Rent-Seeking and the Spatial Allocation of Economic Activity: Evidence from China's Anti-Corruption Campaign[*]

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Abstract

We show direct evidence of the distortionary effects of rent-seeking activities, by studying the impact on Beijing's restaurant sector of China's 2012 anti-corruption campaign, which placed strict limits on lavish spending by public officials. We find that restaurants located closer to government offices experienced a relative decline in consumer demand. We further show that the spatial distribution of establishments became less concentrated around government offices, compared to before the campaign. Our results underscore the influence of rent-seeking activities on the prior spatial distribution of the restaurant sector, suggesting that they distort economic outcomes beyond industries targeted by the rent-seeking itself.

JEL classification: D72, D73, R10, R12, R38
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1 Introduction

Political connections can significantly impact the allocation of economic resources within a society. Individuals or entities with close ties to those in power can exert influence to secure favorable treatment, contracts, or access to resources, and those without connections may find it challenging to compete on a level playing field. Political connections can thus shape economic decisions, favoring certain individuals or groups over others, and potentially leading to inefficiencies and distortions in resource allocation. What is more, their value to those who benefit from them entails a second layer of distortions, as resources are devoted to securing or maintaining the connections themselves, through rent-seeking activities ranging from lobbying to outright bribery.

Yet it is hard to detect these distortions, in the sense of causally tying specific outcomes to those rent-seeking activities. This is especially true in contexts where such activities may be illegal, as they often are, and where there is little transparency about the interactions between public officials and the businesses they regulate or otherwise affect. This is very much the case in developing countries, but also in industrialized, stable democracies.

We provide causal evidence of the direct distortionary effect of rent-seeking activities, by studying a specific instance in which a sharp policy intervention dramatically changed the incentives for engaging in certain kinds of such activities: the "Eight-Point Regulation" (8PR) initiative in China. The Chinese government launched the 8PR initiative in December 2012, as part of what was billed as the largest anti-corruption campaign in the country's history, aimed at combatting official extravagance and revitalizing the government's public image.[1]

A key feature of 8PR was a ban on government officials spending on receptions, meetings, business meals, and other leisure activities, which had been common practices used by those officials to increase their own consumption, and by private individuals and businesses to buttress relationships with the officials. The subsequent crackdown had a pronounced impact on China's restaurant sector, particularly high-end establishments, which experienced its slowest growth in more than two decades (Yang and Jing, 2013).

[1] On the broad implications of the anti-corruption campaign, see Sudworth (2014).

The dramatic impact of the anti-corruption crackdown on this particular sector gives us a window into the influence of pre-existing rent-seeking practices on the distribution of economic activity. Specifically, we compare the performance of Beijing restaurants before and after the implementation of 8PR, based on their geographical proximity to government offices. Our first key finding is that restaurants located near centers of power were more significantly affected by the 8PR measures, compared to similar establishments situated farther away. Second, we find that the spatial distribution of establishments subsequently became less concentrated around government offices, compared to before 8PR. Put together, the results show that the pre-existing spatial allocation of the restaurant sector was strongly influenced by the rent-seeking activities that the 8PR policy aimed to curb.

Our analysis starts by combining establishment-level data for restaurants in Beijing's six inner districts from 2010 to 2014, scraped from Dianping – China's most popular website for consumer product and retail service reviews (roughly equivalent to Yelp in the United States) – with geocoded information on the location of restaurants. To account for potentially unobserved characteristics of establishments located in different areas, we implement a spatial differences-in-differences strategy. The key idea, intuitively speaking, is that restaurants near government offices can be considered the "treated" group, more intensely affected by 8PR. This is for two complementary reasons: the kind of spending targeted by the 8PR intervention was disproportionately likely to take place in restaurants closer to government offices in the low accountability environment pre-intervention, and these restaurants might also be under greater scrutiny in the higher accountability regime under 8PR. Assuming parallel trends in demand across "treatment" and "control" groups before 8PR, the differential change in performance indicates the causal impact of the relative reduction in rent-seeking activities brought about by the policy.

