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Land Allocation and Industrial Agglomeration: Evidence from the 2007 Reform in China

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Abstract

This paper highlights the crucial role of land allocation mechanisms in fostering industrial agglomeration by examining China's 2007 industrial land market reform. By introducing transparency into the land-selling process, the reform facilitated more buyers to compete for land (as evidenced by increased land sale prices), enabling local governments to allocate land to the most suitable users. Utilizing comprehensive data sets that include information on initial local industrial structure, new industrial establishments, and industrial land transactions, the empirical analysis finds that the reform significantly increased the entry of firms from industries aligned with local specialization, particularly in regions that implemented the reform more strictly. Industries characterized by substantial unrealized agglomeration economies or highly localized spillover effects experienced amplified effects. A well-functioning capital market further enhanced the land market reform's impact. Supporting evidence demonstrates the reform's positive effect on economic growth (as evidenced by changes in nighttime luminosity), potentially through increasing local firms' TFP.

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1. Introduction

Land use policies significantly impact economic and industrial development (Fischel, 1999; McDonald and McMillen, 2011; Gyourko and Molloy, 2015; Henderson et al., 2022). As one critical place-based policy, granting specific industries preferred access to land can profoundly reshape local industrial agglomeration and affect industrial productivity and economic growth (Rauch, 1993). However, previous research on place-based policies has largely focused on the importance of industrial parks (Neumark and Simpson, 2015), paying little attention to the crucial role of industrial land allocation mechanisms in facilitating the clustering of interconnected industrial firms. Designing such policies presents significant challenges for policymakers, especially in developing countries with weak institutions that hinder the efficient allocation of productive resources (Stiglitz, 1988; Krueger, 1990). This paper addresses this research gap by examining the impact of an industrial land market reform in China. We demonstrate that introducing transparency in land transaction mechanisms can foster competition and streamline the allocation of local land to the most suitable users. In the context of China, this approach effectively aligns new entrants with local specialization and enhances industrial agglomeration.

In China, all urban land is owned by the state.[1] Local governments have considerable authority to allocate land for various uses at their discretion, subject to a hierarchical, top-down land quota regulation. Industrial land use has dominated other types of land use in urban areas: every year, over 50% of newly sold urban land is for industrial use.[2] Before 2007, most industrial land in China was sold through nontransparent negotiations that lacked competition. Only a few potential buyers with connections to local governments were informed of the land for sale. Additionally, there were no clear criteria on how to select the winners. Existing research documents that such an opaque transaction format has led to a mismatch between the land purchasing firms and local industrial structure, potentially impeding industrial agglomeration (e.g., Zhang, 2006; Xing and Bo, 2007). Given that Chinese manufacturing firms exhibited lower levels of industrial agglomeration compared to developed countries like the United States, the United Kingdom, and France (Lu and Tao, 2009), nontransparent negotiated sales could result in significant efficiency losses.

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[1] Besides China, numerous countries, including Cuba, India, Israel, Kenya, North Korea, Saudi Arabia, and Vietnam, have substantial portions of land owned by their governments.

[2] Figure A1, in Appendix A, reports the annual land sale area for each type of land use from 2004 through 2015 based on data from the 2005–07 editions of the *Yearbooks of Land and Resources* and the official website of China's Ministry of National Land and Resources (www.landchina.com).

In July 2007, the Chinese central government introduced a nationwide industrial land transaction mechanism reform that replaced negotiated sales with public auctions (the 2007 reform). There has been widespread controversy surrounding the effectiveness of this reform, arguing that despite the reform, land allocation remains under government control, and the auctions do not function as genuine ones. However, we notice two critical differences between the new transaction mechanism and the negotiated sales before the reform, informed by in-person and online interviews with local government officials. First, at the beginning of the process, the local government is required to announce the availability of land for sale via official websites and media outlets and provide detailed information on the land (known as "*yu gong gao*" in Chinese), ensuring that as many firms as possible are aware of the land for sale and, hence, promoting competition. Second, there is a screening stage (known as "*yu shen qing*" in Chinese) open to the public before the official auction starts, which is recorded and subject to inspection. During this stage, all interested firms must apply to the local government, provide information on the business they intend to run, and propose a tentative bidding price. The local governments then screen the applicants, applying specific minimum standards and comparing the expected payoffs from all applicants. Their final selection outcomes must be posted to the public. These two procedures promote fair competition for land, giving high-productivity firms a better chance of winning land over low-productivity firms, potentially leading to higher sale prices of industrial land. As a result, under the new transaction mechanism, firms in industries that align better with local production advantages and are thus potentially more productive are more likely to secure land and cluster in localities that offer production benefits compared to the period of negotiated sales. Our findings provide compelling evidence to support these conjectures.

Our primary empirical analysis examines the impact of the new transaction mechanism introduced by the 2007 reform on industrial agglomeration. Specifically, we investigate whether the reform has increased the likelihood of new entries in industries where a county exhibits significant specialization. Following Glaeser et al. (1992), we measure county-industry-specific specialization using a given industry's local employment share relative to its share in national employment.[3] We demonstrate that this specialization index can signify local industry-specific production advantages, which could arise from factors such as thick upstream or downstream markets or shared inputs such as a skilled labor force or natural resources. We also find a

[3] A typical Chinese prefecture has one core city (comprised of urban districts), numerous rural counties, and several county towns; in this paper, we call urban districts, rural counties, and county towns "counties" for simplicity.

significant and positive correlation between the productivity of new establishments after entry and the degree of local specialization in their respective industries. This correlation remains robust even after controlling for various firm characteristics, consistent with the agglomeration economies literature (Rosenthal and Strange, 2004; Moretti, 2011; Combes and Gobillon, 2015).[4] Therefore, if we observe that the 2007 reform has created or strengthened a positive association between the likelihood of entry and local industrial specialization, it would suggest that the reform has facilitated the spatial agglomeration of new firms in counties where they can potentially reap production benefits.

Using a panel of county-industry-level observations from 2005 through 2010, we find that immediately after 2007, there was an influx of firms in industries aligning better with local specialization, in sharp contrast to the period before 2007. Our primary regression analysis investigates whether the implementation of the 2007 reform has contributed to the increased concentration of new firms in industries that match local specialization. Because of variations in the effectiveness of local governments in implementing market reforms, the degree to which the reform has been applied varies across different prefectures, which are the jurisdictions supervising county-level units in China. We shall exploit this variation to identify the impact of the reform. In particular, using the county-industry panel, we conduct regression analysis to investigate how the relationship between entry likelihood (or entry size) and local industrial specialization has changed along the following two dimensions of policy variations: the first comes from the reform's launch in 2007, which divides the sample into pre- and post-treatment periods and the second comes from different local reform implementation stringency levels.[5] Our data structure allows us to include a comprehensive set of fixed effects in the regression to account for various confounding factors. Firstly, we control for county-year fixed effects, thus dealing with all potential omitted variables varying at the county level (both time-invariant and time-varying). Secondly, we include prefecture-industry-year fixed effects to account for the confounding effects of the prefecture-industry-specific shocks, such as the concurrent prefecture-wide, industry-specific policies (e.g., priority industry policies and pollution reduction regulations) and economic shocks specific to a given prefecture-industry pair. These fixed effects can also deal with all potential

[4] Subsection 3.2 presents the detailed results.

[5] We measure a county's reform implementation stringency using the share of industrial land sales made through the new transaction mechanism after 2007 in the prefecture that supervises the county. We will carefully address the endogeneity problems associated with this reform stringency variable constructed with the *ex-post* land transaction data in subsections 4.2.2 and 4.2.3.

omitted variables that vary at the industry or prefecture level (both time-invariant and time-varying). Additionally, we include the initial total employment in each industry in each county to control for the confounding effect of the scale of incumbent firms. We also check the pre-policy trends, address empirical concerns about the reform stringency measure and specialization index, and take care of the confounding effects of other policies or macro shocks that co-occurred with the reform, which all generate results that support our main story.

The regression results show that in the post-reform period, there are more entrants from industries where the county has a higher degree of specialization than in the pre-reform period, and the increase is more pronounced in counties that have more stringently implemented the reform. Specifically, if the local specialization index of a two-digit industry[6] increases by one standard deviation, then after the reform, the entry likelihood and employment of new firms from this industry into this county on average will increase by 3.6 percentage points and 23%, respectively. Moreover, an increase of one standard deviation in reform stringency leads to additional increases in these two outcomes of 1.5 percentage points and 11%, respectively. Our investigation of pre-policy trends shows that before the reform, the alignment of new entrants with local specialization in counties that would later implement the reform more stringently did not differ from other counties. We also provide direct evidence that the reform has facilitated the clustering of new firms in localities where they can leverage upstream and downstream linkages or access shared inputs such as labor and natural resources. These findings offer valuable insights into how the reform interacted with various factors driving industrial agglomeration, thereby reshaping the spatial distributions of industrial firms. Moreover, dynamic analysis reveals a persistent impact of the reform on the clustering of new firms, indicating the ongoing positive externalities of agglomeration economies.

Additional analyses reveal that the reform's effect on firm entry is prevalent across firms of different sizes and export activities, and the main results are robust when we examine industries in a more refined category (i.e., the three-digit level) or include county-industry fixed effects in the regressions. Land transaction data also confirm that during the post-reform period, land was more likely to be sold to firms in industries where the county has high specialization, and this positive correlation is more prominent in regions that implemented the reform more stringently.

Furthermore, we explore the heterogeneity of the reform's impact across different industries

[6] China's industrial classification codes (GB/T 4754-2002) are comparable to the US Standard Industrial Classification.

and geographical areas to shed light on potential mechanisms at play. The results show that the reform's effect is more prominent among industries with substantial unrealized agglomeration economies or highly localized spillover effects. We also find that a well-functioning capital market can enhance the reform's effect.

The critical change made by the 2007 reform is mandating the disclosure of information on land for sale and making selecting winners more transparent to the public. This increased transparency would induce more potential buyers to compete for the land. Consequently, the land sale price would be higher through the new transaction mechanism than through negotiation. Although the information on the number of bidders for each land transaction is not available in our land transaction data set, we provide corroborating evidence of increased competition due to the new mechanism from land sale prices. In particular, using land transaction data, we run regressions at both the land-parcel and prefecture-year levels and find strong evidence that the new transaction mechanism led to increased sale prices of industrial land. The evidence from the total land sale area suggests that the price increase was unlikely to be driven by a reduction in industrial land supply.

All these findings suggest that despite the local governments retaining control over the land allocation process, which makes it susceptible to government manipulation, the reform has effectively facilitated the clustering of new industrial firms in localities where they can potentially obtain productivity benefits. Our back-of-the-envelope calculation based on the regression estimates suggests that compared to the counterfactual scenario where the reform is absent, the reform generates a 1.3% increase in the national total factor productivity (TFP) of new entrants over the three years after the reform through improving match quality between new firms' industry types and locality's specialization. As supporting evidence of the positive impact on local economic development, we exploit a data set of nighttime lights that covers the counties in our primary analysis. We find that during the post-reform period, local nighttime lights grew more in counties with a higher initial average specialization, particularly in regions that implemented the reform more strictly.

Our paper speaks to several strands of the literature. First, previous research on the determinants of the geographic distribution of manufacturing firms shows that in a market-oriented economy, firms tend to form clusters in places where they enjoy a comparative advantage (e.g., Ellison and Glaeser, 1997, 1999; Kim, 1999; Kahn and Mansur, 2013). Spatial concentration can reduce the costs of obtaining inputs or shipping goods to downstream customers, enhance the advantage of scale economies associated with a large labor pool, and speed up the flow of ideas.[7] By contrast, previous literature has documented that non-economic factors (e.g., political/ethnic connections) have profoundly shaped economic resource allocations in regulated markets, which may cause efficiency losses (e.g., Burgess et al., 2015; Chen et al., 2017; Kahn et al., 2021). Our findings suggest that in such markets, even a minor modification of the allocation mechanism of productive factors such as land can significantly alter the spatial distribution of new firms by facilitating them to cluster in regions that have a higher degree of specialization in their respective industries. This enables firms to gain from agglomeration economies or natural advantages, which is a new angle that previous research has seldom explored. Furthermore, our counterfactual calculations quantify the increase in TFP from improving the match quality between industries and localities and find nonnegligible productivity gains.

Second, our paper contributes to the literature on the importance of transparency for improving governance in the developing world, as reviewed by Kosack and Fung (2014). For example, Reinikka and Svensson (2005, 2011) find that newspaper campaigns in Uganda to provide school funding information to communities reduced the leakage of funds and improved test scores. Similarly, Banerjee et al. (2018) find that providing program information to targeted beneficiaries increased the subsidy from a subsidized rice program in Indonesia. In addition, Banerjee et al. (2020) evaluate an e-governance reform of the fund flow system in India and find that the reform significantly reduced fund leakage by improving program transparency and making it easier to audit claims about work done and payments. While previous research has focused on providing information to citizens, our paper examines the impact of making land sales information available to firms in China. Our paper shows that making the land-selling process more transparent to private firms improves the efficiency of land allocation by enhancing competition and allowing the public to monitor local officials more effectively.

Third, a growing body of studies examines land use policies in urban China.[8] A few recent papers analyze land misallocation in China. For example, Fu, Xu, and Zhang (2021) show evidence of land misallocation across Chinese prefectures; they find that a growing share of land quotas has been distributed to less productive prefectures. Fang et al. (2021) suggest that China's

[7] For example, see Ellison and Glaeser (1997); Rosenthal and Strange (2004); Duranton and Overman (2005); Arzaghi and Henderson (2008); Ellison, Glaeser, and Kerr (2010); Greenstone, Hornbeck, and Moretti (2010); and Helsley and Strange (2014).

[8] For example, see Deng et al. (2008); Lichtenberg and Ding (2009); Brueckner et al. (2017); Cai, Wang, and Zhang (2017); Tan, Wang, and Zhang (2020); Lin et al. (2020); and He et al. (2023).

inland-favoring policy from 2003 has created a cross-prefecture misallocation of land quotas. Henderson et al. (2022) show that prefectural leaders' political incentives have created inefficiencies in local land allocation between residential and industrial uses. Our paper complements the previous research by focusing on local land allocation across different industries and showing that the 2007 reform has led to a more efficient composition of local industries and spatial distribution of industries within prefectures.

Lastly, our study contributes to a large body of literature that evaluates place-based policies. Previous work has examined various local policies such as taxes,[9] investment subsidies,[10] government transfers,[11] and industrial parks.[12] To our knowledge, there is little research on industrial land allocation, although preferential access to land for firms is considered an important place-based policy (Rauch, 1993).[13] We show that it is crucial to introduce transparency into industrial land allocation because it can significantly affect the matching patterns between counties and firms and, thus, productivity and economic growth. Our findings have important policy implications for governments in designing place-based policies to promote local industrial development.

The rest of the paper is organized as follows: Section 2 overviews the institutional context surrounding the 2007 reform in China's industrial land market. Section 3 introduces the data and main variables and presents graphical evidence. Section 4 presents our estimation strategy and primary empirical findings. Section 5 demonstrates the reform's impacts on local productivity and economic growth. Section 6 corroborates the evidence of the reform's effect on land allocation and increased competition due to the new transaction mechanism. Section 7 concludes.

2. Institutional background

[9] For example, see Duranton, Gobillon, and Overman (2011); Brülhart, Jametti, and Schmidheiny (2012); and Briant, Lafourcade, and Schmutz (2015).

[10] For example, see Criscuolo et al. (2019).

[11] For example, see Becker, Egger, and von Ehrlich (2015).

[12] For example, see Neumark and Kolko (2010); Busso, Gregory, and Kline (2013); Kline and Moretti (2014); Neumark and Simpson (2015); Wang (2013); Schminke and Van Biesebroeck (2013); Alder, Shao, and Zilibotti (2016); Chen, Poncet, and Xiong (2017); Zheng et al. (2017); and Lu, Wang, and Zhu (2019).

[13] Rauch (1993) suggests that industrial park developers can attract industrial seed firms by adopting discriminatory land pricing over time.

In China, the state has granted de jure ownership of urban land to local governments in their jurisdictions since 1988. According to the Law of Land Management, prefecture-level governments play a central role in planning urban land development, which has been subject to a hierarchical, top-down land quota regulation since 1998.[14] In practice, a prefecture's land reserve and allocation committee, which includes the prefecture's key leaders and bureau directors from relevant government departments,[15] is in charge of general land use planning and guideline setting.

A typical Chinese prefecture has one core city (comprised of urban districts), numerous rural counties, and several county towns; we call urban districts, rural counties, and county towns "counties" here for simplicity. The prefecture government allocates the land quota across different counties within its jurisdiction in a land use plan for the short term and the next five years, considering the prefecture's spatial layout of economic activities and population. Based on the plan, the prefecture government designates a quota of a certain amount of land in each county for industrial use every year. The GDP-oriented competition between local leaders incentivizes them to boost industrial output by allocating more land quota to industrial usage and devoting public revenues to production-related infrastructure investment (Wang et al., 2020; Henderson et al., 2022). Notably, although more than half of the land quota is allocated to industrial use (see Figure A1 in Appendix A), the prefecture government typically relies on residential land sales to generate most of the land-leasing revenues to finance the provision of infrastructure (Table A1 in Appendix A).

County governments are directly responsible for administering industrial firms within their jurisdiction. A critical issue is how efficiently each county government allocates industrial land to firms in various industries given the land quota. Below we discuss how the industrial land transaction mechanism changed between the pre- and post-reform eras.

2.1 Industrial land transactions before the reform

[14] The central government allocates a land quota to each province; each province then allocates the quota to prefectures (or so-called prefecture-level cities) within its jurisdiction, considering each prefecture's economic development, population growth, and arable land for food security. The land quota constraint is imposed on the sum of all urban land, including residential, commercial, and industrial land. Local governments have incentives to bargain with upper-level governments for larger quotas and sometimes succeed (Wang, Zhang, and Zhou, 2020).

[15] These government departments include the Urban Planning and Land Bureau, Development and Reform Committee, Economy and Information Technology Committee, and so forth.

Before 2007, most industrial land transactions were conducted through negotiations, and industrial land was allocated to firms in a somewhat opaque way. Often, information on land for sale was not publicly posted, so only a few firms knew about it. As for which firms were informed about the land for sale and which firm obtained the land in the end, there was no clear rule. Due to a lack of competition and transparency, personal connections or luck often determine the winner. As an article published in July 2003 in the *China Land*, a magazine journal affiliated with the Ministry of National Land and Resources, wrote, "In practice, the negotiated sales are often under the sole control of the top leader in charge of the local land management…not everyone has the opportunity, eligibility or connection to participate in a negotiation sale."[16] Therefore, the firms that obtained land in a given county were not necessarily the ones that could make the best use of it. The sale price was set through negotiation between the selected firm and the local government, and it was low on average.

The misallocation of industrial land in the early 2000s raised at least three severe concerns that alerted the Chinese central government. The first was the inefficient utilization of land. For instance, new entrant firms might be low quality or a poor match to the local industrial specialization. Previous research has widely documented that in the middle and western regions of the country, counties within the same prefecture tried to attract new entrants from similar industries, although they had quite different dominant industries (e.g., Zhang, 2006; Xing and Bo, 2007). Moreover, because the underdeveloped secondary land market has significantly inhibited land transfers to more efficient users, the initial land allocation often has a crucial and long-lasting impact on final land use efficiency.[17] All these factors could generate nontrivial efficiency loss and undermine future economic development.

A second concern was the loss of land sale revenues and the under-compensation of farmers. According to the *Yearbooks of Land and Resources*, the average transaction price of residential land in 2006 was around 823 yuan per square meter, seven times more than the average sale price of industrial land, which was 119 yuan per square meter.[18] An article published in the *South China*

[16] See the article "*Four Major Drawbacks of the Opaque Negotiation Land Sales*" by Zhengshan Liu and published in volume 7 of *China Land* in 2003.

[17] Although the primary land market in which transactions are between state and private land users has grown significantly in terms of both transaction volume and value, the secondary land market in which transactions are between private users still lags far behind due to the lack of relevant laws and regulations (World Bank and DRCSC, 2014).

[18] Table A2, in Appendix A, reports the annual land sale revenue and per unit land price for each type of

Morning Post on December 29 of 2006 cited the following statement from the National Audit Office: "In the 87 development zones it surveyed across the nation, 60 had sold a total of 78.7 million square meters of land cheaply between 2003 and the middle of last year (2005) at a loss of 5.56 billion yuan."[19] Local governments had to rely more heavily on residential land revenue to finance the infrastructure required for industrial development, which distorted the residential land market (Wang et al., 2020; Henderson et al., 2022). Furthermore, there was not enough money to cover the cost of the industrial land supply. So, the counties may have undercompensated farmers for their land. The *Post* article also cited statistics from the Ministry of Labor and Social Security: "More than 40 million farmers lost their land to industrial and other projects over the past ten years, and the number grew by 3 million a year." The compensation paid to farmers was often far below a reasonable level (Guo, 2001; Ding, 2007).

Third, the nontransparent land allocation process may have created an environment that fostered corruption, which is also a big concern of the central government.

2.2 Industrial land market post-reform

In 2002, the central government dictated that all urban leasehold sales for purely private development must occur through public auction. However, this policy has only been strictly enforced in the *residential land market* since September 2004. About 90% of industrial land parcels were still transacted through negotiated sales from September 2004 through June 2007.

