft"	"art"	"industrial art"
"machinery manufacturing"	"machine"	"manufacture"		"machinery manufacturing"
"textile clothing"	"textile"	"clothing"		"textile clothing"
"support energy"	"support"	"energy"		"energy"

$$TF - IDF_i = TF_i * IDF_i$$

$$= \text{occurrence probability of phrase } i * \log\left(\frac{D}{N_i}\right),$$

where the TF_i measures the number of the phrase i of government work report as a share of the total number of phrases after step 2, and the IDF_i reflects i's logged inverse probability of occurrence in reference documents. D is the number of all documents of the reference Corpus. N_i is the number of documents that contain the phrase i. When phrase i occurs in all reference documents, the IDF_i would become zero. A commonly used reference document in the textual analysis is the Chinese Web Corpus (zhTenTen).[43] The above formula we adopted is a common way in data science (Manning et al., 2008). The greater value of the TF-IDF score, the more important the phrase appears in the annual work report of local governments; hence, the economic activities linked to the phrase are considered more important and supported. Finally, we retain 650 keywords with the

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[43]The Chinese Web Corpus (zhTenTen) is a Chinese corpus of texts collected from the Internet. The corpus belongs to the TenTen corpus family, which is a set of web corpora built using the same method with a target size of 10+ billion words. Sketch Engine currently provides access to TenTen corpora in more than 30 languages. The corpora are built using technology that collects only linguistically valuable web content. Data from the last version of the Chinese web corpus was crawled by the SpiderLing web spider in August and November 2017 and comprised of more than 15.9 billion words. The corpus was processed with Stanford NLP Core Tools. For detailed information on the data, see Jakubíček et al. (2013).

highest TF-IDF score that describe sector characters.

F.2 Step 4: Mapping

Because the description of the annual work report is not specific enough to help us identify 3-digit or 4-digit industries, we map the keywords from the previous step to the 2-digit level Chinese Industry Classification code.[44]

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[44]Before mapping, we removed some keywords that could not be identified with specific sectors, such as "industrial park" (" 产业园" in Chinese), "cluster development" (" 集群发展" in Chinese), "independent innovation" (" 自主创新" in Chinese). In practice, the description of the annual work report is not specific enough. For instance, the description would mention the development plan for the textile and clothing sector (" 纺织服装" in Chinese, whose 2-digit CIC code is 18) but will not state whether to develop woven clothing manufacturing (" 机织服装制造" in Chinese, whose 3-digit CIC code is 181) or knitted or crocheted clothing manufacturing (" 针织或钩针编织服装制造" in Chinese, whose 3-digit CIC code is 182), or will not distinguish between sports woven clothing manufacturing (" 运动机织服装制造" in Chinese, whose 4-digit CIC code is 1811) and other machine-made clothing manufacturing (" 其他机织服装制造" in Chinese, whose 4-digit CIC code is 1819).

Table F9: Examples: keywords and their corresponded CIC 2-digit Codes

Keyword	Industries
Category 1	
agricultural product processing ("农产品加工" in Chinese)	13 agricultural and non-staple food processing industry ("农副食品加工业" in Chinese)
chemical industry ("化工产业" in Chinese)	26 chemical raw materials and chemical products manufacturing industry ("化学原料和化学制品制造业" in Chinese)
salt chemical industry ("盐化工" in Chinese)	26 chemical raw materials and chemical products manufacturing industry ("化学原料和化学制品制造业" in Chinese)
coal chemical industry ("煤化工" in Chinese)	25 petroleum, coal and other fuel processing industry ("石油、煤炭及其他燃料加工业" in Chinese)
Category 2	
metallurgy ("冶金" in Chinese)	31 ferrous metal smelting and rolling industry ("黑色金属冶炼和压延加工业" in Chinese); 32 non-ferrous metal smelting and rolling industry ("有色金属冶炼和压延加工业" in Chinese);
Category 3	
high-end equipment ("高端装备" in Chinese)	34 general equipment manufacturing industry ("通用设备制造业" in Chinese); 35 special equipment manufacturing industry ("专用设备制造业" in Chinese); 36 automobile manufacturing industry ("汽车制造业" in Chinese); 37 railway, ship, aerospace and other transportation equipment manufacturing industry ("铁路、船舶、航空航天和其他运输设备制造业" in Chinese); 38 electrical machinery and equipment manufacturing industry ("电气机械和器材制造业" in Chinese); 39 computer, communication and other electronic equipment manufacturing industry ("计算机、通信和其他电子设备制造业" in Chinese); 40 instrument manufacturing industry ("仪器仪表制造业" in Chinese)