Our results show a significant negative impact on both customer traffic (5.5%) and average consumer expenditure (2.7%), as proxied by anonymous online reviews, with the effect persisting during our estimation window (2013-2014). To get a sense of magnitudes, a simple back-of-the-envelope calculation translates this into a yearly loss of roughly RMB 3 billion (just above USD 400 million). The adverse effects were most significant for restaurants with arguably higher exposure to rent-seeking practices, such as those located in government-designated hotels and near more important offices, and on weekdays, when government offices are open. We also find that high-end restaurants were more affected, consistent with the effect being driven by the enforced reduction in the demand for lavish spending. Lower-end establishments also suffered, likely due to negative externalities to the industry as a whole. In contrast, sectors not directly affected by 8PR do not show the same spatial patterns, and the effect on restaurants themselves is not meaningfully different depending on their location relative to business agglomerations, as opposed to government offices.

The impact is further underscored by looking at the evolution of the spatial distribution of establishments after the 8PR implementation. By 2016, that distribution was clearly less concentrated around government offices, with the biggest drop in numbers coming from restaurants in close proximity to them. This indicates that the change in demand patterns was not a merely temporary disruption, nor an artifact of changes in behavior by online reviewers, but actually left a mark on the spatial allocation of resources in the restaurant sector. Overall, our findings suggest that the spatial distribution of activity in the sector prior to the anti-corruption intervention was not entirely reflective of underlying economic characteristics, but was instead significantly affected by previously widespread rent-seeking practices.

Our findings present a compelling illustration of the costs directly associated with rent-seeking endeavors: resources dedicated to maintaining political connections distort the allocation of economic activity, affecting sectors unrelated to those efforts themselves. This allows us to gain a more comprehensive understanding of the broader impact of corruption, thus highlighting the challenges faced by anti-corruption policies. The conventional perspective on corruption emphasizes its negative effects on social welfare, even if establishing a clear causal link often proves empirically challenging. In contrast, our study emphasizes that rent-seeking activities have beneficiaries beyond government officials and private agents directly involved in them. In our context, restaurants, particularly those establishments in close proximity to government offices, were negatively affected by the anti-corruption crackdown. This cautionary tale underscores the potential political resistance that anti-corruption initiatives may encounter, especially in contexts where governments may face more constraints on their actions than in China.

Our study connects to a number of different strands of literature. First, we add to the vast body of work that has investigated the economic impact of political connections, corruption, and broad rent-seeking (e.g. surveys by Olken and Pande (2012) and Bombardini and Trebbi (2020), and references therein). Documenting this impact is inherently challenging, given measurement issues and the potential for omitted variables and reverse causality, and the literature has pursued multiple approaches to deal with those challenges. We take advantage of a unique policy experiment, by making use of the heterogeneous implications of the policy across space, and our within-city spatial approach allows us to make statements about the distribution of economic activity while holding underlying economic fundamentals constant. Notably, we focus on the distorting role of rent-seeking activities themselves, in a sector not targeted for influence, as distinct from their intended effect on public or private decision-making.

Within this literature, we also contribute to the effort in examining the impact of policy interventions aimed at curtailing corruption (e.g., Olken, 2007; Ferraz and Finan, 2008; Björkman and Svensson, 2009; Avis et al., 2018). We show that these interventions can have collateral effects on tangentially related sectors, which could presumably affect their political support. On a more specific level, we add to the empirical evidence on the economic ramifications of China's extensive 2012 anti-corruption campaign.[2] Our results underscore that anti-corruption policy interventions, particularly China's, yield substantive economic effects, as opposed to mere "cosmetic" adjustments that risk undermining the intended impact of such interventions.

[2]Some studies document a negative economic impact of the 2012 corruption crackdown (Chen and Zhong, 2017; Zang et al., 2018), while others highlight benefits arising from diminished corruption. For instance, Lin et al. (2016) document a positive impact of anti-corruption reforms on shareholder valuations, attributable to reduced expected bribes to government officials and the intensified development of the market institutions. Giannetti et al. (2019) underscore the performance improvement of firms operating in initially more corrupt settings, particularly small enterprises. Ding et al. (2020) find a positive stock market response to robust anti-corruption measures and lower announcement returns for luxury-goods producers, SOEs, large firms, or politically connected firms. In contrast, Wang (2016) links the increasing dismissal of a high-level government official to slight province-level growth reduction. Chen and Kung (2019) suggest that the campaign was effective in reducing corruption in real estate sales, and had an impact on political selection.