To regulate local governments' industrial land development and make the use of industrial land more efficient, the Chinese central government launched a nationwide reform aiming to reshape the transaction mechanism in the industrial land market. In April 2007, the Ministry of National Land and Resources and the Ministry of Supervision of China jointly issued the "Notification on How to Strictly Implement the Transaction Formats of *Zhaobiao* (Sealed-bid auction), *Paimai* (English auction), and *Guapai* (Two-stage auction) for Industrial Land." From July 2007 on, it became mandatory for all urban industrial land to be sold through these three transaction formats. According to the official statistics, most industrial land sales occurred in a special format of the two-stage auction rather than English auctions.[20] In particular, the two-stage

land use from 2003 through 2008. The data sources are the 2004 to 2009 editions of the *Yearbooks of Land and Resources.* Information on land sale revenue is not available for the other years.

[19] See /www.scmp.com/article/576876/minimum-prices-industrial-land-rise-next-year.

[20] Among all the industrial land sold via so-called "public auctions" during 2007–15, 94% was sold by

auction in the industrial land market has an additional screening stage ("*yu shen qing*" in Chinese), which makes it different from the typical two-stage auction in the residential land market as specified by Cai, Henderson, and Zhang (2013). Next, we detail some distinctive features of the post-reform mechanism for industrial land transactions based on our interviews with various local officials in charge of industrial land development.

First, at the beginning of the process, the county government must officially inform the public through official websites and media outlets about the land available for sale and provide detailed land information, including the land's location, area, leasehold length, and the regulation requirements. Informed by local policy documentation, the preliminary notice for land sale ("*yu gong gao*" in Chinese) must be posted online for no less than 30 days to ensure that as many firms as possible can participate in the land sale.[21] Making this information public effectively increases the number of potential bidders, which is critical for promoting competition.

The second distinctive feature is a screening stage open to the public before the official auction. In this stage, all interested firms must submit confidential applications to the county government, providing essential information about the business they intend to run and the minimum price they would bid if chosen to proceed to the auction stage. This screening stage plays a crucial role as it enables the county government to gather information to weigh the short-run and long-run benefits each applicant (firm) can bring to the county. The county government assesses the potential gross payoff of each applicant based on factors such as expected investment, output values, tax revenues, job creation, and the tentative bidding price. Specific minimum standards known to the public are in place for expected investment intensities, output value per unit of land, new jobs created, and pollution emissions. The county government selects the winner from the applicants who meet all these standards and have the potential to generate the highest payoff. Notably, the government is obligated to make the selection standards public. For example, the government must explain the reasons for failures to the unselected applicants in official documents. In addition, the chosen applicant's identity and detailed application information must be announced

two-stage *auctions*, 5% by English auctions, and the remaining 1% through sealed bid auctions. By contrast, for all the residential land sold by public auctions during 2007–15, the respective shares were 74.5%, 24.7%, and 1.8%.

[21] See https://fszrzy.foshan.gov.cn/zwgk/fggw/xxyxgfxwj/content/post_758292.html. As supporting evidence, we collected a sample of 142 preliminary notices announced by the Shanghai government in 2010 from its official website and found that, on average, the posting time length was 120 days, with a minimum of 38 days.

to the public in the auction stage. Therefore, any potential collusion between local officials and the chosen applicant would face a significant risk of media exposure or even legal action initiated by those who were not selected.

Next, the county government signs a pre-screening contract ("*yu shen qing xie yi*" in Chinese) with the chosen applicant. This contract comprehensively outlines details regarding the business type, output value, employment, taxes, and the minimum bidding price the selected firm presented during the pre-screening stage. Once the firm commences its operations within the county, it becomes relatively straightforward for the county government to assess the veracity of the information provided and take appropriate measures if any false representations are made. An illustrative instance took place in Fuzhou, the provincial capital city of Fujian Province, where the local government mandated the reclaiming of land from a microelectronic firm due to its failure to fulfill the investment intensity and output commitments outlined in the pre-screening contract.[22]

Third, once the county government and the selected firm have reached a deal in the screening stage and signed the pre-screening contract, the county government officially starts the *Guapai* auction (i.e., a two-stage auction). Typically, it sets the reserve price at the pre-auction deal's agreed minimum bidding price. The selected firm enters the auction, places a bid equal to the reserve price, and wins the land. Although it is theoretically possible for new bidders to enter the auction stage and offer bids surpassing the reserve price, such instances are rare in practice. This rarity can be attributed to two reasons: one is that a new bidder who enters the auction without going through the mandatory pre-screening stage does not meet the requirement for a legitimate buyer of the land; the other is that the regulatory details of the industrial land for sale (such as the business type, building height, and floor area ratio) are typically tailored by the county government to meet the specific demands of the selected firm as part of the pre-screening agreement signed before the auction, which may not be suitable for other bidders. Consistently, we find that the reserve prices usually equal the sale prices for a subsample of land sales that provides reserve price information (see Figure A2 in Appendix A). Although it is cosmetic, this final auction process is mainly conducted to enable the public to monitor and supervise the transaction outcomes.[23]

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[22] See https://zhuanlan.zhihu.com/p/377733738 for the news report and https://www.court.gov.cn/fabu/xiangqing/23941.html for the lawsuit.

[23] In the residential land market, when there is a corrupt pre-auction deal between a bidder and the land bureau officials, the two-stage auction may facilitate the bidder to send signals to other potential bidders to deter entry by placing a bid just equal to the reserve price right after the auction starts, as Cai, Henderson, and Zhang (2013) point out. However, the industrial land market requires a pre-auction screening process,

Finally, the auction outcome (winning bidder, price, winning firm's industry type, and so forth) is posted online. Furthermore, the entire application, screening, and auction process must be fully recorded and subject to inspection by the Ministry of Supervision. This is in sharp contrast to the mechanism during the pre-reform period. Overall, the new transaction mechanism makes information on industrial land sales transparent to potential buyers and enables the central government to monitor local officials with the help of the public. Hereafter, we refer to this new transaction mechanism as public sales.

For industrial land, panel A in Figure 1 displays the trends over time in the share of industrial land transactions conducted through public sales (represented by triangles) and the per unit land sale price (represented by squares). The sale price of industrial land jumped after 2007, consistent with the sharp rise in the fraction of public sales.

Notably, while the reform is a national policy, it is primarily enforced by prefecture-level governments that are responsible for guiding and supervising industrial land allocation in all counties under their jurisdiction, as previously discussed. According to the two documents issued by the Ministry of National Land and Resources in 2006 and 2009,[24] after the reform was introduced, a local government could still sell industrial land through negotiation under certain particular circumstances. For example, negotiations can be used when only one buyer shows up after the county government notifies the public about the land for sale or when the land was allocated to the user for free due to government policies or certain special economic conditions. The vague terms of these exceptions allowed some prefectures to be slow in implementing the reform. Prefectural governments' interpretations of those exception terms generated different implementation environments for the reform in counties under their respective jurisdictions. Our land transaction data show that after the reform was launched, there was salient variation in the share of industrial land transactions conducted through public sales across prefectures, reflecting different levels of local reform stringency (see subsection 3.3 for details). In some prefectures, the

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which is open to all potential bidders. The screening is officially conducted and monitored. Even if we observe that the reserve price is equal to the sale price in the two-sage auction held afterward, this does not imply that there is no competition in the pre-screening stage. We find clear evidence of competition from the price data.

[24] See "Rules for Transferring the Use Rights of State Owned Land through Negotiations," The People's Republic of China, Ministry of National Land and Resources Document 114 (2006); and "Notification on How to Further Implement the Rules for Transferring the Use Rights of Industrial Land," The People's Republic of China, Ministry of National Land and Resources Document 101 (2009).

shares of public sales jumped to 100% right after 2007 (e.g., Suqian prefecture in Jiangsu province and Yangjiang prefecture in Guangdong province). Others slowly adopted the new transaction mechanism for industrial land sales (e.g., Siping prefecture in Jilin province and Xinxiang prefecture in Henan province).[25] Our identification will exploit this important spatial variation in reform stringency.

Another reform imposed a minimum land price constraint on industrial land sold beginning in January 2007 (Ministry of National Land and Resources, 2006). The central government sets the minimum price according to local economic conditions. All counties nationwide were graded into one of 15 classifications based on the local value of land, which was largely determined by the county's initial economic and geographic conditions. According to this grade, a minimum land price (60–840 yuan per square meter) was set for every county-level unit in China.[26] This policy was designed to prevent county governments from selling land at below-cost prices to lure investments. Approximately 70% of the industrial land transactions in our sample from July 2007 through December 2015 had a sale price strictly above the regulatory minimum price.[27] In Figure 1, panel B shows that the average industrial land price spread (the average ratio of the actual to minimum prices) has been rising since 2007, along with the share of public sales, suggesting that there has been increased competition in industrial land sales since the 2007 reform even after teasing out the effect of the minimum land price regulations. Furthermore, Figure 1, panel C shows a strong positive correlation between each prefecture's average price spread and the prefecture's share of public sales, suggesting that variations in reform stringency affect the degree of competition in the industrial land markets of different prefectures.[28] Figure 1, panel D shows that

[25] For example, in Xinxiang prefecture in Henan province, only 40% of industrial land sales were made via public sales during July 2007–10.

[26] For example, Shanghai's nine core urban districts are ranked in the first classification grade with the highest price. Its *Pudong* district and Beijing's eight core urban districts are in the second category with a minimum price of 720 yuan per square meter. These are followed by 600 yuan per square meter in Shenzhen and Guangzhou. At the other extreme are counties primarily located in poorer provinces in Western China; those in Tibet and Yunnan are in the bottom category with a minimum price of 60 yuan per square meter. Upon approval of the central government, there is a certain degree of flexibility in implementing the minimum price regulation of local governments, with some adjustment costs (Tian et al., 2022).

[27] The minimum price data are from the "Minimum Price Standards for Industrial Land Leasehold Sales," published by the Ministry of National Land and Resources in December 2006.

[28] Panel C in Figure 1 plots each prefecture's average ratio of actual sales to minimum prices in each year against the prefecture's share of public sales in that year from 2007 through 2010, controlling for prefecture

despite the dip in 2008 due to the Global Financial Crisis, the total sale area of industrial land has been rising from 2008 to 2010, suggesting that the price increase after 2008 is unlikely to be driven by a reduction in industrial land supply. We shall conduct a more rigorous investigation on the impacts of the reform on land sale price and quantity in subsection 6.2.

3. Data and variables

3.1 Data

Our primary empirical analysis uses three sets of data. First, we derive the county-industry-specific variables on the initial local industrial structure from the Economic Census conducted by the National Bureau of Statistics at the end of 2004 (hereafter referred to as the 2004 Economic Census). It covers all mining, manufacturing, and utility firms in China. These data report each firm's critical information, such as address, industry classification, number of employees, and output value.

Second, we use the Annual Survey of Industrial Firms (ASIF) conducted by the National Bureau of Statistics to measure the local entry of manufacturing firms from 2005 through 2010.[29,30] This survey covers all state-owned enterprises and private enterprises with annual sales of 5 million yuan or more in mining, manufacturing, and producing and distributing electricity, gas, and water. The ASIF contains firm-level information such as the year of establishment, address of establishment (from which we can extract county information), industry classification, ownership, and employment. Based on this information, we calculate the entry incidence and new entry

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fixed effects and province-specific year fixed effects.

[29] Researchers may also consider using the Firm Registration Data from the State Administration for Industry and Commerce as an additional data set for measuring firm entry. However, there are certain limitations associated with this data set. The most critical one is that the registration addresses provided in this data set frequently deviate from those associated with manufacturing establishments. This discrepancy poses difficulties in accurately identifying the specific county in which a firm has entered, thereby hindering our ability to employ these data effectively for measuring the local entry of industrial firms.

[30] Given that the information on each firm's year of establishment is inaccurate in the 2009 ASIF data, we used the year of establishment reported in the 2010 ASIF data to infer the number of new entrants in every industry in a given county in 2009. Appendix B checks the data quality of the founding year information reported in the 2010 ASIF data.

employment in each two-digit industry in each county from 2005 to 2010.[31] In addition, reliable firm-level variables for TFP calculation, such as annual value added, number of workers, total fixed assets, and total intermediate input, are available in the 2005–07 ASIF data sets. Based on this financial information, we measure the TFP of individual firms.[32]

Third, we use the land transaction data from China's Ministry of National Land and Resources official website (www.landchina.com) to measure local reform stringency, present direct evidence on local land allocation, and provide corroborating evidence of the increased competition in land sales arising from the new transaction format. Our land sample consists of 437,409 industrial land transactions from 1992 through 2015, with 97% occurring after 2004. This data set includes information on all land sales by local governments since 2007. It covers basic transaction information, such as land use type (residential, commercial, or industrial use), lot size, transaction type (negotiation or public sale), sale price, sale date, address, and the industry type of land users (a two-digit classification code). The land transaction data do not allow us to evaluate the reform's effect due to incomplete coverage before 2007 and a substantial lack of industry type information before 2009.[33] Considering that starting in 2009, 80% of industrial land transaction records have industry type information, we utilize land transactions from 2009 to provide supplementary evidence on land allocation across different industries for the county-industry pairs in our primary analysis. Furthermore, we present corroborating evidence of increased competition resulting from the new mechanism by examining land sale price and area using the land transaction data.

Finally, to provide supporting evidence of the reform's effect on local economic growth, we gathered nighttime illumination data covering all the counties in our main analysis based on the Global Defense Meteorological Program Operational Linescan System Nighttime Lights Time Series 1992–2013 (Version 4) from the website of the National Centers for Environmental

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[31] While analyzing the ASIF dataset, it is important to note that the observations primarily represent firms rather than plants (or establishments). However, it is commonly understood that the location of the firm in this data set corresponds to the location of production. Previous studies utilizing this dataset, such as Brandt et al. (2012) and Li et al. (2022), have acknowledged that the majority of firms in the ASIF dataset are single-plant firms. For instance, Brandt et al. (2012) specifically demonstrate that over 95% of the firms in the ASIF dataset fall into the category of single-plant firms.

[32] Appendix C presents the details on constructing firm-level TFP using the ASIF.

[33] A substantial lack of industry-code information for land transaction records before 2007 makes it difficult to ascertain the industry type associated with those transactions. Furthermore, between 2007 and 2008, only 50% of industrial land transactions included information on land users' type of industry.

Information at the National Oceanic and Atmospheric Administration (www.ngdc.noaa.gov/eog/download).[34] In addition, we collected data on county-level socioeconomic characteristics in 2001 from the Fiscal Statistical Compendium for All Prefectures and Counties (*Quanguo Dishixian Caizheng Tongji Ziliao*). These characteristics include each county's gross domestic product (GDP), secondary and tertiary sector GDP shares, total population, and share of rural population. We use these data to measure local initial characteristics.

3.2 Measuring county-industry-specific specialization

We derive each county's initial degree of specialization in a particular industry from the firm-level employment data reported in the 2004 Economic Census. Specifically, following Glaeser et al. (1992), we measure the specialization of industry j in county k as the ratio of the employment share of industry j in county k to industry j's total employment share in the whole country, referred to as the county-industry specialization index:

$$specialization_{kj} = \frac{\text{industry } j\text{'s employment in county } k \text{ / total employment in county } k}{\text{industry } j\text{'s employment in China/total employment in China}} \cdot \quad (1)$$

The index measures how specialized a county is in an industry relative to what would be expected if employment in that industry was scattered evenly across the country. In our sample, about 50% of the pairs have a specialization index greater than 1; the average is around 2, as shown in panel B in Table 1.

Previous studies have indicated that a concentrated presence of industries in a particular geographic area often signifies local production advantages arising from natural strengths or industry-specific benefits known as localization externalities (e.g., Ellison and Glaeser, 1999; Kim, 1999).[35] Building upon this perspective, we argue that new firms in industries where the county

[34] The intensity of Earth-based nighttime lights was recorded by the Operational Linescan System developed by the United States Air Force Defense Meteorological Satellite Program. We then projected these data onto a GIS map of China's 2010 administrative boundaries to calculate the intensity of nighttime lights at the county level.

[35] As suggested by Ellison and Glaeser (1999) and Kim (1999), the geographic concentration of industries may arise in two ways. First, natural advantages can lead to industrial agglomeration. For example, in China, the food and beverage industries are spatially concentrated in the areas that are the leading producers of agricultural products (e.g., Heilongjiang, Guangxi, and Yunnan provinces); the textile industry is

already exhibits considerable specialization may be better aligned with the local industrial production environment. For example, this advantage can be attributed to industry-specific upstream or downstream linkages or the sharing of industry-specific inputs such as labor and natural resources. Consequently, these firms can be more productive after entry.

To support this argument, we first examine the correlation between the county-industry-specific specialization index and measures of within-county industry-specific upstream and downstream employment and relevant inputs such as a skilled labor force or natural resources.[36] As shown in columns (1)-(4) of Table 2, the specialization index well reflects the alignment of a specific industry with local production advantages. Next, we regress the TFP of new firms on the initial specialization index of the firms' industries within the county where they are located.[37] Column (5) of Table 2 demonstrates a significant positive correlation between TFP and industrial specialization, indicating that new entrants are likely to achieve higher productivity levels if they enter a county that is more specialized in their industry. Specifically, a one-standard-deviation increase in the local industrial specialization in 2004 (approximately 4) is associated with TFP gains of 3% for new entrants during 2005–07. In column (6), the result remains robust after we introduce two additional county-industry characteristics into the regression to capture the impact of the market structure of each industry within a given county, namely, the average firm size and the employment share of the largest firm, both derived from the 2004 Economic Census. The positive correlation between TFP and specialization aligns with the empirical evidence that industrial agglomeration can lead to increased productivity for firms and workers, which is documented by extensive literature (Rosenthal and Strange, 2004; Moretti, 2011; Combes and Gobillon, 2015).

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agglomerated in the areas that are the primary producers of cotton (e.g., Jiangsu, Shandong, and Xinjiang provinces). Second, the localized industry-specific externality is another primary source of geographic concentration. For example, the stationery, educational, and sporting goods industries are spatially concentrated in Guangdong and Jiangsu provinces; the instruments, meters, cultural, and official machinery industries are geographically agglomerated in Shanghai; and the leather and fur products industry is concentrated in Fujian and Guangdong provinces.

[36] See subsection 4.4 for the details on constructing these county-industry specific variables driving agglomeration economies.

[37] As reliable financial information, such as the annual output value, assets, investment, and costs, is available only in the 2005–07 ASIF data sets, the regressions in columns (5) and (6) of Table 2 focus on the TFP of new entrants during this period.

In all the regressions in Table 2, we include the prefecture-specific industry fixed effects and county fixed effects to account for the impacts of the prefectural government industry policies and industry-neutral locational characteristics on industrial agglomeration and productivity. For the firm-level regressions in columns (5) and (6), we further include firm-level attributes such as ownership types and the share of exports in total sales to control for firm-level heterogeneity. To alleviate the concern that the TFP premium may be driven by the sorting of firms with greater assets or closer government connections into the counties with high specialization within a given prefecture, we regress the total assets, capital investment, and the government-investment status of the new firms on the specialization index while controlling for prefecture-specific fixed effects and county fixed effects. As Table A2 in Appendix A indicates, all the coefficients on the specialization index are statistically insignificant.

Notably, the positive correlation between TFP and specialization is the key motivating finding for our primary analysis. In particular, it implies that firms could have achieved additional productivity gains by entering counties specialized in their respective industries. This finding aligns with Lu and Tao (2009), which illustrates that although industrial agglomeration in China steadily increased over time, driven by economic reforms starting from the late 1970s, it remained considerably lower in the mid-2000s compared to developed countries such as France, the United Kingdom, and the United States. The previous literature has identified local protectionism under the fiscal decentralization policy as the critical factor hindering firms from clustering in locations where they possess a comparative advantage (Young, 2000; Wen, 2004; Lu and Tao, 2009). Allowing the market to play a role in allocating industrial land may facilitate the spatial agglomeration of manufacturing firms and, hence, generate productivity gains.

3.3 Constructing the reform stringency measure

Another key measure assesses the stringency of the reform's implementation in an area using the land transaction data set. In particular, each county's reform stringency level is measured as the share of industrial land transactions during 2008–10 conducted through public sales in the prefecture supervising the county.[38] We calculate this share at the prefecture level because prefecture-level governments have the authority to establish guidelines on the formats of land

[38] The main analysis uses industrial land sales during 2008–10 to calculate the level of local reform stringency. The main results are robust when using other post-reform periods in the calculation (e.g., July 2007–10).

transactions to which counties within their jurisdiction must adhere.[39] The average share of public sales in the 300 prefectures in our sample is about 85%, and the standard deviation is about 17.4%. For the main regression analysis, each county's level of reform stringency is measured by its prefecture's share of public sales, standardized to have a mean of zero and a standard deviation of one.

The reform stringency index exhibits notable spatial differences across prefectures, which can be attributed primarily to the effectiveness of local governments in implementing market reforms. We use the following three variables characterizing the degree of local marketization to measure this effectiveness. First, each prefecture's auction share of residential land sales conducted from September 2004 to June 2007 can serve as a proxy for the local government's ability to implement market reforms.[40] As discussed in section 2, starting from September 2004, it became mandatory for all urban residential land to be sold through public auction. The local government's effectiveness in executing market reforms affected the implementation of land transaction mechanism reforms in residential and industrial land markets in 2004 and 2007, respectively. Therefore, it is reasonable to expect that the local governments that effectively carried out public auctions for residential land sales before 2007 would have a greater capacity to implement the new transaction format in industrial land sales after 2007. Second, Fan et al. (2011) calculated a marketization index at the provincial level to assess the degree to which the local economy was driven by market forces in 2006.[41] We expect that prefectures located in provinces where market forces outweigh government intervention initially are more likely to implement the 2007 reform effectively. Third, we borrow the *hukou* registration index for each province from Zhang et al.

[39] The main results are robust to using land transactions of counties or county cities to measure their respective reform stringency levels, considering the greater administrative autonomy of these units compared to urban districts.