Notes: The 2-digit codes listed in the second column are from the Industrial Classification of National Economy (GB/T4754-2017). The classification of industries involved in high-end equipment refers to the Classification of Strategic Emerging Industries (2018) issued by the National Bureau of Statistics. Most equipment manufacturing industries have high-end segments. Therefore, almost all equipment manufacturing industries are involved.

The mapping process divides keywords into three categories, and the final industrial measures are based on the first two types of keywords. The first category of keywords could exactly be matched to certain 2-digit CIC codes. For instance, as shown in Table F9, "agricultural products processing" ("农产品加工" in Chinese) and "chemical sector" ("化工产业" in Chinese) could be mapped to agricultural and non-staple food processing sector ("农副食品加工业" in Chinese, whose 2-digit CIC code is 13) and chemical raw materials and chemical products manufacturing sector ("化学原料和化学制品制造业" in Chinese, whose 2-digit CIC code is 26), respectively. Keywords in the second category could be mapped into no more than three 2-digit CIC codes. For instance, in Table F9, "metallurgy" ("冶金" in Chinese) could be mapped into ferrous metal grinding and rolling sector ("黑色金属冶炼和压延加工业" in Chinese, whose 2-digit CIC code is 31) and non-ferrous metal smelting and rolling sector ("有色金属冶炼和压延加工业" in Chinese, whose 2-digit CIC code is 32). In this case, we consider all these possible 2-digit CIC sectors mentioned in the annual work report. Lastly, the third category consists of keywords that could be mapped into more than three 2-digit CIC codes. For instance, as shown in Table F9, the key "high-end equipment" ("高端装备" in Chinese) could potentially be mapped to seven 2-digit CIC codes, which involves almost all equipment manufacturing sectors. On the other hand, "high-end equipment" tend to be frequently mentioned in many annual work reports by the local government to cater to the central government's development plan, which has nothing to do with local industrial policies. Therefore, we do not consider sectors linked by keywords in the third category because large measurement errors could be introduced if they are considered supported sectors.[45] Finally, our measure of industrial policy ($IndPol_{ckt}$) is constructed as follows:

$$IndPol_{ckt} = \begin{cases} 1 & : \text{sector } k \text{ is positively mentioned in the annual report by city } c \text{ in year } t \\ 0 & : \text{otherwise} \end{cases}$$

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[45]We do not use the fuzzy matching method to match keywords to CIC 2-digit codes because some similar Chinese keywords may have ambiguous meanings. For instance, as shown in Table F9, "salt chemical sector" ("盐化工" in Chinese) and "coal chemical sector" ("煤化工" in Chinese) are similar sectors in Chinese characteristics. However, the "salt chemical sector" mainly refers to the chlorine alkali activity and its related sectors based on electrolyzed salt water, and they belong to the chemical raw materials and chemical products manufacturing sector ("化学原料和化学制品制造业" in Chinese, whose 2-digit CIC code is 26). In contrast, the "coal chemical sector" refers to the process in which coal is converted into gas, liquid and solid fuels, and chemicals by chemical processing using coal as the raw material. These mainly include gasification, liquefaction, the dry distillate of coal, tar processing, and the lithic acetylene chemical sector. As a result, it should be classified into the petroleum, coal, and other fuel processing sector ("石油、煤炭及其他燃料加工业," whose 2-digit CIC code is 25).

G   Data Appendix

CCER Officials Dataset

CCER Officials Dataset is collected by the Political Economy Research Group of the National School of Development, Peking University (Yao et al., 2020). The dataset covers 4743 officials with available resumes, from the central government to the prefecture-level chief officials and from January 1994 to December 24, 2017. Table G10 shows all types of officials in this dataset.