Our work also relates to the literature exploring the determinants of the spatial distribution of urban consumer amenities, by examining the impact of anti-corruption regulations on the geography of restaurants within a city. Prior research has shown that urban amenities tend to cluster in areas with higher levels of population, urban density, and demand aggregation (Glaeser et al., 2001; Waldfoger, 2008; Berry and Waldfoger, 2010; Couture, 2014; Schiff, 2015; Couture and Handbury, 2020; Leonardi and Moretti, 2023). We extend this literature by showing that the location of political power centers also affects the spatial concentration of consumer amenities. This adds to the growing body of evidence underscoring the pivotal role of the spatial distribution of political power in shaping the geographical patterns of economic activity (Ades and Glaeser, 1995; Davis and Henderson, 2003; Campante and Do, 2010, 2014; Rodden, 2010; Galiani and Kim, 2011; Campante et al., 2019). Moreover, our analysis sheds light on how shifts in the political landscape – heightened political accountability, in our case – can induce changes in the geography of consumer amenities.

Our third contribution is the use of large-scale data from online platforms to measure local economic activity. This approach is becoming increasingly popular in gauging economic changes in urban spaces due to its accessibility, timely updates, and geocoded information (Blumenstock et al., 2015; Toole et al., 2015; Jean et al., 2016; Naik et al., 2017; Dong et al., 2017; Glaeser et al., 2018; Davis et al., 2019; Dong et al., 2019). By utilizing establishment-level information at a fine spatial resolution, our study provides a deeper understanding of the impact of the 8PR at the within-city scale, which is difficult to capture through traditional economic measures like GDP, population, and employment obtained from official sources at more aggregate levels. Moreover, our scalable approach can be easily replicated in other cities, enabling researchers to study the effects of aggregate shocks across different regions.[3]

The remainder of the paper is structured as follows: Section 2 provides an overview of

[3] We also contribute to the discussion of the association between conspicuous consumption and corruption (Lambsdorff, 2002; Gokcekus and Suzuki, 2014). This association is not unique to business-government relationships, where firms engaging in bribes face a higher cost of capital and spend more time with bureaucrats (Kaufmann and Wei, 2000). Our findings are consistent with the literature showing that harsh corruption control policies targeting corruption-induced conspicuous consumption can effectively limit lavish consumption behaviors (Tajaddini and Gholipour, 2018).

the Eight-Point Regulation and its impact on the restaurant sector, and Section 3 goes over data sources and descriptive statistics. Section 4 outlines the methodology, and Section 5 presents and discusses the estimation results. Section 6 concludes.

2 Background: China's Anti-Corruption Campaign and the "Eight-Point Regulation"

Chinese officials have long been known for their extravagant spending at luxurious establishments such as high-end restaurants, private clubs, and massage parlors, at the expense of taxpayers and businesses. This practice has been associated with institutional and interpersonal relationships, business culture, and the long-established fringe benefit in exchange for public officials' loyalty (Cai et al., 2011; Gong and Xiao, 2017; Agarwal et al., 2020; Wang and Yan, 2020). Since 2010, the Ministry of Finance has been pressured by criticism, facilitated by social media, to publicize figures for the "three expenses."[4] In 2010 and 2011, central government departments spent 9.47 billion yuan and 9.36 billion yuan ($1.47 billion), respectively, on these expenses. However, these reported figures lacked transparency and received minimal audits, which had drawn substantial backlash over insufficient accountability (Chen, 2013).

In December 2012, soon after the 18th National Congress of the Chinese Communist Party (CCP), the Chinese central government implemented austerity measures with the issuance of the "Eight-Point Regulations" (8PR). These regulations required that officials shun all forms of extravagance, stipulating that "there should be no welcome banner, no red carpet, no floral arrangement or grand receptions for officials' visits." The regulations also specified that "leaders must practice thrift and strictly follow relevant regulations on accommodation and cars."[5]

In a nutshell, the 8PR marked the Chinese government's highly public campaign aimed

[4]"Three public expenses", also known as "san gong xiao fei," refer to Chinese officials' spending on vehicles, banquets, and international travel at the public expense.