[40] We use residential land transaction data from landchina.com to calculate each prefecture's residential auction share of residential land sales between September 2004 and June 2007.

[41] Numerous previous studies have extensively relied on the marketization index system developed by Fan et al. (2011) to assess the effectiveness of local market institutions in China (e.g., Hasan et al., 2014; Tan et al., 2020; Liu et al., 2021; Ding et al., 2022). Here, we utilize a sub-index from this index system specifically for measuring how much the local economy was driven by market forces in 2006. The construction of the sub-index is based on the following five aspects: (1) the degree of market allocation of resources; (2) the tax burdens of farmers; (3) the degree of government intervention in enterprises; (4) the non-tax burdens of enterprises; and (5) the scale of the local government.

(2019) to measure the institutional barriers to market-driven resource allocation.[42] This index reflects the stringency of local *hukou* qualifications calculated based on the requirements for migrants to obtain local *hukou*. We expect that prefectures with higher migration costs imposed through the *hukou* system would experience slower progress in implementing market reforms.

We regress each prefecture's reform stringency measure on these three variables, along with a set of prefecture-level initial economic characteristics. These economic characteristics include each prefecture's GDP, population, shares of GDP in the secondary and tertiary sectors in 2007, and the prefecture's growth rates of GDP, population, and secondary and tertiary sectors' GDP shares between 2003 and 2007. Table 3 shows that, as expected, the three marketization variables are all significantly associated with the reform stringency measure. In particular, the reform stringency increases as the auction share of residential land sales conducted during the pre-reform period increases, increases as the marketization index rises, and decreases as the *hukou* registration index increases. However, none of the prefecture-level economic characteristics show a significant correlation with local reform stringency (the p-value of the joint significance test = 0.5902). We shall predict an *ex-ante* reform stringency based on these three pre-reform institutional variables and use it in our robustness checks as an alternative reform stringency measure.

There are two key identification concerns regarding our reform stringency measure. The first one is the potential influence of the effectiveness of local governments in implementing market reforms on local land allocation before the launch of the 2007 reform. To address this concern, subsection 4.2.1 examines the pre-policy trends and demonstrates that these related factors only enhanced the spatial agglomeration of new entrants once the reform policy was implemented. The second concern is regarding the potential issues of endogeneity associated with the reform stringency measure, as it is constructed from post-reform land transactions. We will address them in subsections 4.2.2 and 4.2.3.

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[42] China's household registration system, also known as *hukou*, imposes high costs on working and living outside one's *hukou* location through restricted access to social services (e.g., education and healthcare) and employment opportunities in the public sector. The *hukou* registration index we borrowed from Zhang et al. (2019) is computed for the period before the major *hukou* reform launched in 2014. Considering that the index is solely available for 120 prefecture-level or province-level cities, we utilize the average hukou registration index at the province level for our analysis. Note that numerous studies have relied on this index to measure local *hukou* registration stringency (e.g., Zhang et al., 2020; Sun et al., 2021; Liao and Zhang, 2021).

3.4 Primary regression sample

For each county in our sample, we use the ASIF data set to measure the entry incidence and employment size of new manufacturing firms from the industries that were already stably established within the county.[43] Our study period commences in 2005 as we measure each industry's local specialization based on the 2004 Economic Census data. The period ends in 2010 due to changes in the sample coverage of the ASIF data beginning in 2011. For the primary regression analysis, we construct a panel of county-industry (two-digit) observations over the six survey years.[44] We exclude observations from Zhejiang province because, as a pioneer province, it introduced competition in its allocation of industrial land before the 2007 nationwide reform.[45] We also exclude observations from the Tibet Autonomous Region and Hainan Island due to the very few industrial land transactions during our study period in these regions. The regression sample covers 2,143 counties in 305 prefecture- or province-level cities. In Table 1, panel A reports the summary statistics of the main dependent variables.

3.5 Graphical evidence: firm entry and specialization

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[43] Considering that around 85%-90% of new entries between 2005 and 2010 occurred in industries that already had a certain level of employment in the counties, our regression analysis focuses on industries that were already present in a particular county prior to the reform and maintained a stable employment size throughout our study period. Specifically, to be included in the sample, the industry must have had at least one reported firm in the respective county every year from 2005 to 2010.

[44] Although the main analysis is conducted at the two-digit industry level, the main results are robust to using variables measured at the three-digit level.

[45] According to our interviews with local officials in Zhejiang province, the local authorities tried to allocate land before 2007 using a screening process similar to the land transaction mechanism during the post-reform period. An analysis of industrial land sale prices from January to June 2007 reveals that Zhejiang province exhibited the highest average ratio of actual sale price to minimum land price among all provinces, significantly exceeding one. This observation suggests that competition in land allocation existed in Zhejiang before the reform was implemented in July 2007. This is not surprising as Zhejiang has historically pioneered economic reforms. Before the reform, its economy was dominated by private enterprises, in sharp contrast to other provinces. For example, the 2004 Economic Census shows that China's average share of employment in state-owned enterprises was 40%, but only 6% in Zhejiang.

Before conducting the primary regression analysis, we present visual evidence demonstrating how the relationship between entry likelihood (or entry employment size) and specialization has evolved throughout our study period. This analysis uses the primary regression sample constructed in section 3.4. Figure 2 illustrates the temporal trends of the relationship between entry likelihood and specialization (panel A) and the relationship between the employment of new entrants and specialization (panel B). During the pre-reform period (before 2007), these relationships are close to zero and statistically insignificant.[46] This finding suggests that, on average, new firms in industries aligning better with a county's specialization were not significantly more likely to enter that county than new ones in other industries before 2007. In contrast, immediately following 2007, we observe a shift in these relationships, with them becoming positive and statistically significant. This finding suggests that, during the post-reform period, there was an influx of firms in industries better matched to local specialization.

4. Primary empirical analysis

In this section, we delve into the empirical strategy and primary findings regarding the central question addressed in this paper: Has the implementation of the 2007 reform resulted in an increased concentration of new firms in industries that align well with local specialization? In addition, we present a series of validity investigations and robustness checks to ensure the reliability of the main findings. We also explore the heterogeneity of the reform's impact across different geographical areas and industries, aiming to shed light on potential mechanisms at play. Moreover, to gain insights into the factors driving industrial agglomeration, we examine whether the reform has facilitated the clustering of new firms in localities where they can leverage the upstream and downstream linkages and benefit from sharing inputs such as labor and natural resources. Lastly, we investigate the reform's effect on incumbents.

4.1 Main regression analysis: Firm entry, specialization, and reform

[46] To obtain the figures in Figure 2, we regress the entry dummy or entry employment of a specific industry in a particular county on the interaction terms of the county-industry-specific specialization and year dummies. Additionally, we include various control variables, namely the prefecture-industry-year fixed effects, county-year fixed effects, and the employment scale of incumbent firms. We will elaborate on the purpose behind incorporating these control variables in subsection 4.1.

Our empirical analysis investigates whether the reform has increased the likelihood of new entries in industries in which the county has a considerable specialization, using the panel of county-industry observations from 2005 through 2010 constructed from the ASIF. In particular, we examine how the relationship between entry probability (or entry size) and local industrial specialization has changed with the time variation (i.e., before and after the introduction of the reform in 2007) and regional variation (i.e., localities with different levels of reform stringency). The regression specification is as follows:

$$\begin{aligned} y_{kjt} &= \phi_0 specialization_{kj} + \phi_1 specialization_{kj} \times stringency_{c(k)} \\ &+ \phi_2 specialization_{kj} \times Post07_t + \phi_3 specialization_{kj} \times Post07_t \times stringency_{c(k)} \\ &+ \gamma_{kt} + \eta_{c(k)jt} + \lambda x_{kj} + \varepsilon_{kjt} \end{aligned} \tag{2}$$

where y_{kjt} represents a dummy variable indicating whether there was at least one new entrant in industry j in county k in year t or the log of the total employment of the new entrants plus one; $specialization_{kj}$ is the specialization index of industry j in county k in 2004; $stringency_{c(k)}$ represents the level of reform stringency in prefecture c that supervises county k; $Post07_t$ is a dummy variable that equals one if $t \geq 2007$ and zero otherwise; x_{kj} represents the log of initial total employment in industry j in county k, which controls for the effect of the employment scale of incumbent firms; and ε_{kjt} is the error term. The standard errors are two-way clustered by prefecture and industry. All the regressions are weighted by the number of industrial land parcels sold during 2008–10 in the prefecture that contains the county.[47]

In regression specification (2), we include a comprehensive set of fixed effects to account for potential confounding factors. Firstly, we address concerns regarding prefecture-industry-specific shocks. Certain prefectures may have implemented policies to upgrade their industrial composition throughout our study period.[48] Additionally, some prefectures with a dominant presence of polluting industries may have been implementing stricter environmental regulations after 2007

[47] In the regressions, we give greater weight to the county-industry observations from the prefectures that sold more industrial land parcels during the post-reform period. The results remain the same if we use each county's GDP in the secondary sector in 2005 as an alternative weight (obtained from the Fiscal Statistical Compendium for All Prefectures and Counties), as shown in Table A3 in Appendix A.

[48] For instance, from 2003 to 2013, Shenzhen in Guangdong Province introduced various measures to push industrial upgrading by moving low- and middle-end companies and welcoming R&D firms. See https://unhabitat.org/sites/default/files/2019/11/the_story_of_shenzhen_2nd_edition_sep_2019.pdf for details.

(Chen et al., 2018). Moreover, specific industries within certain prefectures may have been more exposed to the 2008 Global Financial Crisis. To mitigate these concerns, we include prefecture-industry-year fixed effects to capture the effects of both time-invariant and time-varying factors at the prefecture-industry level. These prefecture-industry-year fixed effects are represented by $\eta_{c(k)jt}$, where $c(k)$ in the subscript represents the prefecture that supervises county k. Another concern is that prefectures with less realized demand for industrial land after the reform may be less willing to implement the reform. Furthermore, some industries may have been granted specific national development policies or experienced certain international shocks. The inclusion of prefecture-industry-year fixed effects could mitigate these concerns as well. Secondly, certain counties possess inherent advantages regarding geographic features, climate conditions, natural resources, economic conditions, and policy environment, which could facilitate industrial agglomeration locally. To address this concern, we include county-year fixed effects, represented by γ_{kt}, enabling us to account for the impacts of time-invariant and time-varying county characteristics. Notably, including these fixed effects implies that our identification stems from the variation in the specialization index across counties within a particular prefecture.

In specification (2), ϕ_0 captures the relationship between the entry likelihood (or entry size) and the local specialization during the pre-reform period for counties with the average reform stringency level (referred to as average-stringency counties hereafter); $(\phi_0 + \phi_1)$ captures this pre-reform relationship for counties with a post-reform stringency level that is one standard deviation above the sample average (referred to as high-stringency counties hereafter); ϕ_2 captures the change in this relationship after the reform for average-stringency counties; and $(\phi_2 + \phi_3)$ captures the change for high-stringency counties. Note that ϕ_3 is the key parameter of interest because it specifically captures how *the stringency level of the reform* influences the relationship between the likelihood of new entrants in a particular industry entering a particular county and the county's specialization in the industry *after the reform was launched*.

Columns (1) and (3) in Table 4 exclude the terms associated with the reform stringency measure from specification (2). The findings in these columns align with the patterns shown in Figure 2. The main results corresponding to specification (2) are presented in columns (2) and (4) of Table 4. We find that the triple interaction terms are positively and statistically significant for both outcome variables: After 2007, counties that more strictly implemented the reform had significantly more new entrants in industries that better matched their specialization. By contrast, the probability of entry is uncorrelated with the quality of the match before 2007, and this result holds for all the counties regardless of the reform stringency levels, as shown by the estimates of

ϕ_0 and ϕ_1. These results suggest that the new transaction mechanism has significantly strengthened the relationship between new entrant firms and local specialization, thereby enhancing the spatial agglomeration of these new firms.

The economic magnitude of the effect of the 2007 reform is remarkable. After 2007, on average, an increase of one standard deviation in the local specialization index in a two-digit industry (which is about 4, as shown in Table 1) is associated with increments of 3.6 percentage points and 23% in the entry likelihood and employment of new entrants in this industry in the locality, respectively. An increase of one standard deviation in the local reform stringency level leads to additional increases in the entry likelihood and new employment of 1.5 percentage points and 11%, respectively.

4.2 Validity and robustness checks

This subsection further investigates the validity of regression specification (2) by checking the pre-policy trends, addressing the endogeneity issues of the reform stringency measure, mitigating the confounding factors associated with the specialization index, and conducting various robustness checks to ensure the reliability of the main results.

4.2.1 Checking pre-policy trends

The key validity assumption is that counties with different levels of reform stringency share common time trends in the relationships between the outcome variables and local specialization in the absence of the reform. To check whether this parallel trends assumption holds, we estimate the following dynamic effect model:

$$\begin{aligned} y_{kjt} = & \sum_{l=2005}^{2010} \phi_0^l specialization_{kj} \times Year_t^l \\ & + \sum_{l=2005}^{2010} \phi_1^l specialization_{kj} \times stringency_{c(k)} \times Year_t^l \\ & + \gamma_{kt} + \eta_{c(k)jt} + \lambda x_{kj} + \varepsilon_{kjt} \end{aligned} \tag{3}$$

where $Year_t^l$ is a dummy variable that equals one if $t = l$, $l = 2005, \cdots, 2010$, and the definitions of the other variables follow the main regression model (2). Hence, ϕ_1^l are the parameters of interest, which capture the year-specific coefficients on $specialization_{kj} \times stringency_{c(k)}$. The standard errors are two-way clustered by prefecture and industry. All the regressions are weighted by the number of industrial land parcels sold during 2008–10 in the prefecture that contains the county. It is important to note that the regression model (3) does not include county-industry fixed effects, which means that there is no base year for this analysis.[49]

Columns (1) and (3) in Table 5 present the results of the regressions that omit the triple interactions from specification (3). As also presented in Figure 2, immediately after 2007, new firms started to cluster in counties where their industries aligned better with local industrial structure, in sharp contrast to the pre-reform period. Columns (2) and (4) show the results of the regressions according to specification (3). The estimates of ϕ_1^l are small and insignificant before 2007; that is, the relationship between the entry likelihood (or entry size) and specialization does not exhibit different time trends between counties with different levels of reform stringency *during the pre-reform period*, which supports the parallel trends assumption. Right after 2007, there were apparent increases in the estimates of ϕ_1^l, and the coefficients have remained significantly positive since then. The results demonstrate that the reform's effect on newly entering industrial firms occurred immediately after its introduction and has persisted.

4.2.2 Alternative reform stringency measures

The reform stringency measure derived from post-reform land transaction data may be influenced by post-2007 industrial development conditions, potentially introducing estimation bias. To mitigate the concern, we predict an *ex-ante* reform stringency for each prefecture based on the regression results from column (1) of Table 3, which identifies three pre-reform institutional variables contributing to the variation in our reform stringency measure (see subsection 3.3 for more details). This *ex-ante* reform stringency measure can serve as a proxy for the local institutional quality that underlies the effectiveness of implementing market reforms and may be less likely to be influenced by changes in local industrial outcomes after 2007. We re-run our primary regression model (2) by replacing our *ex-post* reform stringency measure with this *ex-ante* stringency measure (standardized to have a mean of zero and a standard deviation of one). The results in Table 6 align closely with the main results reported in Table 4, except the magnitudes of the coefficients on the triple interaction term are slightly larger.[50] The findings suggest that the

[49] We will discuss the results of the regression model incorporating county-industry fixed effects in subsection 4.2.5.

[50] The standard errors in Table 6 are two-way clustered by prefecture and industry. Furthermore, because the alternative stringency measure is a generated regressor, we also calculate the standard errors based on

effectiveness of the local government in executing market reforms underlying the spatial variation in the extent of the reform stringency did not change the allocation of industrial land until the launch of the reform in 2007.[51]

Furthermore, we consider several alternative measures of local reform stringency and report the results of the additional robustness checks in Table A4b, in Appendix A. First, the main results are robust to using industrial land sales during July 2007–10 to calculate the level of local reform stringency, as shown in columns (1) and (4). Second, considering the greater administrative autonomy of counties and county cities compared to urban districts, we use the industrial land sales of each county or county city to calculate its reform stringency. For urban districts, we use the share of public sales of all the urban districts in the respective prefectures to measure their reform stringency. The main results are robust, as shown in columns (2) and (5). Third, to minimize the effect of each county's industrial development on its own level of reform stringency, we exclude the county's own industrial land transactions when calculating its local reform stringency. The main results are also robust, as shown in columns (3) and (6).

4.2.3 Addressing concerns about the reform stringency measure

In this subsection, we tackle confounding factors associated with our reform stringency measure from five different aspects.

Firstly, a potential concern is that the reform stringency measure may be correlated with the pre-trends in local industrial outcomes. To address this concern, in the main regression model (2),

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1,000 bootstrap replications. We cluster the bootstrap replications on prefectures to account for the potential correlation of new entries in the same prefecture. The results are similar.

[51] In addition, we utilize the *ex-ante* stringency measure as an instrument for the reform stringency measure to account for potential endogeneity. The instrumental variable (IV) estimation results are reported in Table A4a in Appendix A. The first-stage F-statistic is larger than 10, suggesting that the instrument is powerful. The results mirror the main results, although the coefficients on the triple interaction term are three to four times larger than the OLS estimates shown in Table 4. However, it is important to exercise caution when interpreting the IV results because these three pre-reform institutional variables may have additional effects on the local industrial composition beyond the land allocation channel after 2007. For instance, it is worth considering that prefectures with superior market institutions were more inclined to undertake reforms to enhance credit and labor markets, thereby improving the efficiency of resource allocation. Considering these additional effects, we regard the IV results as supplementary evidence.

we include a set of triple interaction terms between the specialization index, post-reform dummy, and prefecture-level characteristics related to the growth trends of industrial development conditions, including each prefecture's GDP, population, shares of GDP in the secondary and tertiary sectors in 2007, and the prefecture's growth rates of GDP, population, and secondary and tertiary sectors' GDP shares between 2003 and 2007. In addition, we include the interactions between the specialization index and these prefecture-level characteristics in the regressions. Columns (1) and (6) in Table 7 show that the main results remain robust.

Secondly, the implementation of the reform coincided with the minimum land price regulation enforced in January 2007 (see the background section for details). There may be concern that local reform stringency is correlated with the minimum land price. We control its impact by including the triple interaction term between the specialization index, post-reform dummy, and each prefecture's average minimum land price, along with the interaction term between the specialization index and the average minimum land price. Columns (2) and (7) in Table 7 report the results, which show that the main results remain robust.

Thirdly, the central government announced an economic stimulus package of 4 trillion yuan on November 9, 2008, referred to as the 4 Trillion Program (FTP) program hereafter, to minimize the influence of the 2008 global financial crisis. The FTP program aimed to boost investment by injecting vast financial resources into state-owned banks during 2009–11. The reform stringency may be correlated with local investment growth brought in by the FTP program, which may directly affect local land allocation and firm entry. To address this concern, we use the growth rate of each prefecture's bank loans during the FTP program (from 2006–08 to 2009–11) to measure local investment growth and add the triple interaction between the specialization index, post-reform dummy, and growth rate of bank loans, along with the interaction term between the specialization index and growth rate of bank loans, into the main regression model (2). As columns (3) and (8) in Table 7 show, the main results remain robust.

Fourthly, there may be concern that local geographic conditions may be correlated with the reform stringency and, at the same time, affect firm entry.[52] To address this concern, we add the triple interaction between the specialization index, post-reform dummy, and geographic characteristics, including each prefecture's total developable land area and elevation (both in logs), and the interaction between the specialization index and geographic characteristics. As columns (4) and (9) in Table 7 show, the main results remain robust.

[52] For example, Saiz (2010) shows that steep-sloped terrain effectively curtails housing development.

Lastly, there is a potential concern that the reform stringency measure may be correlated with the ages and, thus, career-advancement perspectives of prefecture leaders (Wang et al., 2020), which could directly influence local industrial composition. To mitigate the confounding effect of local leaders' characteristics, we include the triple interaction between the specialization index, post-reform dummy, and the ages of prefecture leaders as of 2007, as well as the interaction between the specialization index and the leaders' characteristics. The party secretary and mayor who governed a prefecture for the longest duration during 2008–10 are referred to as the prefecture's leaders. Columns (5) and (10) in Table 7 show that the main results remain robust.[53] Due to missing data on prefecture-level economic characteristics, bank loan data, geographic characteristics, or leaders' information, the sample size varies slightly across the columns in Table 7.

4.2.4 Addressing concerns about the specialization index

The 2008 global financial crisis occurred right after the introduction of the 2007 reform. Thus, our main estimates could be biased if the crisis substantially affected industries with greater local specialization. For example, it is possible that in a given county, the crisis may have had a stronger effect on the industry that was the leading contributor to local exports (e.g., a large share of the county's total output value was attributed to the industry's export value) than on other industries, and, at the same time, the industry with a higher specialization index was more likely to become the major contributor to local exports. To address this concern, we calculate the ratio of the export value of each industry in each county to the county's total output value (referred to as the industry's export share within the county) and include this export share and the relevant interaction terms in the main regression model (2).[54] As columns (1) and (4) in Table 8 show, our main results remain

[53] To examine whether the ages of prefecture leaders are one of the driving forces for the variation of reform stringency, we re-run regressions in Table 3 by including the age information of the prefecture leaders who were in office during the time window when the reform was launched nationwide. The results reported in Table A5 of Appendix A show that none of these characteristics have significant coefficients. The biographical information of the prefectural leaders was manually gathered from their personal curriculum vitae, accessible on the Baidu Baike website.