Table G10: Types of Officials in CCER Officials Dataset

#	Description
	Prefectural Leaders
1.	City party secretaries and mayors (including prefecture-level district under province-level municipality).
	Provincial Leaders
2.	Members of provincial party standing committees.
3.	Provincial party secretaries and provincial governors.
	Central Leaders
4.	Ministers and vice ministers of ministries and commissions directly under the state council.
5.	Head and deputy of the following departments under the CPC central committee, including:
	5.1 Central Commission for Discipline Inspection of the CPC;
	5.2 General Office of the CPC Central Committee;
	5.3 Organization Department of the CPC Central Committee;
	5.4 Publicity Department of the CPC Central Committee;
	5.5 United Front Work Department of the CPC Central Committee;
	5.6 International Department of the CPC Central Committee;
	5.7 Committee of Political and Legal Affairs of the CPC Central Committee (Central Committee for Comprehensive Social Management);
6.	Member and alternate member of the central committee.
7.	State councilor of the People's Republic of China.

The dataset contains both officials' time-invariant biographic information and time-varying resume information, which is annually changed information for the career experience of officials after being promoted to the county level. In this paper, we focus on the sample of city party secretaries (including prefectural-level cities and sub-provincial cities). The detailed resume information enables us to identify where a particular official serves before she/he becomes a party secretary in a certain city.

China Work Report Database

The data source of prefectural government work reports is People's Data (http://data.people.com.cn/), a comprehensive online archive with an official certification. The archive incorporates full text of prefecture-level government work reports since the 1990s.

China Customs Database

Information on city exports is derived from the China Customs Database, which covers the universe of Chinese exports and imports, and were harmonized and generously provided by the University of California, Davis, Center for International Data (Feenstra et al., 2018). The data reports the annual trade information on values, quantities, and partner countries at the HS 8-digit level for all Chinese cities in the period under investigation (i.e., 1997 to 2013).

Firm Survey Data

The annual city-industry-specific employment is sourced from the Annual Survey of Industrial Production (ASIP) conducted by the National Bureau of Statistics (NBS) of China (1998 to 2013). The dataset surveys all types of firms (state-owned / non-state owned) whose revenue is more than five million RMB each year in the manufacturing sector. The sample size varies from 165,119 in 1998 to 336,768 in 2007. ASIP provides us with employment at the firm level, and we aggregate it to obtain total employment at the city-industry level. Notably, the ASIP industry classification uses the China Standard Industrial Classification (GB/T4754-1994 and GB/T4754-2002) at the 4-digit level.

Firm Administrative Registration Database

The number and paid-in capital of newly registered firms are from the Firm Administrative Registration Database that China's State Administration for Industry and Commerce (SAIC) maintains. The data reports the administrative information of the universe of enterprises in China. The data contains basic information such as firm name, location, industry classification, year of establishment, ownership type, legal representative, shareholders, and registered capital value. The industry classification of the Firm Administrative Registration Database uses a CIC 2-digit code.

China City Statistical Yearbooks

We collect prefecture-level socioeconomic characteristics from China City Statistical Yearbooks (1997-2013). The variables include prefectural population and GDP. Note that the yearbooks do not contain information for some prefectures, especially those in province-level units of autonomous regions for ethnic minorities.

NERI Marketization Index

NERI Marketization Index provides a set of measures on Chinese local market development at the province level (Fan et al., 2011; Wang et al., 2017). It contains five aggregate scores for each province in each year: (i) the government-market relationship score; (ii) the non-state-owned sector development score; (iii) the product market development score; (iv) the factor market development score; and (v) the score of market intermediaries and institutional environment. We use the (iii) and (iv) for our analysis. The two scores are aggregated using a factor analysis approach based on several measures of market development collected from statistical materials or field surveys of firms.

Specifically, the product market development score is based on the following variables: (a) the share of products whose prices are determined by the market and not regulated by the government; (b) the proportion of sample firms that agree with the statement "there are too many restrictions on market entrance;" (c) the proportion of sample firms that encounter local trade protections when selling to other provinces in the country.

The factor market development score is based on the following variables: (a) the share of non-state-owned financial institutions in deposits; (b) the share of non-state-owned financial institutions in loans; (c) the ratio of foreign direct investment to GDP; (d) the proportion of rural migrants in the local workforce; (e) the ratio of technology market volume of the transaction to the number of scientists and engineers.