[5]For more information on the crackdown on corruption and public officials' spending in China, please refer to https://www.chinabusinessreview.com/chinas-crackdown-on-corruption-and-government-spending-a-timeline/.

at curtailing the conspicuous displays of wealth by those in power. It mandated an end to luxury banquets and leisure activities, motor vehicle passes, and VIP membership cards. The campaign advertised a zero-tolerance stance on corruption, illustrated by the fact that the Central Commission for Discipline Inspection (CCDI) punished 182,000 officials nationwide for disciplinary violations in 2013, representing an increase of over 20,000 relative to 2012 and approximately 40,000 relative to 2011 (Garrick and Bennett, 2016).

The campaign reportedly resulted in the closure of high-end stores and recreational facilities, club membership cancellations, limitations on banquets, and bans on extravagant spending with public funds (Yang and Jing, 2013). This had a severe impact on luxury goods dealers, high-end caterers, lavish entertainment venues, and massage parlors. The China Cuisine Association reported a 9% growth rate in the catering service market in 2013, the lowest in 21 years. Sales of premium liquor and Chinese specialty dishes decreased by up to 70%. Nearly 60% of restaurants reported a decrease in reservations, and government-sponsored banquets decreased by almost a third compared to the previous year (Jacobs, 2013). The growth rate of luxury retailers also dropped by 5% to 2% in 2013. Some estimates indicated that GDP growth was reduced by approximately 0.1-0.2 percentage points (Yan, 2014).

The impact of the campaign is borne out in the data. The China Family Panel Survey (CFPS) – a nationally representative survey conducted by the Institute of Social Science Survey (ISSS) at Peking University – contains information on household dining-out expenditures. Among a variety of household characteristics, it also records information on whether the household includes any government employees. Using the 2012 and 2014 waves – namely, immediately before and after the implementation of 8PR – we find that households with family members employed at government bureaus reduced their dining-out expenditure per person by approximately 712 RMB (2.4 percentage points as a percentage of total expenditure, and 3.7 as a percentage of income), relative to other households.[6]

[6]Full results are available in Table A.1 in the Appendix. Specifically, we estimate a differences-in-differences specification as follows:

$$dining\_out_{jt} = \gamma_0 + \gamma_1 \cdot govemployee_j \cdot post_t + \gamma_2 \cdot X_{jt} + \omega_j + \delta_{kt} + \xi_{jt}$$

where $dining\_out_{jt}$ denotes the measure of dining-out expenditure of household j in year t. $govemployee_j$ is a dummy variable equal to 1 if household j has family members working at government bureaus and

This reduction was greater for households living in provincial capitals, as opposed to non-capitals, consistent with the idea that the effect would be larger in more politically sensitive locations.[7]

3 Data

3.1 Restaurant Data

We collected quarterly data between 2010-2014 from an online business review and local guide platform – Dianping, the Chinese equivalent of Yelp, covering the main urban areas of Beijing. Dianping regularly publishes price and review information for local businesses in Chinese cities.[8] We focus on the inner six districts of Beijing — Dongcheng, Xicheng, Chaoyang, Haidian, Fengtai, and Shijingshan, where most retail stores and government ministries are located. Our sample consists of 30,974 restaurants and includes information on restaurant names, addresses, cuisine types, customer reviews, ratings, self-reported expenses, and year of establishment. Dianping reviews are anonymous, reducing the risk that posting behavior would be affected by accountability concerns.

We use the dates of online review postings to build a panel dataset of restaurant consumer expenditures and customer visits. For each restaurant, we count the quarterly number of customer reviews as a proxy for customer traffic and compute the quarterly average expenditure per person as a proxy for average cuisine price. All restaurant addresses are geocoded to measure their locations.

To examine the evolving spatial organization of restaurants after the 8PR, we also col-

0 otherwise. The variable $post_t$ is a dummy variable equal to 1 in 2014 and 0 in 2012. X_{jt} represents demographic attributes of household j in year t. We also include household fixed effects and county-year fixed effects as controls, and cluster standard errors by household.