[54] We include the export share of each industry in each county, the interaction term between the export share and reform stringency, the interaction term between the export share and post-reform dummy, and the triple interaction term between the export share, reform stringency, and post-reform dummy. As some observations are missing the export share data, the sample sizes in the regressions corresponding to columns

robust. In addition, we investigate the reform's effects on the new entry of exporting and non-exporting firms separately. While the main results hold for both types of entrants, the effects are larger for the entry of non-exporting firms. Panel A in Table A6 in Appendix A reports the results.

Another concern is that the degree of specialization of a given county in an industry may be correlated with the industry's market structure in that county. For example, the specialization index may be correlated with the degree of concentration of local employment in a small number of firms. The local firm size distribution could affect the degree of competition in local input markets and local non-tradable goods markets and hence may affect firm entry. We measure each industry's local market structure using two county-industry variables: (1) each industry's average firm size in each county and (2) the employment share of the largest firm in each industry in each county. As shown in columns (2), (3), (5), and (6) in Table 8, the main results are robust to including these two county-industry variables and the relevant interaction terms.

4.2.5 Additional robustness checks

<u>*Different-sized new entrants*</u>

Because the private firms covered by the ASIF data are those with annual sales of 5 million yuan or more, there may be a concern that the findings based on this data set only apply to larger firms. We address this concern by checking whether the estimated effects of the reform are concentrated among the relatively large industrial firms in the ASIF data. We divide all the new entrants into three types by the value of annual sales: small, medium, and large. Those whose annual sales value is at or above the 75th percentile of the distribution in the respective year are large; those at or below the 25th percentile are small; and the rest are medium. We then run the main regression model (2) for the three types separately and report the results in panel B in Table A6 in Appendix A. The results show that the 2007 reform exerted similar effects across the three types of new entrants. Therefore, the paper's findings are also relevant for small firms not covered by the ASIF data but have annual sales close to the "5 million yuan" threshold.

<u>*Three-digit industrial classification*</u>

(1) and (4) are slightly smaller than the size of the regression sample.

Our main analysis investigates industries at the two-digit level. We consider industries at the three-digit level to capture within-industry connections at a more refined level.[55] In Table A8, in Appendix A, columns (1) and (3) report the three-digit-level results corresponding to the main regression model (2), and columns (2) and (4) present the results corresponding to the dynamic effect model (3). Consistent with our main results, we find that after 2007, counties that implemented the reform more stringently attracted more entrants in industries where the counties have high specialization at the narrower industrial classification.

County-industry fixed effects

We incorporate county-industry fixed effects into regression specification (2) to address concerns regarding potential confounding effects resulting from unobserved heterogeneity at the county-industry level. Columns (1) and (3) of Table A9 in Appendix A indicate that while the coefficients on the specialization index and its interaction with the reform stringency are absorbed by these additional fixed effects, the main findings remain robust. Furthermore, we include these fixed effects in regression specification (3) and remove the interaction terms associated with the 2007 year dummy. The results, presented in columns (2) and (4) in Table A9, show that the main results are still present. However, the significance levels decrease due to the smaller sample size within county-industry cells.

4.3 Heterogeneous effects

This subsection investigates how the reform's effect varies across industries or regions to shed light on potential mechanisms. To accomplish this, we multiply the respective industry or region characteristics of interest with $specialization_{kj} \times Post07_t \times stringency_{c(k)}$ and $specialization_{kj} \times Post07_t$ and include these two additional terms into the main regression model (2). We conduct the following four checks. The first two checks focus on industry heterogeneity, while the last two explore regional heterogeneity.

[55] We use ASIF data to construct a panel of 33,913 county-industry (three-digit) observations in 2,117 county-level units from 304 prefecture- or province-level Chinese cities across six survey years (2005, 2006, 2007, 2008, 2009, and 2010). The sample restrictions follow the main analysis. Table A7, in Appendix A, reports the summary statistics of the variables used for the analysis.

Firstly, we examine whether the reform's effect changes across industries characterized by different levels of unrealized agglomeration economies. Previous studies have highlighted the significant disparity in spatial agglomeration levels across various industries in China, potentially influenced by variations in government interventions (Lu and Tao, 2009; Ge, 2009). Some industries may initially possess greater unrealized agglomeration economies, which could make them more likely to benefit from the 2007 reform. We have adopted two strategies to measure the industry-specific initial level of unrealized agglomeration economies. Firstly, based on the industry-specific EG indices calculated by Ellison and Glaeser (1997) using the geographic information of manufacturing plants in the U.S.[56], we identify six industries that would be highly agglomerated without institutional frictions, including (1) the textile industry, (2) the tobacco processing industry, (3) the leather, furs, down, and related products industry, (4) the chemical fibers industry, (5) the transportation equipment manufacturing industry, and (6) the arts and crafts and other manufacturing industries. The average EG index of these industries is approximately four times higher than that of the other industries, based on the geographic locations of manufacturing plants in the U.S. in 1987. However, when considering the spatial locations of Chinese manufacturing firms in 2005, the EG indices of these six industries do not show a significant difference compared to those of the other industries. Hence, we consider that these six industries had significant unrealized agglomeration economies in China before the 2007 reform. As anticipated, the findings in columns (1) and (4) of Table 9a indicate a more substantial impact of the reform on these industries.

In addition, as a cross-check, we borrowed each industry's change in the EG index between 1998 and 2009 in China from Wen and Xian (2014).[57] The EG index serves as a conventional

[56] The EG index is developed by Ellison and Glaeser (1997) to measure a particular industry's spatial agglomeration degree. The EG index is superior to the spatial Gini index as it can account for the impacts of industrial market structure. Ellison and Glaeser (1997) provide the EG indices for all 459 manufacturing industries defined by the 4-digit classifications of the US Census Bureau's 1987 S.I.C system. We aggregated these figures to the 3-digit industry level by calculating the average EG index across all the 4-digit industries within each 3-digit industry, with weights assigned based on the employment share of each 4-digit industry. Next, we matched the U.S. 3-digit industries with their corresponding Chinese 4-digit industries. Using this mapping, we calculate the EG index for each 2-digit industry in China based on the geographic locations of manufacturing plants in the US in 1987. In particular, we obtained this index by averaging the EG indices of all the 4-digit industries within each 2-digit industry, weighted by the employment share of each 4-digit industry.

[57] Table A10 in Appendix A presents the change in the EG index between 1998 and 2009 for all 30

measure of industrial agglomeration, and China experienced a 125.9% increase in the average EG index during this period. Comparing across industries, a higher increase in the EG index may indicate a greater degree of untapped agglomeration economies in the initial year of 1998 before large-scale urban reforms were launched. As expected, the results reported in columns (2) and (5) of Table 9a demonstrate a more pronounced effect of the reform in industries with higher levels of unrealized agglomeration economies.[58]

Secondly, we explore the potential variations in the effects of the reform across industries characterized by different rates of spatial decay of agglomeration spillovers. Previous studies have demonstrated that productivity spillovers decline rapidly with distance (e.g., Rosenthal and Strange, 2003; Arzaghi and Henderson, 2008; Baum-Snow et al., 2024). Industries that experience a fast decline in spillover effects can only benefit from localized productivity externalities within a limited geographical area, making the spatial locations of firms in these industries crucial for enhancing productivity. Consequently, we expect the reform's impact to be more substantial for these industries. Consistent with our expectations, the findings reveal a more prominent impact of the reform on industries characterized by highly localized agglomeration externalities, indicated by a rapid attenuation speed of agglomeration spillovers (see columns (3) and (6) of Table 9a). We borrow the industry-specific estimates of decay rates from Li et al. (2022).[59]

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two-digit manufacturing industries, calculated by Wen and Xian (2014). The industries with the highest growth in the EG index during this period include (1) the leather, furs, down, and related products industry, (2) the chemical fibers industry, (3) the instruments, meters, cultural, and office machinery industry, and (4) the recycling and disposable waste industry.

[58] It is worth noting that two of the six most agglomerated industries, as identified by the geographic information of the manufacturing plants in the U.S., are also among the industries experiencing the greatest growth in the EG index from 1998 to 2009. These two industries are the leather, furs, down, and related products industry, and the chemical fibers industry.

[59] We borrow the industry-specific estimates of decay rates from Li et al. (2022), which suggests that the extent to which spillovers attenuate with space is associated with the source of agglomeration economies for a particular industry. Specifically, they find that agglomeration benefits disappear faster in industries producing more innovative products but slower in industries where transportation costs per shipment are higher. Table A10 in Appendix A presents their estimates of the attenuation speeds for 29 two-digit manufacturing industries. The industries with the greatest attenuation speed of agglomeration economies include (1) the chemical fibers industry, (2) the instruments, meters, cultural, and official machinery industry, (3) the stationery, educational, and sports goods industry, (4) the rubber products industry, and (5) the leather, furs, down, and related fibers.

Thirdly, we investigate whether the reform's effects vary depending on frictions in the local capital market. A well-functioning capital market may enhance the reform's impact by facilitating credit acquisition for land purchase of firms that align with local productivity advantages. To analyze this, we utilize a province-level index of market-oriented credit allocation in 2006, as provided by Fan et al. (2011).[60] This index is constructed based on each province's proportion of short-term loans from financial institutions granted to the non-state-owned economic sector, encompassing agricultural, township, private, and foreign enterprise loans. The results, reported in columns (1) and (3) of Table 9b, indicate that the reform's effect is more pronounced in regions characterized by a higher degree of marketization in credit allocation. These findings suggest that market reforms in the capital market can reinforce the positive effect on resource allocation efficiency derived from land market reforms.

Lastly, we examine whether the characteristics of local politicians influence the magnitude of the reform's effects. In China, local politicians often play a crucial role in shaping local public policies. Previous literature has highlighted the significance of age as a factor in their career advancements, with younger politicians having a higher likelihood of promotion and thus more likely to implement policies that boost short-term GDP performance (e.g., Wang et al., 2020). However, the results in columns (2) and (4) of Table 9b indicate that the reform's effect remains unchanged across local leaders with varying career advancement perspectives. The last two heterogeneous effects suggest that enhancing the role of the market may outweigh incentivizing politicians to improve resource allocation efficiency.

4.4 Sources of agglomeration economies

The concentration of industries in a specific geographic area often stems from thick upstream or downstream markets or shared inputs such as a skilled workforce or natural resources. This subsection aims to provide direct evidence that the 2007 reform has led to an increased clustering of firms in counties where these sources of agglomeration economies are particularly strong.

Firstly, we gauge the thickness of the local market of suppliers or customers specific to a

[60] As discussed in Section 3.3, previous studies have extensively employed the marketization index system developed by Fan et al. (2011) to evaluate a province's progress in marketization from multiple angles. For this analysis, we focus on a specific sub-index derived from this system to gauge how much the market influences credit allocation.

particular industry by calculating this industry's upstream or downstream employment in each county. Specifically, we compute the employment scale of an industry's upstream (or downstream) segment in a county by aggregating the employment figures from all manufacturing industries within that county, weighted by the respective industries' contribution to the input value (or output value) of the specific industry, as derived from the 2002 input-output table provided by the National Bureau of Statistics of China. In regression specification (2), we replace the specialization index of a particular industry in a given county with the industry's upstream or downstream employment in that county. The results, reported in columns (1) and (2) of Table 10, indicate that the reform has facilitated the entry of firms into the counties where economic activities in the upstream or downstream markets of their respective industries are concentrated.

Secondly, agglomeration economies can also arise from the availability of a relevant workforce. For example, industries heavily reliant on highly educated workers can benefit from clustering in areas with a larger population of highly educated individuals. To measure this industry-specific local advantage, we construct an interaction term between the county's college-educated population (in logarithmic form and calculated from the 2000 Population Census Data) and the industry's share of college-educated employees (calculated from the 2004 Economic Census Data), referred to as the county-industry labor matching measure. We then run regression model (2), replacing specialization with this labor matching measure, and report the results in column (3) of Table 10. The findings indicate that the 2007 reform has led to increased agglomeration of new firms in industries that employ a larger share of highly educated workers in counties with a greater abundance of highly educated potential workers.

Lastly, we focus on productivity benefits resulting from a specific type of natural endowment, namely, the amount of flat cropland. The production in the food processing industry can benefit from the availability of flat cropland as it eases access to agricultural raw materials, such as grains. Consequently, we examine whether the 2007 reform has increased the agglomeration of new firms in this industry in the counties with a relative abundance of flat cropland. We calculate a county's amount of cropland with a slope of less than 6 degrees to measure this county's flat cropland area. (Appendix D discusses the details.) In regression specification (2), we replace the specialization index of a particular industry in a given county with the interaction between the log of the county's flat cropland area and a dummy variable indicating whether the industry corresponds to food processing. The results, reported in column (4) of Table 10, show that the 2007 reform has facilitated the entry of new firms in the food processing industry into the counties with extensive flat cropland.

In sharp contrast, before 2007, the probability of entry was uncorrelated with any of these four measures directly characterizing the sources of agglomeration economies. This result holds for all counties regardless of the reform stringency levels. Overall, these findings are aligned with our main results and provide valuable insights into how the reform interacted with various factors driving industrial agglomeration.

4.5 Incumbents

Has the 2007 reform impacted incumbents, aside from new entrants? The reform may have influenced incumbents through land allocation or spillover effects from new entrants. To explore this question, we analyze various characteristics of firms established before 2005 during our study period (2005–10) for each county-industry observation using the ASIF data. These characteristics include total assets, employment size, output value, and total sales value. (Table A11 in Appendix A reports the summary statistics.) We run regression model (2) using these characteristics as the outcome variables (in logarithmic forms). Table A12 in Appendix A reports the results. We find a positive and marginally significant impact of the reform on the total assets of incumbents (with a *p*-value of 0.107). However, the effects of the reform on the other three outcomes are statistically insignificant. These findings suggest that, in the short term, the scale of new entrants may still be too small to significantly impact incumbents, considering that the employment scale of incumbents is 20-50 times larger than that of new entrants (as shown in Table 1). Thus, during our study period, the reform primarily affected new entrants.

5. The reform's impacts on local productivity and economic growth

5.1 Back-of-the-envelope calculation of productivity gains of new entrants

Assuming that industrial agglomeration causes higher productivity for new entrants, the spatial redistribution resulting from the reform may lead to a more efficient land allocation than the pre-reform period. This subsection conducts a back-of-the-envelope calculation to quantify how much the increase in the productivity of new entrants in the post-reform years was due to the 2007 reform, which facilitated improved matching between new entrants and counties, as opposed to the counterfactual scenario where the reform is absent. To simplify the calculation, we make two assumptions. Firstly, we disregard the potential influence on incumbents, as indicated by the findings in subsection 4.5, which suggest that the reform primarily affected new entrants during our study period. Secondly, we assume that the county-industry-specific TFP is time-invariant during our study period. In a sense, we focus on the average productivity gains of new entrants due to a better match with each county's existing production advantages. These simplifications imply that the productivity gains we calculate represent a conservative estimate of the reform's impact on productivity growth.

The reform has changed the distribution of new entrants in different industries across different counties. As such, for county k in year t, we obtain the productivity gain due to the improved matching quality by comparing the average TFP weighted by the counterfactual allocation of new entry employment with the TFP weighted by the actual allocation of new entry employment after the reform:

$$Gain_{kt} = \sum\nolimits_j \theta^1_{kjt} LogTFP_{kj} - \sum\nolimits_j \theta^0_{kjt} LogTFP_{kj} \quad , \tag{4}$$

where $LogTFP_{kj}$ is the TFP (in logarithmic form) of the new firms in industry j in county k; $\theta^1_{kjt} \equiv y^1_{kjt}/\sum_{j'} y^1_{kj't}$; and $\theta^0_{kjt} \equiv y^0_{kjt}/\sum_{j'} y^0_{kj't}$. Here, y^1_{kjt} is the actual employment of the new entrants in industry j in county k in year t, and y^0_{kjt} is the employment of the new entrants in industry j in county k in year t *absent the reform*, predicted as follows: $y^0_{kjt} = \exp(\widehat{\gamma_{kt}} + \widehat{\eta_{c(k)jt}} + \hat{\lambda} x_{kj} + \widehat{\varepsilon_{kjt}})$, where $\widehat{\gamma_{kt}}$ are the estimates of the county-year fixed effects in regression model (3); $\widehat{\eta_{c(k)jt}}$ are the estimates of the prefecture-industry-year fixed effects; $\hat{\lambda}$ is the estimate of the coefficient on the log of the employment scale of incumbent firms; and $\widehat{\varepsilon_{kjt}}$ is the residual. We use the estimates of the regression corresponding to column (4) in Table 5 for the calculation. In words, we calculate, in the absence of the reform, what would have happened to the spatial allocation of the new entry employment in different industries during 2008–10 while leaving the county-specific, prefecture-industry-specific, and unobserved county-industry-specific year trends and the effect of the employment scale of incumbent firms unchanged. In the counterfactual scenario, the spatial distribution of new entrants across industries does not consider the match quality between the firms' industry types and counties reflected by the firms' industry specialization in the counties, which is contrary to the actual case after the reform.

To simplify the comparison, we assume that the county-industry-specific TFP (i.e., $LogTFP_{kj}$ in equation (4)) is time-invariant during our study period (i.e., 2005–10). Specifically, for industry j in county k, we calculate the initial TFP as follows:

$$LogTFP_{kj} = \xi \times specialization_{kj} + t_k + t_j , \tag{5}$$

where $specialization_{kj}$ is the specialization index of industry j in county k in 2004[61]; ξ represents the effect of the specialization index on TFP[62]; and t_k and t_j capture the effects on TFP of the factors specific to county k and industry j, respectively. In addition to the locality-specific and industry-specific productivity factors, the county-industry-specific TFP depends on the degree of specialization of the industry in the county.

Plugging (5) into (4) gives the following equation:

$$\begin{aligned} Gain_{kt} &= Gain_{kt}^{match} + Gain_{kt}^{indcom} \\ &= \underbrace{\xi \sum_j [(\theta_{kjt}^1 - \theta_{kjt}^0) \times specialization_{kj}]}_{matching\ effect} + \underbrace{\sum_j \theta_{kjt}^1 \times t_j - \sum_j \theta_{kjt}^0 \times t_j}_{industry\ composition\ effect} \end{aligned} \tag{6}$$

Equation (6) illustrates that for a given county, a vital force that drives productivity gain is the reallocation of local land across industries according to the degree of local specialization ("matching effect"). Another force arises from changes in the local industry composition and productivity differentials across industries ("industry composition effect").

As our primary interest lies in the matching effect, we calculate the average TFP gain solely attributed to the improved matching quality. We present such TFP gains for the four regions: Eastern Coast, Central China, Northeast China, and Western China.[63] Specifically, region r's productivity gain in year t can be expressed as: $Gain_{rt}^{match} = \sum_k \omega_{krt}\, Gain_{kt}^{match}$, where ω_{krt} is county k's new entry employment share in region r in year t as in the actual data. Table 11

[61] Because, in the short term, the scale of new employment was relatively small compared to the initial total employment (see Table 1), we assume that the local industrial specialization did not change during our study period. We understand that by assuming so, we ignore the reform's effect on local industrial specialization over time; hence, the productivity gains we calculate are a lower bound of the reform's effect on productivity growth.

[62] We set ξ to 0.007 based on the regression results in Table 2.

[63] The East Coast region comprises economically well-developed coastal provinces (and provincial cities) in Eastern China, including Beijing, Fujian, Guangdong, Hebei, Jiangsu, Shandong, Shanghai, and Tianjin. The Central China region consists of the less developed inland provinces in Central China, including Anhui, Henan, Hubei, Hunan, Jiangxi, and Shanxi. The Northeast region consists of three provinces located in northeast China with an economic development level similar to Central China: Heilongjiang, Jilin, and Liaoning. The Western China region comprises the economically least-developed provinces in the country's western part, including Chongqing, Gansu, Guangxi, Guizhou, Neimenggu, Ningxia, Qinghai, Shaanxi, Sichuan, Xinjiang, and Yunnan.

shows the results, illustrating considerable spatial heterogeneity in the productivity gain. The East Coast and Central China regions benefited the most from the reform through enhanced matching quality. For example, in the absence of the reform, the average TFP of the new entrants in the East Coast region would have been 1.464% lower than the observed average TFP over the three years after the reform. The corresponding figures for Central China, Western China, and Northeast China are 1.463%, 0.725%, and 0.866%, respectively.

We next calculate the national average productivity gain in year t as: $Gain_t^{match} = \sum_k \omega_{kt} Gain_{kt}^{match}$, where ω_{kt} is county k's new entry employment share in the whole country in year t as in the actual data. Our calculation suggests that the reform caused the national average TFP of new manufacturing firms to increase by 0.345%, 0.462%, and 0.485% in 2008, 2009, and 2010, respectively, or 1.292% over the three years after the reform, as shown in column (5) in Table 11.[64] The Eastern Coast region contributed 57.6% of the national productivity gain, followed by Central China (26.5%), Northeast China (7%), and Western China (8.9%).

5.2 The reform's effect on nighttime lights

Have counties with pronounced initial industrial specialization and strict reform implementation reaped more productivity advantages from the 2007 reform and hence experienced faster economic growth after 2007? To answer this question, we gathered data on changes in nighttime lights to proxy local economic growth, a methodology employed by Henderson et al. (2012).[65] Our panel data set encompasses approximately 2,000 counties covered by the sample used for the primary

[64] We also incorporate the industry composition effect when calculating the national average productivity gain. To do so, we estimate the industry-specific TFP effect using the sample of 249,112 manufacturing firms established between 1949 and 2004 from the 2005 ASIF while controlling for the county fixed effects and the effects of the establishment's characteristics. Incorporating the industry composition effect brought down the national average TFP gain to 1.141% over the three years after the reform. The decline in average TFP may be because while some counties received more entrants from industries that better match their specialization, those industries per se have lower TFP.

[65] The correlation coefficients between a county's nighttime lights and its GDP in the primary, secondary, and tertiary sectors in 2001 were 0.30, 0.63, and 0.54, respectively. These findings indicate a strong correlation between the intensity of nighttime lights and the scale of local industrial production. Data on county-level sectoral GDP in 2001 were obtained from the Fiscal Statistical Compendium for All Prefectures and Counties (*Quanguo Dishixian Caizheng Tongji Ziliao*).

regression analysis, spanning 2004 to 2013. The regression specification is as follows:

$$
\begin{aligned}
\ln lights_{kt} = &\sum_{l=2004,l\neq 2006}^{2013} \psi_1^l Year_t^l \times \overline{specialization}_k \times stringency_{c(k)} \\
&+ \sum_{l=2004,l\neq 2006}^{2013} \psi_0^l Year_t^l \times \overline{specialization}_k + \delta_k + \mu_{c(k)t} + z_{kt}\vartheta + u_{kt}
\end{aligned}, \qquad (7)
$$

where $lights_{kt}$ represents the nighttime lights in county k in year t; $Year_t^l$ is a dummy variable that equals one if $t = l$, $l = 2004, \cdots, 2013, l \neq 2006$; $\overline{specialization}_k$ represents county k's initial average specialization index (standardized to have a mean of zero and a standard deviation of one)[66]; $stringency_{c(k)}$ represents the level of reform stringency, as constructed for the primary analysis; δ_k represents the county fixed effects; $\mu_{c(k)t}$ represents the prefecture-year fixed effects; z_{kt} represents the county-level initial economic characteristics interacted with year dummies; and u_{kt} is the error term. County fixed effects are included to control for the confounding effects of all time-invariant county characteristics; prefecture-year fixed effects are included to control for the confounding effects of all prefecture-specific shocks; and interaction terms between each county's initial characteristics and year dummies are included to control for the differential time trends in nighttime lights between counties with different initial characteristics.[67] The year 2006 is the omitted category. Standard errors are clustered at the prefecture level.

Figure 3 plots the estimates and 90% confidence intervals of ψ_1^l, the coefficients on the triple interaction terms in specification (7). It shows that during the pre-reform period, these coefficients were close to zero and statistically insignificant (relative to the base year, 2006). They became positive immediately after 2007 and have persisted since then.[68] The findings suggest that during the post-reform period, the intensity of local nighttime lights grew more in counties with a higher level of local industrial specialization; this increase was concentrated in the areas that implemented the reform more strictly.

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[66] The average specialization of each county is calculated by taking the average of the specialization index across all the industries present in that county in the working sample.

[67] These initial characteristics include the county's intensity of nighttime lights in 1992 (in logs), growth in illumination from 1992 through 1999, and a set of county socioeconomic characteristics in 2001, including the county's GDP (in logs), secondary and tertiary sector GDP shares, total population (in logs), and share of the rural population. Data on county-level socioeconomic characteristics in 2001 were obtained from the Fiscal Statistical Compendium for All Prefectures and Counties (*Quanguo Dishixian Caizheng Tongji Ziliao*). Table A13, in Appendix A, reports the summary statistics of the variables.

[68] Table A14 reports the regression results.

6. Evidence from land transaction data

6.1 Land allocation and local specialization

As discussed in subsection 3.1, our land transaction data encompass all industrial land sales after 2007 and, more importantly, provide two-digit industry classification codes for 80% of the transactions from 2009. Based on these two advantages, this data set can supplement the ASIF data by presenting evidence over an extended period during the post-reform era and providing direct insights into local land allocation across different industries. Specifically, we track the records of land sales for each county-industry observation in our primary regression analysis from 2009 through 2015 and run regressions based on specifications (2) and (3) while omitting the independent variables associated with the pre-reform period. The outcome is a dummy variable indicating whether there was at least one land sale for each county-industry-year observation. The stringency measure is calculated as the share of industrial land transactions during 2009–15 conducted through public sales in the prefecture that supervises the county, corresponding to the study period of the land sample. Similar to the main regressions, the standard errors are two-way clustered by prefecture and industry, and the regression is weighted by the number of industrial land sales in the study period of the land sample.

Table A15 in Appendix A reports the results, showing that from 2009 onward, land was more likely to be sold to firms in industries where the county has high specialization, and this positive correlation is more pronounced in areas that implemented the reform more strictly. The coefficients in column (1) of Table A15 are nearly identical to the main results in column (2) of Table 4 based on the information on new entrants from the ASIF data. The results in column (2) based on regression specification (3) demonstrate that the reform's effects are significant and persistent over time.[69][70]

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[69] After 2013, the coefficients on the triple interaction terms became small and insignificant, perhaps because the spatial variation in the level of reform stringency decreased over the years. The land transaction data show that, by the end of the land sample period, more than 85% of industrial land transactions went through public auctions in more than 90% of the prefectures in our sample, and only six prefectures had an auction share below 50%. Two are in Qinghai Province, one in Yunnan Province, one in Jilin Province, one in Anhui Province, and one in Guangdong Province.

[70] To check whether the new entries in the ASIF data accurately depict local land allocation across different industries, we compare the number of newly established firms with the number of land sales during 2009–

6.2 Competition, land sale prices, and area

This subsection presents evidence demonstrating that the new transaction mechanism reshapes the land allocation process by enhancing competition. Since information regarding the number of applicants for land sales is typically unavailable, we rely on land sale price data to provide indirect evidence. As discussed in Section 2, we expect land sale prices to be higher under the new transaction mechanism compared to negotiation when multiple potential buyers participate in the pre-screening stage and compete for the land. Therefore, we examine the relationship between land sale prices and transaction formats to provide corroborating evidence of increased competition due to the new mechanism. The analysis utilizes industrial land transactions during 2007–10, corresponding to the post-reform period of our primary analysis.[71] We conduct both land-parcel-level and prefecture-year-level regression analyses.

First, we conduct a land-parcel-level regression analysis using a subset of land transactions that have two-digit industry codes available. The dependent variable in this analysis is the sale price, measured in logarithmic form. The key independent variable is a dummy variable indicating whether the land was sold through a public sale. Additionally, we control for the effects of various land characteristics such as the land's distance to the city center, lot size, land source,[72] and transaction time. To account for the confounding effects of the specific unobserved factors at the prefecture-industry-year and county-year levels, we include fixed effects for these factors. The standard errors are two-way clustered at the county and industry levels.

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10. Although these two databases are not entirely comparable because 20% of land transactions are missing their industry classification codes, the correlation between the numbers of new entries and land sales calculated from these two datasets is 0.5435.

[71] As discussed in subsection 3.1, the land transaction data includes information on all land sales by local governments since 2007 and covers basic transaction information, such as lot size, transaction type (negotiation or public sale), sale price, sale date, and land address. For the regressions in columns (1) and (2), we restrict the sample to those land parcels used for manufacturing industries to be consistent with the main regression and those with two-digit industry codes available. Table A16, in Appendix A, reports the summary statistics of the variables. Of all the land transactions, 75% occurred through public sales, while the rest were through negotiated sales.

[72] There are two primary sources of urban construction land: newly converted farmland and existing urban land stock.

Our findings suggest that, on average, the sale prices for land sold via public sales are more than 40% higher than those sold by negotiation, indicating increased competition (see column (1) in Table 12). Furthermore, to address the concern that land parcels with better locational amenities may be more likely to be selected into a particular transaction format, we include a set of dummies indicating the township where a land parcel is located. Townships are China's most disaggregated administrative units.[73] Hence, a township's locational amenities, such as transport infrastructure, local government policies, and natural characteristics, should be similar. Column (2) in Table 12 shows that the public sale dummy coefficient remains robust after we include the township fixed effects.

Next, we address concerns that the observed price increase may be attributed to reduced industrial land supply. In particular, we examine how a prefecture's total land sale area and average land sale price change in response to the level of reform stringency after 2007. We aggregate industrial land transactions at the prefecture-year level and calculate the total land area and average per unit land sale price for each prefecture-year observation. Using this panel data, we regress each prefecture's total land sale area (or average land sale price) in a given year on interaction terms of the prefecture's reform stringency measure and year dummies. To account for unobserved time-invariant heterogeneity across prefectures, we introduce prefecture fixed effects and exclude the interaction term between the stringency measure and the 2007 year dummy. Additionally, we include province-year fixed effects to control for the province-specific year shocks. To capture the pre-existing time trends in the outcomes across prefectures with different initial land values and economic characteristics, we incorporate the interaction terms between a set of prefecture-level characteristics and year dummies. These characteristics include each prefecture's average regulatory minimum price of industrial land, the prefecture's GDP, population, shares of GDP in the secondary and tertiary sectors in 2007, and the prefecture's growth rates of GDP, population, and secondary and tertiary sectors' GDP shares between 2003 and 2007.

Column (3) of Table 12 presents the results, indicating that from 2007 onward, prefectures with higher reform stringency experienced a greater increase in industrial land prices, consistent with the findings in columns (1) and (2). However, column (4) shows that there was no correlation between reform stringency and total land sale area. This finding helps alleviate concerns regarding the potential reduction of industrial land supply in response to the strict implementation of the 2007 reform.

[73] In the land regression sample, on average, there are five townships per county.

7. Conclusion

In this paper, we examined whether the 2007 reform of the transaction mechanism of industrial land sales has reshaped local land allocation in China. We documented the distinctive features of land transaction mechanisms before and after the reform and found that the new mechanism promotes competition, as reflected by increased land sale prices. Our empirical analysis utilized comprehensive data sets that include information on initial local industrial structure, new industrial establishments, and industrial land transactions. Our results suggest that the 2007 reform has increased the entry of firms in industries that better fit local specialization potentially arising from agglomeration economies or natural advantages. A back-of-the-envelope calculation suggested that through the above channel, the national average TFP of new entrants increased by 1.3% over the three years after the reform. We also presented supporting evidence that the reform has positively impacted local economic growth, potentially through increasing local firms' TFP.

Our findings have important policy implications for the governments of countries with weak institutions in designing place-based policies to promote local industrial development. Making local authorities' land-selling process more transparent to the public could improve the efficiency of land allocation. In particular, it alters the geographic distribution of new entrants by encouraging clustering in areas where industries have a greater degree of local specialization, potentially leading to a more efficient spatial layout of industries. In addition, allocating land according to industry-county-specific characteristics can generate more significant heterogeneity in industrial composition across counties, which can help to alleviate concerns about excessive competition resulting from all counties trying to lure business investment with similar land subsidies.

After four decades of rapid economic growth, China's policymakers face critical challenges in ensuring sustainable economic growth. The recent literature on factor market reforms provides valuable insights into this question by showing that enormous efficiency and welfare benefits can be achieved from correcting factor misallocations in China from various perspectives, including the capital market (Brant, Tombe, and Zhu, 2013; Song and Wu, 2015), labor market (Tombe and Zhu, 2019), and land market (Henderson et al., 2022). This paper adds evidence of the potential benefits of land market reforms. Our findings suggest that even a modest introduction of transparency into the allocation mechanism can foster competition and significantly facilitate the clustering of new firms in localities where they can obtain agglomeration benefits. This, in turn, enhances productivity and stimulates economic growth, even in the presence of government control of the industrial land market.

While this paper focuses on a specific aspect of the reform's overall effect—within-industry agglomeration, it opens up several potential avenues for future research. Firstly, it would be valuable to investigate how the reform has interacted with labor and capital markets, leading to improved factor allocation and aggregate TFP (Hsieh and Klenow, 2009). Furthermore, it is worth examining how market forces and government intervention can be effectively combined in the design of land use policies to foster economic growth. While the invisible hand of the market can enhance allocation efficiency, it is essential to consider the agglomeration externalities for firms (Greenstone et al., 2010) and the dynamic benefits for governments (He et al., 2023) that may necessitate the visible hand of the government. How should policymakers design land allocation mechanisms to balance the visible and invisible hands? We leave this challenging question for future research.

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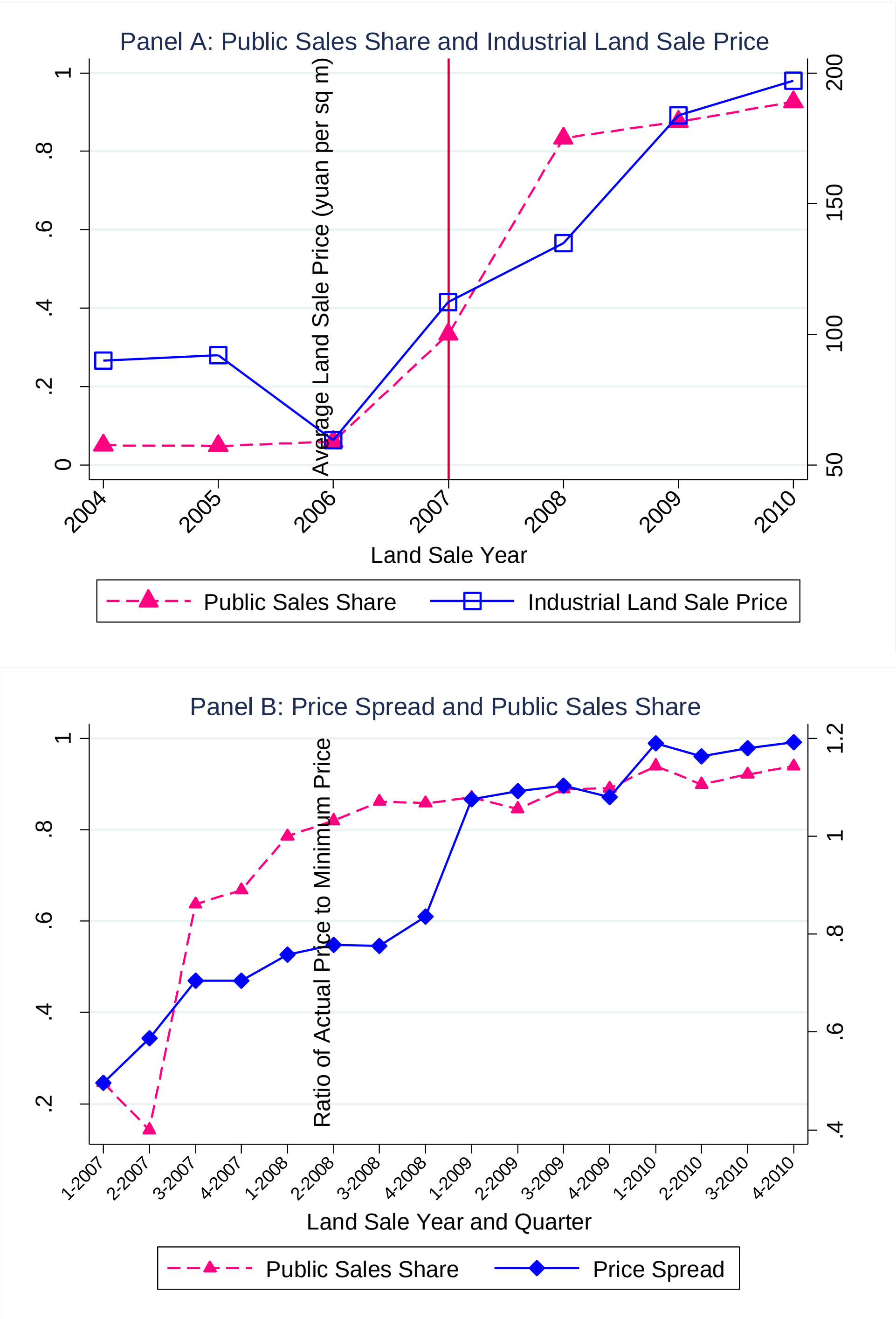
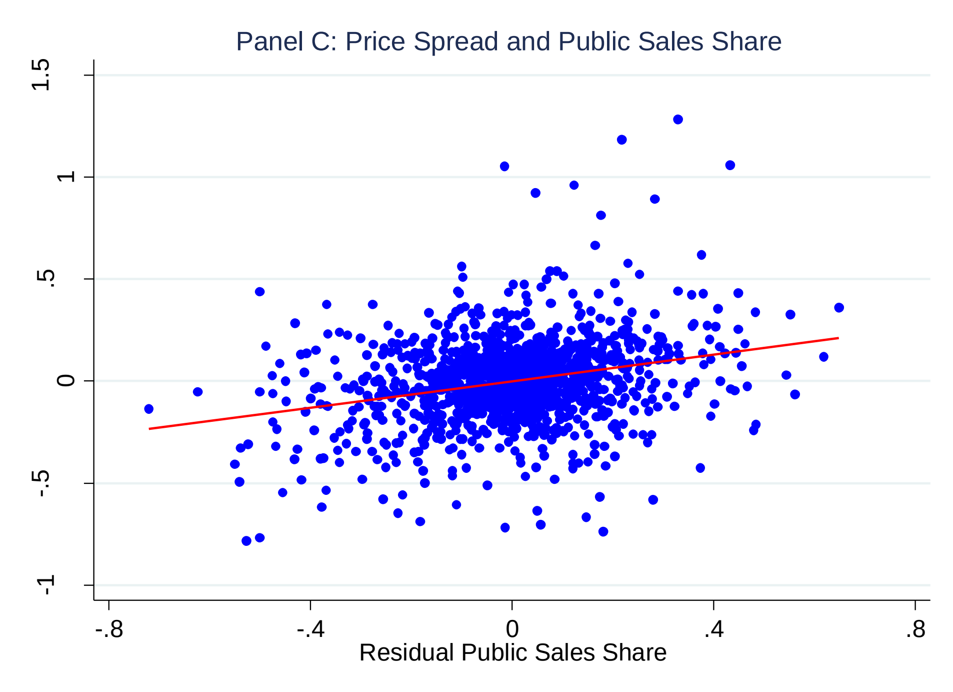
Figure 1: Public sales share and land sale price



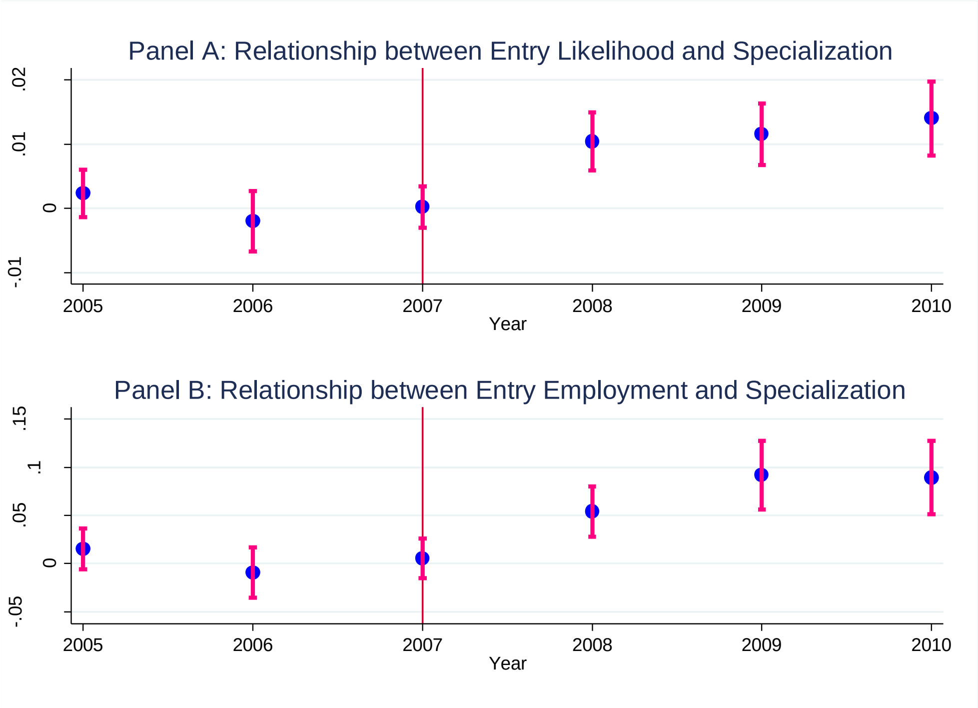
Note: Panel A displays the annual proportion of newly sold industrial land through public sales (represented by triangles) and the yearly per unit industrial land sale price (represented by squares). To derive the data for 2004–06, we use the 2005 to 2007 editions of the *Yearbooks of Land and Resources*. To calculate the data for 2007–10, we utilize the land transaction data collected from the official website of China's Ministry of National Land and Resources (www.landchina.com), respectively. Panel B presents the quarterly average ratio of actual sales to regulatory minimum prices (price spread) and the quarterly proportion of newly transacted industrial land sold through public sales (public sales share) from the first quarter of 2007 through the last quarter of 2010 using the land transaction data. To calculate the price spread for each parcel of industrial land, we assign it the minimum land price of the county where the land is located.

Figure 1: Public sales share and land sale price (cont'd)



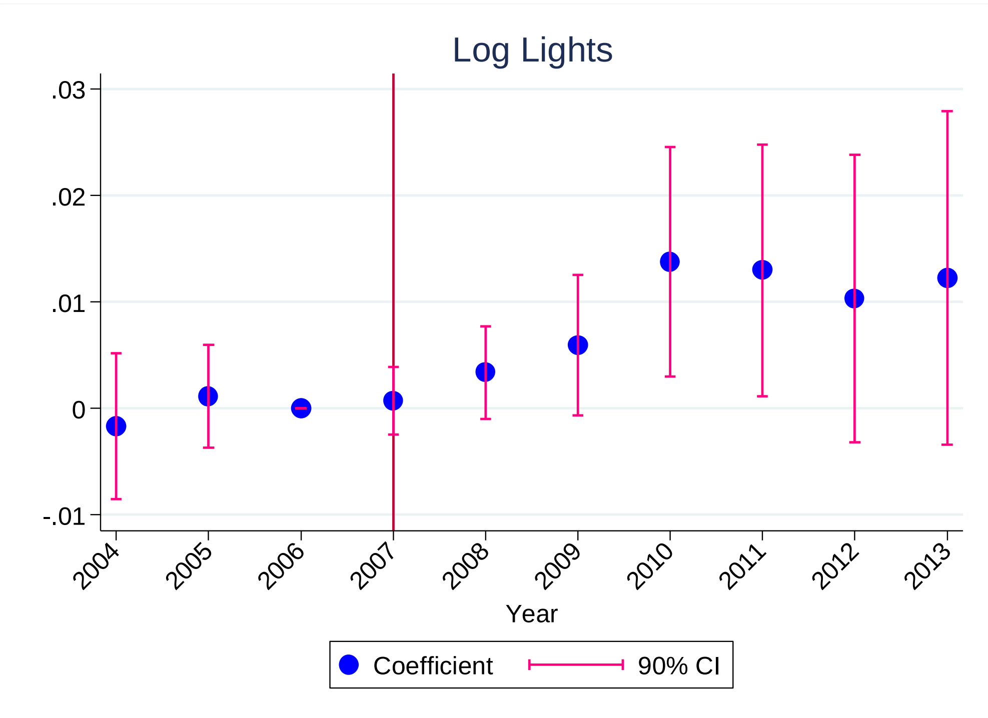
Note: Panel C plots each prefecture's average ratio of actual sales to minimum prices in each year against the prefecture's share of public sales in that year from 2007 through 2010, controlling for prefecture fixed effects and province-specific year fixed effects. The estimated slope coefficient is 0.326, which is significant at the 1% level when clustering the standard errors on the province level. Panel D shows each land use type's annual land sale area using the land parcels sold through public sales or negotiations. The data source is the land transaction data collected from the official website of China's Ministry of National Land and Resources (www.landchina.com).

Figure 2: Firm entry and local industrial specialization



Note: Figure 2 depicts for each year the coefficients and respective 90% confidence intervals of the relationship between entry likelihood and specialization (panel A) and the relationship between employment of new entrants and specialization (panel B) after removing county-year fixed effects, prefecture-industry-year fixed effects, and the effect of the employment scale of incumbent firms.

Figure 3: The reform's effect on local nighttime lights



Note: Figure 3 depicts the point estimates and respective 90% confidence intervals of the coefficients on the triple interaction terms of each county's average specialization index, the reform stringency measure, and year dummies in regression model (7). The base year is 2006.

Table 1: Summary statistics

	Mean	S.D.	Obs.
Panel A: Dependent variables at the county-industry level			
Dummy: having at least one new entrant			
2005	0.178	0.382	20,763
2006	0.137	0.344	20,763
2007	0.172	0.377	20,763
2008	0.239	0.427	20,763
2009	0.321	0.467	20,763
2010	0.336	0.472	20,763
Total employment of new industrial entrant (persons)			
2005	42	221	20,763
2006	34	207	20,763
2007	40	185	20,763
2008	49	217	20,763
2009	121	586	20,763
2010	121	634	20,763
Panel B: Key explanatory and control variables			
Prefecture's public sales share of industrial land transactions during 2008–10	0.869	0.137	20,763
County-industry specialization index	2.068	4.041	20,763
County-industry total employment	2,374	5,613	20,763
County-industry average firm size (persons)	104	232	20,763
County-industry employment share of the largest firm	0.418	0.265	20,763
County-industry upstream employment (persons)	1,149	2,462	20,763
County-industry downstream employment (persons)	996	2,356	20,763
County-industry labor matching measure	1.095	0.542	20,751
County-industry natural endowment matching measure	0.440	1.614	19,535

Note: In Panel B, the county-industry labor matching measure represents the interaction between the county's college-educated population (in the log form) and the industry's proportion of college-educated workers; the county-industry natural endowment matching measure represents the interaction between the county's flat cropland (in the log form) and a dummy variable indicating the presence of the food processing industry. Data on the college-educated population and flat cropland area are missing for a few counties, leading to a slightly smaller number of observations for the labor matching and natural endowment matching measures than the full sample.

Table 2: Local industrial specialization and productivity

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	County-industry-level specialization				Log Firm-level TFP	
Log upstream employment	2.5260***					
	(0.1079)					
Log downstream employment		2.7809***				
		(0.0889)				
Labor matching measure			3.5090***			
			(0.5661)			
Natural endowment matching measure				0.4467***		
				(0.0767)		
Specialization					0.0065*	0.0072*
					(0.0033)	(0.0039)
Log average firm size						-0.0069
						(0.0172)
Employment share of the largest firm						-0.0218
						(0.0684)
Firm-level characteristics					Y	Y
Prefecture*Industry FE, County FE	Y	Y	Y	Y	Y	Y
Observations	20,763	20,763	20,751	19,535	24,272	24,272
R-squared	0.8072	0.8307	0.7438	0.7372	0.4732	0.4732

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses of columns (1)－(4) are clustered at the prefecture level; those in (5) and (6) are two-way clustered at the county and industry levels. In columns (1)–(4), we regress the county-industry-specific specialization on the industry's upstream and downstream employment within the county, the interaction between the county's college-educated population (in the log form) and the industry's proportion of college-educated workers (referred to as labor matching measure), and the interaction between the county's flat cropland (in the log form) and a dummy variable indicating the presence of the food processing industry (referred to as natural endowment matching measure), respectively, while controlling for the county fixed effects and prefecture-specific industry fixed effects. Data on the college-educated population and flat cropland area are missing for a few counties, leading to a slightly smaller number of observations for the labor matching and natural endowment matching measures than the full sample. In columns (5) and (6), we regress the TFP of new firms on the initial specialization index of the firms' industries in the county where they are located while controlling for the county fixed effects, prefecture-specific industry fixed effects, ownership types (state-owned, domestic, privately owned, or foreign-owned), and the share of exports in total sales. Since reliable financial variables for calculating TFP are available in the ASIF 2005–07, the regressions in columns (5) and (6) use only the new establishments from these three years.

Table 3: Determinants of local reform stringency

	(1)	(2)
Dependent variable: Prefecture's reform stringency		
Prefecture's auction share of residential land sales 2004.09–2007.06	0.1666***	0.1516**
	(0.0564)	(0.0605)
Marketization index	0.0412***	0.0386***
	(0.0103)	(0.0107)
Hukou registration index	-0.3645**	-0.3205**
	(0.1509)	(0.1526)
Log prefecture's GDP in 2007		-0.0123
		(0.0241)
Log prefecture's population in 2007		0.0407
		(0.0321)
Prefecture's industrial sector's GDP share in 2007		0.1289
		(0.1859)
Prefecture's tertiary sector's GDP share in 2007		-0.0872
		(0.2059)
Growth rate of prefecture's GDP over 2003–07		0.0801
		(0.1919)
Growth rate of prefecture's population over 2003–07		-0.1815
		(0.2891)
Growth rate of prefecture's industrial sector's GDP share over 2003–07		-0.0864
		(0.1052)
Growth rate of prefecture's tertiary sector's GDP share over 2003–07		0.0261
		(0.0883)
Observations	278	278
R-squared	0.1172	0.1410
p-value testing exclusion of prefecture's economic variables		0.5902

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses are clustered at the province level. GDP = gross domestic product. Each province's marketization index in 2006 is computed by Fan et al., (2011) based on how much market forces drive the local economy. The *hukou* registration index at the province level is from Zhang et al. (2019). The prefecture-level explanatory variables in the regressions are available for 278 prefectures.

Table 4: Entry, specialization, and reform: Main results

	(1)	(2)	(3)	(4)
Dependent variable:	Dummy: New birth>0		Log (new-birth employment+1)	
Specialization*Post2007*Stringency		0.0036**		0.0268**
		(0.0017)		(0.0105)
Specialization*Post2007	0.0089***	0.0088***	0.0573***	0.0566***
	(0.0020)	(0.0019)	(0.0123)	(0.0117)
Specialization*Stringency		0.0005		0.0004
		(0.0011)		(0.0065)
Specialization	0.0002	0.0003	0.0029	0.0036
	(0.0023)	(0.0023)	(0.0133)	(0.0130)
County*Year FE, Prefecture*Industry*Year FE, Log total employment	Y	Y	Y	Y
Observations	124,578	124,578	124,578	124,578
R-squared	0.5030	0.5031	0.5265	0.5267

Note: *** p<0.01, ** p<0.05, * p<0.1. Each county's level of reform stringency is measured by its prefecture's share of industrial land transactions during 2008–10 conducted through public sales, standardized to have a mean of zero and a standard deviation of one. Standard errors in parentheses are two-way clustered at the prefecture and industry levels. Each regression is weighted by the number of industrial land parcels sold during 2008–10 in the prefecture that contains the county.

Table 5: Entry, specialization, and reform: Dynamic effect

	(1)	(2)	(3)	(4)
Dependent variable:	Dummy: New birth>0		Log (new-birth employment+1)	
Specialization*Year2005*Stringency		-0.0003		-0.0013
		(0.0013)		(0.0088)
Specialization*Year2006*Stringency		0.0012		0.0022
		(0.0016)		(0.0081)
Specialization*Year2007*Stringency		0.0006		0.0042
		(0.0017)		(0.0108)
Specialization*Year2008*Stringency		0.0040**		0.0189*
		(0.0016)		(0.0097)
Specialization*Year2009*Stringency		0.0062**		0.0497***
		(0.0023)		(0.0168)
Specialization*Year2010*Stringency		0.0056**		0.0363**
		(0.0021)		(0.0148)
Specialization*Year2005	0.0023	0.0025	0.0152	0.0159
	(0.0022)	(0.0022)	(0.0129)	(0.0127)
Specialization*Year2006	-0.0020	-0.0019	-0.0094	-0.0088
	(0.0028)	(0.0028)	(0.0159)	(0.0156)
Specialization*Year2007	0.0002	0.0003	0.0053	0.0060
	(0.0020)	(0.0019)	(0.0124)	(0.0121)
Specialization*Year2008	0.0104***	0.0104***	0.0541***	0.0544***
	(0.0027)	(0.0025)	(0.0159)	(0.0150)
Specialization*Year2009	0.0116***	0.0115***	0.0919***	0.0914***
	(0.0029)	(0.0026)	(0.0217)	(0.0193)
Specialization*Year2010	0.0140***	0.0140***	0.0892***	0.0891***
	(0.0035)	(0.0032)	(0.0232)	(0.0214)
County*Year FE, Prefecture*Industry*Year FE, Log total employment	Y	Y	Y	Y
Observations	124,578	124,578	124,578	124,578
R-squared	0.5033	0.5035	0.5271	0.5274

Note: See Table 4 for notes.

Table 6: *Ex-ante* reform stringency measure

	(1)	(2)
Dependent variable:	Dummy: New birth>0	Log (new-birth employment+1)
Specialization*Post2007*Stringency	0.0064**	0.0395**
	(0.0023)	(0.0154)
Specialization*Post2007	0.0090***	0.0576***
	(0.0019)	(0.0119)
Specialization*Stringency	-0.0008	-0.0025
	(0.0017)	(0.0094)
Specialization	-0.0000	0.0022
	(0.0022)	(0.0129)
County*Year FE, Prefecture*Industry*Year FE, Log total employment	Y	Y
Observations	122,982	122,982
R-squared	0.5031	0.5269

Note: The *ex-ante* stringency measure serves as a proxy for local institutional quality and is constructed by predicting each prefecture's share of industrial land transactions during 2008–10 conducted through public sales from three pre-reform institutional variables based on the regression results reported in column (1) of Table 3. These three variables are (1) the prefecture's auction share of residential land sales conducted between September 2004 and June 2007; (2) the province-level marketization index measuring the degree to which market forces drive the local economy in 2006 constructed by Fan et al. (2011); and (3) the province-level *hukou* registration index computed by Zhang et al. (2019). Standard errors in parentheses are two-way clustered at the prefecture and industry levels. Each regression is weighted by the number of industrial land parcels sold during 2008–10 in the prefecture that contains the county. Due to missing data on auction shares of residential land sales for some prefectures, the sample size shrinks compared to the main regressions in Table 4.

Table 7: Robustness checks:
Addressing concerns about the reform stringency measure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent variable:	Dummy: New birth>0					Log (new-birth employment+1)				
Specialization*Post2007*Stringency	0.0033*	0.0046**	0.0034*	0.0040**	0.0039*	0.0263**	0.0347***	0.0252**	0.0279**	0.0299**
	(0.0019)	(0.0019)	(0.0018)	(0.0018)	(0.0019)	(0.0126)	(0.0120)	(0.0107)	(0.0110)	(0.0115)
Specialization*Post2007	0.0075	-0.0309	0.0065**	-0.0025	-0.0220	0.1203	-0.2598*	0.0431***	0.0241	-0.1815
	(0.0425)	(0.0193)	(0.0026)	(0.0197)	(0.0209)	(0.2339)	(0.1353)	(0.0155)	(0.1204)	(0.1233)
Specialization*Stringency	0.0001	-0.0001	0.0008	-0.0002	0.0007	-0.0024	-0.0033	0.0020	-0.0021	0.0018
	(0.0013)	(0.0011)	(0.0012)	(0.0012)	(0.0013)	(0.0078)	(0.0065)	(0.0069)	(0.0071)	(0.0074)
Specialization	0.0199	0.0232	0.0029	0.0180	0.0064	-0.0045	0.1566	0.0179	0.0683	-0.0039
	(0.0342)	(0.0163)	(0.0030)	(0.0130)	(0.0184)	(0.2056)	(0.1065)	(0.0174)	(0.0764)	(0.0995)
Specialization*Post2007*Prefecture's economic characteristics, Specialization*Prefecture's economic characteristics	Y					Y				
Specialization*Post2007*Average minimum land price, Specialization*Average minimum land price		Y					Y			
Specialization*Post2007*Bank loan growth during FTP period, Specialization*Bank loan growth during FTP period			Y					Y		
Specialization*Post2007*Prefecture's geographic characteristics, Specialization*Prefecture's geographic characteristics				Y					Y	
Specialization*Post2007*Ages of prefecture's party secretary and mayor, Specialization*Ages of prefecture's party secretary and mayor					Y					Y
County*Year FE, Prefecture*Industry*Year FE, Log total employment	Y	Y	Y	Y		Y	Y	Y	Y	Y
Observations	119,034	124,578	117,978	124,152	123,906	119,034	124,578	117,978	124,152	123,906
R-squared	0.5019	0.5032	0.5012	0.5031	0.5025	0.5259	0.5269	0.5251	0.5267	0.5262

Note: See Table 4 for notes. In columns (1) and (6), each prefecture's economic characteristics include the prefecture's GDP, population, the share of GDP in the secondary and tertiary sectors in 2007, and the prefecture's growth rates of GDP, population, and secondary and tertiary sectors' GDP shares between 2003 and 2007. In columns (3) and (8), we use the growth rate of each prefecture's bank loans during the Four Trillion Program (FTP) program (from 2006–08 to 2009–11) to measure the prefecture's bank loan growth during the FTP period. In columns (4) and (9), each prefecture's geographic characteristics include the prefecture's total developable land area and elevation (both in logs). In columns (5) and (10), a given prefecture's party secretary and mayor are those who governed the prefecture for the longest duration during 2008–10; their ages are as of 2007. Due to missing data on prefecture-level economic characteristics, bank loan data, geographic characteristics, or leaders' information, the sample size varies slightly across the columns in Table 7.

Table 8: Robustness checks:
Addressing concerns about the specialization index

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Dummy: New birth>0			Log (new-birth employment+1)		
Specialization*Post2007*Stringency	0.0036*	0.0033	0.0031*	0.0270**	0.0253**	0.0246**
	(0.0018)	(0.0021)	(0.0017)	(0.0114)	(0.0120)	(0.0103)
Specialization*Post2007	0.0088***	0.0094***	0.0084***	0.0573***	0.0591***	0.0549***
	(0.0020)	(0.0023)	(0.0019)	(0.0121)	(0.0128)	(0.0114)
Specialization*Stringency	0.0003	-0.0013	0.0000	-0.0009	-0.0076	-0.0019
	(0.0013)	(0.0016)	(0.0012)	(0.0073)	(0.0090)	(0.0068)
Specialization	0.0004	0.0006	0.0012	0.0046	0.0056	0.0084
	(0.0020)	(0.0021)	(0.0021)	(0.0118)	(0.0120)	(0.0126)
Export share and the relevant interaction terms	Y			Y		
Log average firm size and the relevant interaction terms		Y			Y	
Largest firm's employment share and the relevant interaction terms			Y			Y
County*Year FE, Prefecture*Industry*Year FE, Log total employment	Y	Y	Y	Y	Y	Y
Observations	124,242	124,578	124,578	124,242	124,578	124,578
R-squared	0.5041	0.5087	0.5055	0.5278	0.5324	0.5290

Note: See Table 4 for notes. Export share is calculated as the ratio of the export value of each industry in each county to the county's total output value. Columns (1) and (4) include the export share of each industry in each county, the interaction term between the export share and reform stringency, the interaction term between the export share and post-reform dummy, and the triple interaction term between the export share, reform stringency, and post-reform dummy. Columns (2) and (5) include the average firm size (in logs) of each industry in each county and the relevant interaction terms. Columns (3) and (6) include the employment share of the largest firm in each industry in each county and the relevant interaction terms. The export share, average firm size, and largest firm's employment share of each industry in every county are constructed using the 2004 Economic Census. As some observations lack the county-industry-specific export share obtained from the Census, the sample sizes in columns (1) and (4) are slightly smaller compared to the other columns.

Table 9a: Heterogeneous effects by industry characteristics

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Dummy: New birth>0			Log (new-birth employment+1)		
Specialization*Post2007*Stringency	0.0028	0.0016	-0.0001	0.0195**	0.0156	0.0077
	(0.0017)	(0.0018)	(0.0021)	(0.0095)	(0.0099)	(0.0107)
Specialization*Post2007*Stringency*Highly agglomerated in the US	0.0045***			0.0398***		
	(0.0007)			(0.0047)		
Specialization*Post2007*Stringency*Change in EG index over 1998-2009		0.5891**			3.2172***	
		(0.2623)			(0.8586)	
Specialization*Post2007*Stringency*Attenuation speed of agglomeration spillovers			0.0015*			0.0077*
			(0.0008)			(0.0038)
Specialization*Post2007	0.0086***	0.0089***	0.0090***	0.0548***	0.0632***	0.0639***
	(0.0021)	(0.0026)	(0.0026)	(0.0133)	(0.0195)	(0.0176)
Specialization*Stringency	0.0005	0.0005	0.0005	0.0004	0.0005	0.0006
	(0.0011)	(0.0011)	(0.0011)	(0.0065)	(0.0065)	(0.0065)
Specialization	0.0003	0.0003	0.0004	0.0037	0.0043	0.0047
	(0.0023)	(0.0023)	(0.0023)	(0.0132)	(0.0133)	(0.0133)
Specialization*Post2007*Respective industry-specific characteristics, County*Year FE, Prefecture*Industry*Year FE, Log total employment	Y	Y	Y	Y	Y	Y
Observations	124,578	124,578	124,230	124,578	124,578	124,230
R-squared	0.5031	0.5031	0.5027	0.5268	0.5268	0.5265

Note: See Table 4 for notes. We identify six highly agglomerated industries in the US using the industry-specific EG index calculated by Ellison and Glaeser (1997). We obtain the change in industry-specific EG index over 1998-2009 from Wen and Xian (2014). We obtain the industry-specific attenuation speed of spillover effects from Li et al. (2022). Due to missing data on the attenuation speed of spillover effects for the recycling and waste disposal industry, the sample size varies slightly across the columns.

Table 9b: Heterogeneous effects by regional characteristics

	(1)	(2)	(3)	(4)
Dependent variable:	Dummy: New birth>0		Log (new-birth employment+1)	
Specialization*Post2007*Stringency	0.0033*	0.0054**	0.0253**	0.0373***
	(0.0019)	(0.0020)	(0.0108)	(0.0129)
Specialization*Post2007*Stringency*Province's financial development	0.0020*		0.0175**	
	(0.0010)		(0.0077)	
Specialization*Post2007*Stringency*Prefectural party secretary's age		0.0003		-0.0002
		(0.0030)		(0.0209)
Specialization*Post2007*Stringency*Prefectural mayor's age		-0.0027		-0.0135
		(0.0031)		(0.0225)
Specialization*Post2007	0.0083***	0.0122***	0.0521***	0.0852***
	(0.0018)	(0.0022)	(0.0109)	(0.0159)
Specialization*Stringency	0.0005	0.0005	0.0005	0.0006
	(0.0011)	(0.0011)	(0.0065)	(0.0066)
Specialization	0.0003	0.0004	0.0043	0.0047
	(0.0023)	(0.0023)	(0.0131)	(0.0134)
Specialization*Post2007*Respective region-specific characteristics, County*Year FE, Prefecture*Industry*Year FE, Log total employment	Y	Y	Y	Y
Observations	124,578	123,906	124,578	123,906
R-squared	0.5032	0.5025	0.5269	0.5262

Note: See Table 4 for notes. Province's financial development in columns (1) and (3) is the provincial-level index of market-oriented credit allocation in the year 2006 constructed by Fan et al. (2011), standardized to have a mean of zero and a standard deviation of one. In columns (2) and (4), a given prefecture's party secretary and mayor are those who governed the prefecture for the longest duration during 2008–10; their ages are as of 2007. Due to missing data on the politicians' characteristics, the sample size varies slightly across the columns.

Table 10: Entry, sources of agglomeration, and reform

	(1)	(2)	(3)	(4)
Dependent variable:	Dummy: New birth>0			
Log upstream employment*Post2007*Stringency	0.0141**			
	(0.0065)			
Log upstream employment*Post2007	0.0341***			
	(0.0080)			
Log upstream employment*Stringency	-0.0022			
	(0.0044)			
Log upstream employment	0.0095			
	(0.0059)			
Log downstream employment*Post2007*Stringency		0.0163**		
		(0.0061)		
Log downstream employment*Post2007		0.0372***		
		(0.0083)		
Log downstream employment*Stringency		-0.0074		
		(0.0051)		
Log downstream employment		0.0095		
		(0.0082)		
Labor matching measure*Post2007*Stringency			0.0244**	
			(0.0118)	
Labor matching measure*Post2007			0.1547***	
			(0.0184)	
Labor matching measure*Stringency			-0.0113	
			(0.0231)	
Labor matching measure			-0.0675	
			(0.0470)	
Natural endowment matching measure*Post2007*Stringency				0.0138***
				(0.0034)
Natural endowment matching measure*Post2007				0.0209***
				(0.0034)
Natural endowment matching measure*Stringency				-0.0030
				(0.0040)
Natural endowment matching measure				0.0037
				(0.0038)
County*Year FE, Prefecture*Industry*Year FE, Log total employment	Y	Y	Y	Y
Observations	124,578	124,578	124,506	117,210
R-squared	0.5032	0.5033	0.5024	0.5104

Note: See Table 4 for notes. We calculate the employment scale for each county in a given industry's upstream (or downstream) segment by summing up all the county's employment numbers across all the two-digit manufacturing industries according to these industries' shares in the input value (or output value) of that particular industry based on the 2002 IO Table provided by the National Bureau of Statistics. The county-industry labor matching measure is the interaction between each county's college-educated population (in the log form and calculated from the 2000 Population Census Data) and each industry's share of college-educated workers (calculated from the 2004 Economic Census Data). The county-industry natural endowment matching measure is the interaction between each county's area of flat cropland (in the log form) and a dummy variable indicating the food processing industry.

Table 11: Average productivity gains due to better matching qualities

	(1)	(2)	(3)	(4)	(5)
	Eastern Coast	Central China	Western China	Northeast	China
2008	0.419%	0.302%	0.154%	0.273%	0.345%
2009	0.538%	0.570%	0.276%	0.186%	0.462%
2010	0.506%	0.591%	0.295%	0.407%	0.485%
Total	1.464%	1.463%	0.725%	0.866%	1.292%

Note: Region r's average productivity gain in year t can be expressed as: $Gain_{rt}^{match} = \sum_k \omega_{krt}\, Gain_{kt}^{match}$, where ω_{krt} is county k's new entry employment share in region r in year t as in the actual data. Columns (1) to (4) report the figures. We calculate the national average productivity gain in year t as: $Gain_{t}^{match} = \sum_k \omega_{kt} Gain_{kt}^{match}$, where ω_{kt} is county k's new entry employment share in the whole country in year t as in the actual data. Column (5) reports the figures for the whole country (mainland part).

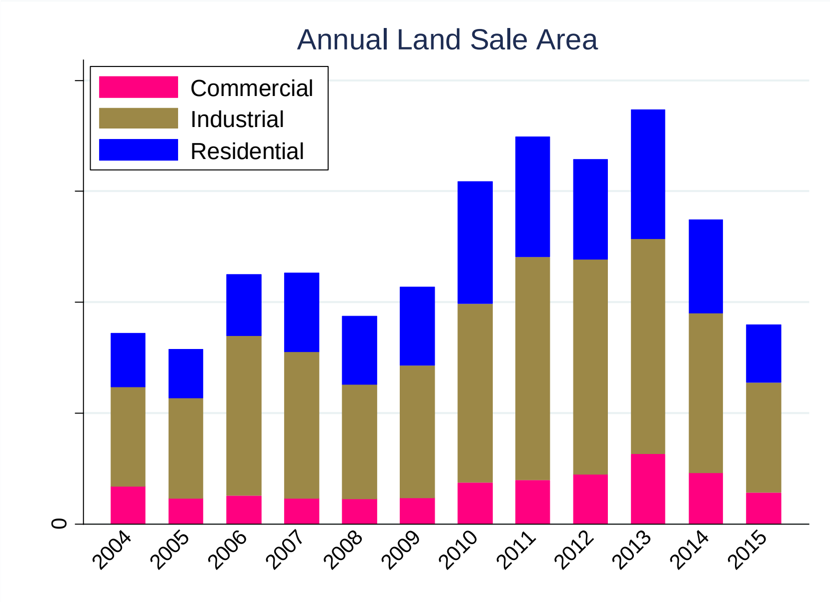
Table 12: Enhanced competition: New transaction mechanism, land sale prices, and area

	(1)	(2)	(3)	(4)
Dependent variable:	Log (per unit land sale price)		Log (average per unit land sale price)	Log (total land area)
	Industrial land transactions, 2007-10		Prefecture-year-level data, 2007-10	
Dummy: Public sale	0.4572***	0.4432***		
	(0.0490)	(0.0629)		
Year2008*Stringency			0.113**	0.056
			(0.054)	(0.069)
Year2009*Stringency			0.077*	-0.046
			(0.038)	(0.120)
Year2010*Stringency			0.058**	0.142
			(0.024)	(0.088)
Land characteristics*Year FE	Y	Y		
Prefecture*Industry*Year FE, County*Year FE	Y	Y		
Township FE		Y		
Prefecture FE, Province*Year FE			Y	Y
Prefecture-level characteristics*Year FE			Y	Y
Observations	65,875	65,875	1,074	1,074
R-squared	0.8071	0.8687	0.798	0.817

Note: In columns (1) and (2), we restrict the sample to those land parcels used for manufacturing industries and those with two-digit industry codes available. In addition, we focus on the land transactions occurring during 2007–10, corresponding to the post-reform period of our primary analysis. In columns (1) and (2), the land characteristics include the land's distance to the city center (in the log form), lot size (in the log form), land source dummies, and land transaction year-month dummies. In columns (3) and (4), we aggregate all the industrial land transactions conducted during 2007–10 at the prefecture-year level and construct the average land sale price and total land sale area for each prefecture-year observation. As the outcomes are missing for some years when no transaction occurs in the respective prefectures, the regression sample in columns (3) and (4) is an unbalanced panel, containing 269 observations in 2007 and 2010 and 268 observations in 2008 and 2009. The reform stringency measure is the one constructed for the primary analysis. The prefecture-level characteristics include each prefecture's average regulatory minimum price of industrial land, the prefecture's GDP, population, shares of GDP in the secondary and tertiary sectors in 2007, and the prefecture's growth rates of GDP, population, and secondary and tertiary sectors' GDP shares between 2003 and 2007. In columns (1) and (2), standard errors are two-way clustered at the county and industry levels. In columns (3) and (4), standard errors are clustered at the province level.

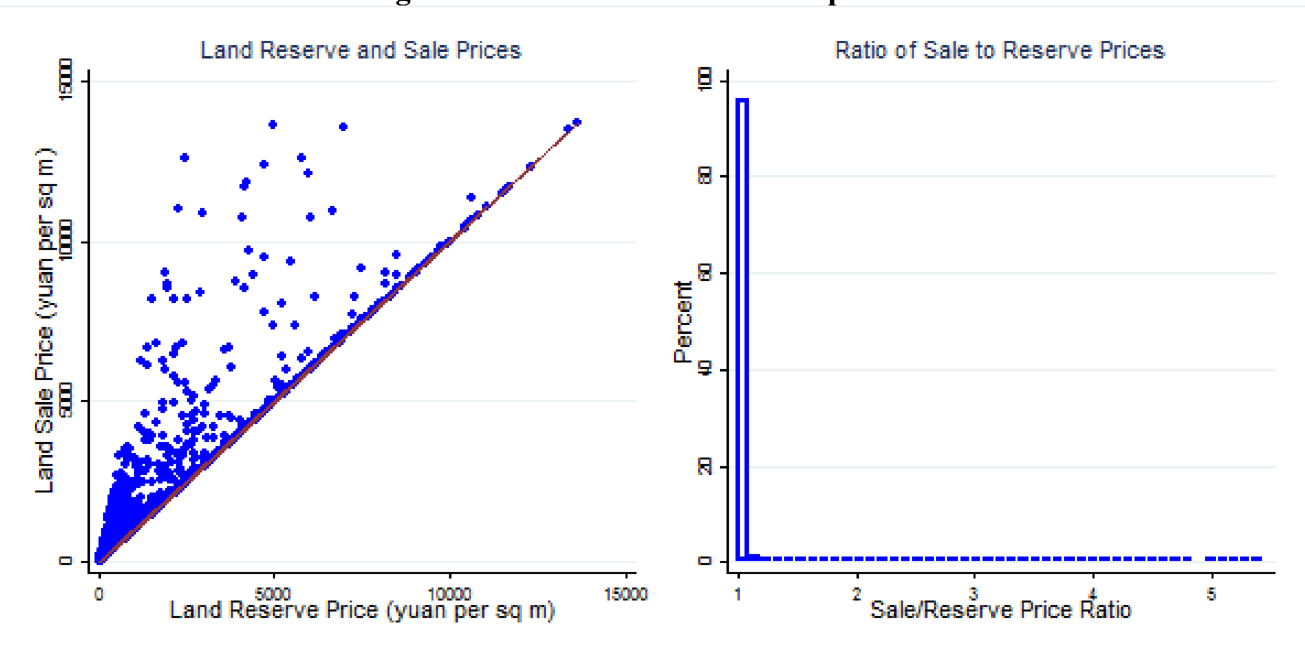
Appendix A: Supplementary figures and tables

Figure A1: Land sale area, by land use type



Note: The unit is hectares or 10,000 square meters. The data sources of the figures from 2004 to 2006 are the 2005 to 2007 editions of the *Yearbooks of Land and Resources*. The data sources of the figures from 2007 to 2015 are the land transaction data collected from the official website of China's Ministry of National Land and Resources (www.landchina.com). When calculating the annual land sale area, we consider only land sold through public sales or negotiations (*churang* in Chinese).

Figure A2: Land sale and reserve prices



Note: For a sample of around 31,000 industrial land transactions that occurred during 2008–11 from Wang, Zhang, and Zhou (2020), we have information on the reserve price at the auction and actual sale price. The graph shows that the actual sale prices almost always equaled the reserve prices. The mean of the ratio of sale to reserve prices is 1.04, and the median is 1.

Table A1: Land sale revenue and price, by land use type

	Total transfer revenue (10,000 yuan)			Average transaction price (yuan per square meter)		
Year	Commercial	Industrial	Residential	Commercial	Industrial	Residential
2003	13,862,155	12,473,194	25,898,970	355	125	598
2004	18,204,124	11,843,779	32,603,199	539	132	670
2005	14,740,716	12,500,084	29,693,471	634	138	680
2006	16,723,438	17,223,893	45,291,292	659	119	823
2007	23,495,054	21,102,025	75,308,844	871	156	1,131
2008	24,162,876	17,424,231	59,117,077	1,108	202	1,148

Note: The data sources are the 2004 to 2009 editions of the *Yearbooks of Land and Resources.*

Table A2: Local industrial specialization and the characteristics of new firms

	(1)	(2)	(3)
Dependent variable:	Log (total assets)	Log (capital investment)	Dummy: government investment
Specialization	-0.0020	-0.0092	-0.0003
	(0.0050)	(0.0061)	(0.0006)
County FE, Prefecture*Industry FE	Y	Y	Y
Observations	24,272	24,272	24,272
R-squared	0.4481	0.4246	0.5194

Note: Standard errors in parentheses are two-way clustered at the county and industry levels. We regress the total assets, capital investment, and government-investment status of new firms on the initial specialization index of the firms' industries in the county where they are located while controlling for the county fixed effects and prefecture-specific industry fixed effects.

Table A3: Entry, specialization, and reform: Alternative regression weights

	(1)	(2)	(3)	(4)
Dependent variable:	Dummy: New birth>0		Log (new-birth employment+1)	
Specialization*Post2007*Stringency	0.0042*		0.0291*	
	(0.0023)		(0.0143)	
Specialization*Post2007	0.0082***		0.0573***	
	(0.0025)		(0.0164)	
Specialization*Stringency	0.0004		0.0020	
	(0.0016)		(0.0090)	
Specialization	0.0001		0.0001	
	(0.0025)		(0.0156)	
Specialization*Year2005*Stringency		0.0004		0.0034
		(0.0016)		(0.0095)
Specialization*Year2006*Stringency		0.0004		0.0006
		(0.0022)		(0.0126)
Specialization*Year2007*Stringency		0.0017		0.0118
		(0.0022)		(0.0138)
Specialization*Year2008*Stringency		0.0064***		0.0336***
		(0.0015)		(0.0097)
Specialization*Year2009*Stringency		0.0054**		0.0461**
		(0.0022)		(0.0175)
Specialization*Year2010*Stringency		0.0047***		0.0327***
		(0.0013)		(0.0082)
Specialization*Year2005		0.0036		0.0201
		(0.0026)		(0.0153)
Specialization*Year2006		-0.0033		-0.0199
		(0.0030)		(0.0186)
Specialization*Year2007		-0.0010		-0.0012
		(0.0022)		(0.0142)
Specialization*Year2008		0.0093***		0.0447**
		(0.0032)		(0.0177)
Specialization*Year2009		0.0119***		0.1008***
		(0.0028)		(0.0230)
Specialization*Year2010		0.0132***		0.0853***
		(0.0033)		(0.0217)
County*Year FE, Prefecture*Industry*Year FE, Log total employment	Y	Y	Y	Y
Observations	124,578	124,578	124,578	124,578
R-squared	0.5830	0.5834	0.6131	0.6137

Note: Each regression is weighted by each county's GDP in the secondary sector in 2005, obtained from the *Fiscal Statistical Compendium for All Prefectures and Counties*. See Table 4 for additional notes.

Table A4a: Entry, specialization, and reform: IV estimation

	(1)	(2)
Dependent variable:	Dummy: New birth>0	Log (new-birth employment+1)
	2SLS	
Specialization*Post2007*Stringency	0.0147**	0.0907**
	(0.0058)	(0.0390)
Specialization*Post2007	0.0087***	0.0556***
	(0.0021)	(0.0121)
Specialization*Stringency	-0.0018	-0.0054
	(0.0038)	(0.0214)
Specialization	0.0002	0.0037
	(0.0022)	(0.0127)
County*Year FE, Prefecture*Industry*Year FE, Log total employment	Y	Y
Observations	122,982	122,982
R-squared	0.0254	0.0352
First-stage F-stat	22.247	22.247

Note: We use Specialization*Post2007*Ex-ante stringency and Specialization*En-ante stringency to instrument for Specialization*Post2007*Stringency and Specialization*Stringency. The *ex-ante* stringency measure is each prefecture's share of industrial land transactions during 2008–10 conducted through public sales predicted from three pre-reform institutional variables based on the regression results reported in column (1) of Table 3. These three variables are (1) the prefecture's auction share of residential land sales conducted between September 2004 and June 2007; (2) the province-level marketization index measuring the degree to which market forces drive the local economy in 2006 constructed by Fan et al. (2011); and (3) the province-level *hukou* registration index computed by Zhang et al. (2019). Standard errors in parentheses are two-way clustered at the prefecture and industry levels. Each regression is weighted by the number of industrial land parcels sold during 2008–10 in the prefecture that contains the county. Due to missing data on auction shares of residential land sales for some prefectures, the sample size shrinks compared to the main regressions in Table 4.

Table A4b: Entry, specialization, and reform: Alternative reform stringency measures

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:		Dummy: New birth>0			Log (new-birth employment+1)	
Specialization*Post2007*Stringency (2007.7-2010)	0.0031*			0.0202*		
	(0.0017)			(0.0105)		
Specialization*Stringency (2007.7-2010)	0.0002			-0.0004		
	(0.0013)			(0.0070)		
Specialization*Post2007*Stringency (consider administrative relationships)		0.0042**			0.0224**	
		(0.0018)			(0.0098)	
Specialization*Stringency (consider administrative relationships)		-0.0004			-0.0008	
		(0.0014)			(0.0083)	
Specialization*Post2007*Stringency (exclude own county)			0.0023*			0.0187**
			(0.0014)			(0.0079)
Specialization*Stringency (exclude own county)			0.0009			0.0038
			(0.0010)			(0.0049)
Specialization	0.0003	-0.0021	0.0004	0.0035	-0.0122	0.0043
	(0.0023)	(0.0032)	(0.0023)	(0.0130)	(0.0167)	(0.0132)
Post2007*Specialization	0.0089***	0.0093***	0.0089***	0.0575***	0.0606***	0.0577***
	(0.0019)	(0.0020)	(0.0020)	(0.0117)	(0.0127)	(0.0120)
County*Year FE, Prefecture*Industry*Year FE, Log total employment	Y	Y	Y	Y	Y	Y
Observations	124,578	121,260	124,422	124,578	121,260	124,422
R-squared	0.5010	0.5326	0.5031	0.5240	0.5566	0.5267

Note: See Table 4 for notes. In columns (1) and (4), Stringency (2007.7–2010) represents the share of industrial land sales that went through the new transaction mechanism in each prefecture that supervises the respective county between July 2007 and December 2010. In columns (2) and (5), for a given county or county city, the stringency measure is calculated as the share of industrial land sales that went through public sales in the respective county unit between 2008 and 2010; for a given urban district, the stringency measure is calculated as the share of industrial land sales through public sales in all the urban districts within the same prefecture between 2008 and 2010. In columns (3) and (6), the stringency measure is calculated for each given county unit as the share of industrial land sales that went through public sales in other county units within the same prefecture between 2008 and 2010. Each regression is weighted by the number of industrial transactions that occurred within the geographical scales and during the period for which we calculate the reform stringency measure.

Table A5: Determinants of local reform stringency: Adding local leaders' characteristics

	(1)	(2)
Dependent variable: Prefecture's reform stringency		
Prefecture's auction share of residential land sales 2004.09–2007.06	0.1663***	0.1524**
	(0.0562)	(0.0613)
Marketization index	0.0409***	0.0382***
	(0.0108)	(0.0115)
Hukou registration index	-0.3713*	-0.3029*
	(0.2059)	(0.1761)
Age of prefecture's party secretary	-0.0016	-0.0023
	(0.0035)	(0.0037)
Age of prefecture's mayor	0.0024	0.0028
	(0.0028)	(0.0031)
Log prefecture's GDP in 2007		-0.0168
		(0.0252)
Log prefecture's population in 2007		0.0459
		(0.0298)
Prefecture's industrial sector's GDP share in 2007		0.1377
		(0.1819)
Prefecture's tertiary sector's GDP share in 2007		-0.0964
		(0.1979)
Growth rate of prefecture's GDP over 2003–07		0.0960
		(0.1943)
Growth rate of prefecture's population over 2003–07		-0.1685
		(0.2859)
Growth rate of prefecture's industrial sector's GDP share over 2003–07		-0.0973
		(0.1115)
Growth rate of prefecture's tertiary sector's GDP share over 2003–07		0.0213
		(0.0876)
Observations	277	277
R-squared	0.1223	0.1485
p-value testing exclusion of prefecture's economic variables		0.4462

Note: See Table 3 for notes. A given prefecture's party secretary and mayor are those who governed the prefecture for the longest duration during 2008–10; their ages are as of 2007.

Table A6: Entry, specialization, and reform: Additional robustness checks
Panel A: Exporting and non-exporting firms

	(1)	(2)	(3)	(4)
Dependent variable:	Dummy: New birth>0		Log (new-birth employment+1)	
	Exporting firms	Non-exporting firms	Exporting firms	Non-exporting firms
Specialization*Post2007*Stringency	0.0022**	0.0031*	0.0142**	0.0217**
	(0.0009)	(0.0016)	(0.0059)	(0.0092)
Specialization*Post2007	0.0030**	0.0086***	0.0182**	0.0513***
	(0.0012)	(0.0019)	(0.0080)	(0.0111)
Specialization*Stringency	-0.0006	0.0013	-0.0045	0.0053
	(0.0010)	(0.0009)	(0.0059)	(0.0051)
Specialization	0.0012	-0.0001	0.0074	0.0021
	(0.0009)	(0.0022)	(0.0053)	(0.0129)
County*Year FE, Prefecture*Industry*Year FE, Log total employment	Y	Y	Y	Y
Observations	124,578	124,578	124,578	124,578
R-squared	0.3806	0.4997	0.3974	0.5172

Note: See Table 4 for notes.

Panel B: Different-sized manufacturing firms

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Dummy: New birth>0			Log (new-birth employment+1)		
	Large	Medium	Small	Large	Medium	Small
Specialization*Post2007*Stringency	0.0035**	0.0046***	0.0020*	0.0221**	0.0258***	0.0109**
	(0.0014)	(0.0014)	(0.0011)	(0.0084)	(0.0081)	(0.0053)
Specialization*Post2007	0.0052***	0.0085***	0.0044***	0.0346***	0.0430***	0.0199***
	(0.0016)	(0.0016)	(0.0012)	(0.0099)	(0.0092)	(0.0056)
Specialization*Stringency	-0.0012	-0.0004	0.0005	-0.0071	-0.0018	0.0021
	(0.0010)	(0.0011)	(0.0010)	(0.0055)	(0.0070)	(0.0052)
Specialization	-0.0002	-0.0017	0.0013	-0.0004	-0.0026	0.0084
	(0.0015)	(0.0015)	(0.0012)	(0.0088)	(0.0085)	(0.0062)
County*Year FE, Prefecture*Industry*Year FE, Log total employment	Y	Y	Y	Y	Y	Y
Observations	124,578	124,578	124,578	124,578	124,578	124,578
R-squared	0.3998	0.4623	0.4275	0.4066	0.4805	0.4380

Note: In panel B, entrants whose value of annual sales is at or above the 75th percentile of the distribution in the respective year are large; those at or below the 25th percentile are small; and the rest are medium. See Table 4 for additional notes.

Table A7: Summary statistics, three-digit industries

	Mean	S.D.	Obs.
Dependent variables at the county-industry level, three-digit industry			
Dummy: New birth>0			
2005	0.104	0.306	33,913
2006	0.078	0.268	33,913
2007	0.096	0.294	33,913
2008	0.131	0.337	33,913
2009	0.196	0.397	33,913
2010	0.195	0.396	33,913
New-birth employment (persons)			
2005	21	157	33,913
2006	16	146	33,913
2007	19	124	33,913
2008	22	146	33,913
2009	61	377	33,913
2010	59	429	33,913
Explanatory and control variables at the county-industry level, three-digit industry			
Specialization index	5.316	15.910	33,913
Total employment	1,208	3,444	33,913

Table A8: Entry, specialization, and reform: Using the three-digit industrial classification

	(1)	(2)	(3)	(4)
Dependent variable:	Dummy: New birth>0		Log (new-birth employment+1)	
Specialization*Post2007*Stringency	0.0013**		0.0087**	
	(0.0006)		(0.0035)	
Specialization*Post2007	0.0026***		0.0137***	
	(0.0006)		(0.0032)	
Specialization*Stringency	-0.0001		-0.0012	
	(0.0003)		(0.0023)	
Specialization	-0.0001		-0.0001	
	(0.0004)		(0.0023)	
Specialization*Year2005*Stringency		-0.0004		-0.0017
		(0.0005)		(0.0032)
Specialization*Year2006*Stringency		0.0002		-0.0008
		(0.0003)		(0.0021)
Specialization*Year2007*Stringency		-0.0001		-0.0008
		(0.0005)		(0.0027)
Specialization*Year2008*Stringency		0.0012		0.0052
		(0.0007)		(0.0036)
Specialization*Year2009*Stringency		0.0024***		0.0174***
		(0.0007)		(0.0047)
Specialization*Year2010*Stringency		0.0014*		0.0080*
		(0.0007)		(0.0043)
Specialization*Year2005		0.0002		0.0018
		(0.0005)		(0.0029)
Specialization*Year2006		-0.0004		-0.0020
		(0.0004)		(0.0023)
Specialization*Year2007		0.0004		0.0021
		(0.0006)		(0.0033)
Specialization*Year2008		0.0032***		0.0146***
		(0.0006)		(0.0029)
Specialization*Year2009		0.0026***		0.0183***
		(0.0006)		(0.0042)
Specialization*Year2010		0.0036***		0.0196***
		(0.0007)		(0.0041)
County*Year FE, Prefecture*Industry*Year FE, Log total employment	Y	Y	Y	Y
Observations	203,478	203,478	203,478	203,478
R-squared	0.4965	0.4968	0.5020	0.5025

Note: See Table 4 for notes.

Table A9: Entry, specialization, and reform: Adding county-industry fixed effects

	(1)	(2)	(3)	(4)
Dependent variable:	Dummy: New birth>0		Log (new-birth employment+1)	
Specialization*Post2007*Stringency	0.0036**		0.0268**	
	(0.0017)		(0.0105)	
Specialization*Post2007	0.0088***		0.0566***	
	(0.0019)		(0.0117)	
Specialization*Year2005*Stringency		-0.0009		-0.0055
		(0.0021)		(0.0124)
Specialization*Year2006*Stringency		0.0006		-0.0020
		(0.0027)		(0.0146)
Specialization*Year2008*Stringency		0.0034		0.0147
		(0.0025)		(0.0133)
Specialization*Year2009*Stringency		0.0056		0.0456*
		(0.0035)		(0.0238)
Specialization*Year2010*Stringency		0.0050		0.0321
		(0.0032)		(0.0214)
Specialization*Year2005		0.0021		0.0100
		(0.0020)		(0.0100)
Specialization*Year2006		-0.0023		-0.0147
		(0.0025)		(0.0132)
Specialization*Year2008		0.0101***		0.0484***
		(0.0027)		(0.0134)
Specialization*Year2009		0.0112***		0.0854***
		(0.0025)		(0.0192)
Specialization*Year2010		0.0136***		0.0831***
		(0.0030)		(0.0190)
County*Year FE, Prefecture*Industry*Year FE, County*Industry FE	Y	Y	Y	Y
Observations	124,578	124,578	124,578	124,578
R-squared	0.6378	0.6382	0.6679	0.6686

Note: In the regressions of columns (2) and (4), the base year is 2007. See Table 4 for additional notes.

Table A10: Industry-specific characteristics

Industry code	Industry name	Change in EG index from 1998-2009	Attenuation speed of agglomeration economies	Share of highly educated workers
13	Food processing	0.0037	1.05	0.096
14	Food production	0.002	1.59	0.125
15	Beverage production	0.0022	2.21	0.143
16	Tobacco processing	0.0025	-0.364	0.231
17	Textile industry	0.0025	1.58	0.052
18	Garments & other fiber products	-0.0028	0.647	0.048
19	Leather, furs, down & related products	0.0101	4.05	0.041
20	Timber processing, bamboo, cane, palm fiber & straw products	0.0058	1.57	0.056
21	Furniture manufacturing	0.0063	0.751	0.067
22	Papermaking & paper products	0.0007	0.554	0.081
23	Printing & recording press	0.0016	0.534	0.109
24	Stationery, educational & sports goods	-0.0029	4.57	0.054
25	Petroleum processing, coking products, & gas production & supply	0.0022	2.34	0.185
26	Raw chemical materials & chemical products	0.002	1.9	0.149
27	Medical & pharmaceutical products	0.0028	1.14	0.271
28	Chemical fibers	0.0103	8.52	0.126
29	Rubber products	0.0012	4.13	0.082
30	Plastic products	0.0033	0.921	0.081
31	Nonmetal mineral products	0.0025	1.85	0.058
32	Smelting & pressing of ferrous metals	0.0029	0.97	0.153
33	Smelting & pressing of nonferrous metals	0.0063	1.9	0.145
34	Metal products	0.0006	1.24	0.090
35	Machinery & equipment manufacturing	0.0012	1.81	0.127
36	Special equipment manufacturing	0.0002	2.06	0.169
37	Transportation equipment manufacturing	0.0009	2.74	0.172
39	Electric equipment & machinery	0.0052	1.28	0.140
40	Electronic & telecommunications	0.0054	1.55	0.180
41	Instruments, meters, cultural & official machinery	0.0132	5.34	0.200
42	Arts and crafts and other manufacturing	0.0005	4.35	0.061
43	Recycling and disposal of waste	0.0102	N.A.	0.079

Note: The change in a particular industry's EG index from 1998 to 2009 is obtained from Wen and Xian (2014), which provides the EG index of all 30 manufacturing industries in 1998, 2005, and 2009 (Table 4 of Wen and Xian (2014)). We cross-check the two-digit-industry-level EG calculated by Wen and Xian (2014) and Lu and Tao (2009) for the overlapping years (i.e., 1998 and 2005) and find that they are almost identical. An industry's attenuation speed of agglomeration economies is estimated by Li et al. (2022).

Table A11: The reform's effect on incumbent firms: Summary statistics

	Mean	S.D.	Obs.
Total Assets (1,000 yuan)			
2005	538,058	2,401,440	20,763
2006	608,579	2,778,098	20,763
2007	712,999	3,378,855	20,763
2008	791,690	3,705,310	20,763
2009	755,204	4,014,674	20,763
2010	579,743	4,428,429	20,763
Total employment of incumbent firms (persons)			
2005	1,696	4,702	20,763
2006	1,699	4,867	20,763
2007	1,727	5,269	20,763
2008	1,675	5,181	20,763
2009	1,475	5,005	20,763
2010	1,875	7,722	20,763
Total output value (1,000 yuan)			
2005	643,726	2,953,005	20,763
2006	773,754	3,498,394	20,763
2007	957,282	4,385,716	20,763
2008	1,107,227	4,933,665	20,763
2009	1,012,550	4,697,014	20,763
2010	1,064,932	8,891,060	20,763
Total sales value (1,000 yuan)			
2005	630,997	2,917,025	20,763
2006	758,803	3,446,168	20,763
2007	939,239	4,318,279	20,763
2008	1,082,819	4,856,855	20,763
2009	991,477	4,632,425	20,763
2010	897,354	7,930,153	20,763

Note: Incumbent firms are those established before 2005. We calculate these firms' total assets, employment size, total output value, and total sales value during our study period (2005-10) for each county-industry observation using the ASIF data.

Table A12: The reform's effect on incumbent firms: Regression results

	(1)	(2)	(3)	(4)
Dependent variable:	Log (assets)	Log (employment)	Log (output value)	Log (sales value)
Specialization*Post2007*Stringency	0.0077	-0.0011	0.0083	0.0075
	(0.0047)	(0.0040)	(0.0056)	(0.0057)
Specialization*Post2007	0.0566***	0.0208***	0.0618***	0.0606***
	(0.0064)	(0.0045)	(0.0064)	(0.0065)
Specialization*Stringency	0.0130	0.0186	0.0153	0.0150
	(0.0235)	(0.0210)	(0.0240)	(0.0239)
Specialization	0.3514***	0.3147***	0.3412***	0.3420***
	(0.0318)	(0.0284)	(0.0312)	(0.0311)
County*Year FE, Prefecture*Industry*Year FE	Y	Y	Y	Y
Observations	124,578	124,578	124,578	124,578
R-squared	0.6511	0.6878	0.6321	0.6367

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses are two-way clustered at the prefecture and industry levels. Each regression is weighted by the number of industrial land parcels sold during 2008–10 in the prefecture that contains the county. The outcome variables are the total assets, employment size, total output value, and total sales value of the firms established before 2005 in each county-industry observation in each year from 2005 to 2010 derived from the ASIF data. The regression model follows specification (2) but excludes the log of the initial total employment in each county-industry observation, derived from the 2004 Economic Census, from the right-hand side of the regression.

Table A13: The reform's effect on local nighttime lights: Summary statistics

	Mean	S.D.	Obs.
GDP in 2001 (10,000 yuan)	298,864.128	391,264.026	2,058
Secondary sector GDP share in 2001	0.347	0.155	2,058
Tertiary sector GDP share in 2001	0.379	0.153	2,058
Population in 2001 (10,000 persons)	47	31	2,058
Rural population share in 2001	0.714	0.259	2,058
Lights in 1992	2,393.292	3,028.623	2,058
Lights growth over 1992-99	0.840	0.898	2,058
Lights			
2004	6,021.715	6,212.817	2,058
2005	6,215.779	6,375.277	2,058
2006	6,830.595	6,983.641	2,058
2007	7,062.720	7,087.279	2,058
2008	7,155.003	7,108.010	2,058
2009	7,305.655	7,139.260	2,058
2010	8,184.864	7,539.184	2,058
2011	8,567.345	7,730.245	2,058
2012	8,873.305	7,837.964	2,058
2013	9,560.982	8,098.198	2,058

Table A14: The reform's effect on local nighttime lights: Regression results

	(1)
Dependent variable: Log (lights)	
Year2004*County average specialization*Stringency	-0.0017
	(0.0042)
Year2005*County average specialization*Stringency	0.0011
	(0.0029)
Year2007*County average specialization*Stringency	0.0007
	(0.0019)
Year2008*County average specialization*Stringency	0.0034
	(0.0026)
Year2009*County average specialization*Stringency	0.0059
	(0.0040)
Year2010*County average specialization*Stringency	0.0138**
	(0.0066)
Year2011*County average specialization*Stringency	0.0130*
	(0.0072)
Year2012*County average specialization*Stringency	0.0103
	(0.0082)
Year2013*County average specialization*Stringency	0.0123
	(0.0095)
Year2004*County average specialization	0.0038
	(0.0043)
Year2005*County average specialization	0.0035
	(0.0026)
Year2007*County average specialization	-0.0018
	(0.0021)
Year2008*County average specialization	-0.0025
	(0.0026)
Year2009*County average specialization	-0.0031
	(0.0034)
Year2010*County average specialization	-0.0055
	(0.0052)
Year2011*County average specialization	-0.0062
	(0.0059)
Year2012*County average specialization	-0.0104
	(0.0068)
Year2013*County average specialization	-0.0115
	(0.0075)
County FE, Prefecture*Year FE, County-level characteristics*Year FE	Y
Observations	20,580
R-squared	0.9908

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses are clustered at the prefecture level. The year 2006 is the omitted category. Reform stringency is the share of industrial land sales that went through the new transaction mechanism in each prefecture that supervises the respective county between 2008 and 2010. County average specialization represents the average specialization index across all industries in each county. It is standardized to have a mean of zero and a standard deviation of one. The county-level characteristics include each county's 2001 GDP (in logs), secondary and tertiary sector GDP shares, total population (in logs), the share of the rural population, nighttime lights in 1992 (in logs), and the growth of nighttime lights from 1992 to 1999.

Table A15: Post-reform results from land transaction data

	(1)	(2)
Dependent variable:	Dummy: industrial land sale >0	
Specialization*Stringency	0.0033***	
	(0.0011)	
Specialization	0.0063***	
	(0.0017)	
Specialization*Year2009*Stringency		0.0027
		(0.0017)
Specialization*Year2010*Stringency		0.0053***
		(0.0013)
Specialization*Year2011*Stringency		0.0055**
		(0.0022)
Specialization*Year2012*Stringency		0.0035**
		(0.0017)
Specialization*Year2013*Stringency		0.0045**
		(0.0019)
Specialization*Year2014*Stringency		-0.0007
		(0.0020)
Specialization*Year2015*Stringency		0.0024
		(0.0018)
Specialization*Year2009		0.0040*
		(0.0023)
Specialization*Year2010		0.0066***
		(0.0018)
Specialization*Year2011		0.0104***
		(0.0024)
Specialization*Year2012		0.0055**
		(0.0023)
Specialization*Year2013		0.0092***
		(0.0024)
Specialization*Year2014		0.0035*
		(0.0021)
Specialization*Year2015		0.0049**
		(0.0020)
County*Year FE, Prefecture*Industry*Year FE, Log total employment	Y	Y
Observations	145,341	145,341
R-squared	0.5154	0.5155

Note: See Table 4 for notes. Stringency represents the share of industrial land sales through the new transaction mechanism in each prefecture that supervises the respective county between 2009 and 2015, corresponding to the study period of the land sample. The regression is weighted by the number of industrial transactions within the prefecture during 2009–15.

Table A16: Summary statistics, land regression sample

	Mean	S.D.	Obs.
Sale price (yuan per sq m)	181.914	137.175	65,875
Dummy: Public sale	0.730	0.444	65,875
Lot size (10,000 sq m)	3.559	5.095	65,875
Distance to city center (km)	39.584	26.862	65,875
Dummy: Converted from farmland	0.627	0.484	65,875
Land transaction year			
Dummy: 2007	0.217	0.412	65,875
Dummy: 2008	0.159	0.366	65,875
Dummy: 2009	0.256	0.436	65,875
Dummy: 2010	0.369	0.482	65,875

Note: For the regressions in columns (1) and (2) in Table 12, we restrict the sample to those land parcels used for manufacturing industries to be consistent with the primary regression and those with two-digit industry codes available. In addition, the sample is restricted to industrial land transactions during 2007–10, corresponding to the post-reform period of our primary analysis. We exclude observations from Zhejiang to be consistent with the primary regression sample. This table reports the summary statistics of the variables.

Appendix B: Data quality of the 2010 ASIF

Although previous studies have widely used the Annual Survey of Industrial Firms (ASIF) data sets, recently, researchers have raised concerns about the data quality of the 2010 ASIF. Since we used the 2010 ASIF to identify new entrants in 2009 and 2010, we conducted two checks to evaluate the quality of the *founding year information* reported in the 2010 ASIF. First, we compared the number of new entrants (above-scale industrial firms) calculated from the ASIF with the number of all the new registrations calculated from the Firm Registration Data at the State Administration for Industry and Commerce.[74] We found that the correlation coefficient between the two data sources at the industry-province level increased from 0.50 in 2005 to 0.64 in 2010. The high correlations ensure that the quality of the founding year information reported in the 2010 ASIF is at least as good as that of the earlier years. Second, for the sample of new establishments generated from the 2010 ASIF, we checked their registration dates by hand through tianyancha.com, a commercial website that provides firm registration information to the public. About 66% of the establishments registered in 2010, 13% in 2009, 15% during 2005–08, and 5% before 2005. Since it is possible that a parent firm could register before the opening of its industrial establishment, the results here confirm that the founding year information reported in the 2010 ASIF is accurate.

[74] We thank Zhikuo Liu from Fudan University for sharing the data.

Appendix C: Measuring the TFP of manufacturing firms in the ASIF data set

Based on the financial information in the Annual Survey of Industrial Firms (ASIF), such as the value of annual output, assets, investment, and costs, we measure the total factor productivity (TFP) of individual firms following the method proposed by Levinsohn and Petrin (2003) and Petrin, Poi, and Levinsohn (2004), referred to as the LP method. Developed based on Olley and Pakes (1996), the LP method has been widely used in the literature to compute firm-level TFP (e.g., see Wooldridge, 2009; Ackerberg, Caves, and Frazer, 2015; Chor, Manova, and Yu, 2021). We run the following regression:

$$\log y_{it} = \mathrm{TFP}_{\mathrm{it}} + \beta_{1j} \log k_{it} + \beta_{2j} \log l_{it} + \beta_{3j} \log m_{it} + g_j(\log m_{it}, \log k_{it}) + u_{it}$$

where y_{it}, k_{it}, l_{it}, and m_{it} represent the value added, total fixed assets, number of employees, and total value of intermediate inputs of firm i in year t, respectively. In the equation, $g_j(\log m_{it}, \log k_{it})$ is a function of the value of intermediate inputs and total fixed assets, which captures the productivity shock, where j denotes the three-digit industry category of firm i. By running the regression for each industry separately, we allow all the parameters in the equation to differ across three-digit industries. Using the regression results, we predict the TFP for individual firms in the ASIF.

Reliable financial information, such as the annual output value, assets, investment, and costs, is available in the 2005–07 ASIF data sets. Based on the data, we measure the TFP of new births during 2005–07, which are examined in the regressions in Table 2. Table C1 reports the summary statistics of each year's TFP measure and the variables we use to calculate the TFP.

Table C1: Summary statistics of data for the TFP calculation, new firms

	Mean	S.D.	Obs.
added, 1,000 yuan	6,997	14,756	7,581
er of people employed	127	196	7,581
fixed assets, 1,000 yuan	11,283	30,506	7,581
intermediate input, 1,000 yuan	17,653	43,315	7,581
TFP)	4.228	1.109	7,581
added, 1,000 yuan	7,273	16,142	7,297
er of people employed	116	218	7,297
fixed assets, 1,000 yuan	10,555	28,175	7,297
intermediate input, 1,000 yuan	18,967	85,179	7,297
TFP)	4.303	1.104	7,297
added, 1,000 yuan	8,963	19,526	10,019
er of people employed	109	182	10,019
fixed assets, 1,000 yuan	10,803	28,125	10,019
intermediate input, 1,000 yuan	21,724	68,448	10,019
TFP)	4.474	1.136	10,019

Appendix D: The food processing industry

We calculate each county's amount of cropland with a slope of less than 6 degrees using two data sets: (1) satellite-based data on land use in 1990 provided by the Institute of Remote Sensing and Digital Earth of the Chinese Academy of Sciences and (2) the Digital Elevation Model slope map provided by the Geographic Data Sharing Infrastructure, College of Urban and Environmental Science, Peking University. Table D1 indicates a significant positive correlation between a county's area of flat cropland and its actual gain output from the *1996 Summary of Rural Economic Statistics of Counties in China*. Table D2 shows that a county's total area of flat cropland is a strong predictor of its high specialization in food processing compared to other industries.

Table D1: Flat cropland and grain output

	(1)	(2)
Dependent variable: Log (grain)		
Log (flat cropland+1）	0.3523***	0.3483***
	(0.0469)	(0.0428)
Prefecture FE		Y
Observations	2,028	2,028
R-squared	0.2086	0.7215

Note: We regress each county's grain output in 1995 on the county's flat cropland area, controlling for the prefecture fixed effects (column (2)). The information on the grain output is obtained from the Summary of Rural Economic Statistics of Counties in China (*Zhongguo Fenxian Nongcun Jingji Tongji Gaiyao*). Standard errors are clustered at the prefecture level.

Table D2: Flat cropland and specialization

	(1)	(2)	(3)	(4)
Dependent variable: Specialization				
Industry sample	Food processing	Agriculture, excluding food processing	Minerals	Other industries
Log (flat cropland+1）	0.3408***	-0.2283*	-0.1030	-0.1028***
	(0.0767)	(0.1188)	(0.0718)	(0.0207)
Prefecture FE	Yes	Yes	Yes	Yes
Observations	1,416	2,552	4,406	11,161
R-squared	0.5125	0.2979	0.1406	0.0637

Note: For each type of industry, we run the following regression to investigate the correlation between a county's flat cropland area and the county's specialization in the industry. The types of agriculture include (1) the food processing industry, (2) the beverage production industry, (3) the tobacco processing industry, (4) the textile industry, and (5) the timber processing, bamboo, cane, palm fiber, and straw products industry. The types of minerals include (1) the petroleum processing, coking products, and gas production and supply industry; (2) the raw chemical materials and chemical products industry; (3) the nonmetal mineral products industry; (4) the smelting and pressing of ferrous metals industry; and (5) the smelting and pressing of nonferrous metals industry. Standard errors are clustered at the prefecture level.