[7] When interpreting these results, it is important to consider two important caveats. First, we do not have information on the reimbursable expenses of government employees. This means that the decrease in dining-out expenditures among affected households may be due to under-reported expenses that can be reimbursed by government funds. Second, it is possible that the expenses associated with extravagant restaurant consumption were shifted to businesses offering reimbursement for excess spending to bribe corrupt government officials (Cai et al., 2011; Lin et al., 2016). In any case, reported expenditures seem to conform to the Newcomb-Benford law of anomalous numbers, in terms of the first digits reported, for both types of households, before and after 8PR implementation, indicating no evidence of underreporting.

[8] In 2015, Dianping merged with Meituan and became Meituan-Dianping. Our estimation window for the main analysis covers only the pre-merger period.

lected post-2014 restaurant data from Dianping. However, our data retrieval has become restricted since our initial collection for the 2010-2014 period, with access to only restaurant counts at the level of 1 km$\times$1 km grid cells up to 2016. Individual restaurant reviews and pricing information were no longer available. Despite this limitation, the restaurant count data at the grid cell level was sufficient to discern potential medium-run reallocations of restaurants following the policy intervention.

3.2 Government Offices

We geocoded 120 government bureaus in Beijing, including 74 central government ministries and 46 local government bureaus, to locate political power centers in the city. Tables A.2-A.5 provide a complete list of state and municipal government bureaus in Beijing. To visualize the distribution of power centers and restaurants in the inner six districts of Beijing, we present Figure A.1, where the red and blue pentagrams represent state and municipal government bureaus, respectively, and the green dots indicate the restaurants in our sample.

Figure A.1 illustrates that power centers are mainly concentrated in the city center, while restaurants are more widely distributed. Many restaurants are located near power centers, potentially benefiting from the economic activity in the city center and high demand for government meetings and receptions. However, a considerable number of restaurants are also located in peripheral areas, providing ample variation in the distance between restaurants and power centers. This is crucial for identifying the impact of the anti-corruption campaign on restaurant consumer expenditure.

3.3 Descriptive Statistics

Table A.6 displays the summary statistics of restaurant data used in our analysis. Our dataset comprises 348,798 customer reviews on Dianping, with each restaurant receiving an average of 11 reviews. The distribution of review numbers is heavily right-skewed, suggesting that many restaurants receive low customer traffic while a few popular places attract a significant number of customers. We also collected 208,878 self-reported expenditure records for all restaurants in our sample. On average, the reported expenditure was 60 RMB (just under 10 USD), with considerable variability. The distribution of expenditure is also skewed to the right, likely due to the presence of excess spending.

The average distance between a restaurant and its nearest government bureau is 1.9km, consistent with the concentration of restaurants around government buildings, as shown in Figure A.1. To account for any changes in public transportation infrastructure that may have induced the spatial reallocation of customer traffic, we also calculated the distance between each restaurant and the closest subway station in Beijing's inner six districts. We geocoded all subway stations in this area and found that the average shortest distance from a restaurant to its closest station is 1.8 km with a standard deviation of 2.0 km. Notably, the distance from the nearest subway station changes over time, as Beijing underwent significant subway expansion during our study period.[9]

4 Empirical Strategy

We exploit the implementation of the 8PR anti-corruption campaign as a natural experiment, differentially affecting restaurants depending on their proximity to government offices. Intuitively, we can think of establishments located near government offices as the "treatment" group more affected by 8PR measures, with more distant establishments serving as "control" units. The idea is that the lavish spending pre-campaign was more likely to take place in nearby restaurants. This is because of convenience, but also because, in the pre-existing environment of essentially no enforcement against that type of consumption, its very conspicuousness served as a way for officials to signal power and status, in the manner of so-called "Veblen goods" (Bagwell and Bernheim, 1996). In the post-8PR period, where enforcement was present, it would have been arguably riskier to engage in these activities closer to where other government officials or interested observers may be, thus reinforcing the spatial pattern.

We start by dividing Beijing's inner six districts into 3 km $\times$ 3 km grid cells and then

[9]For further information on the rapid growth of the subway system in Beijing during our study period from 2012-2014, please refer to Du and Zheng (2020).

estimate variants of a difference-in-differences specification as follows:

$$ln(y_{ict}) = \beta_0 + \beta_1 \cdot location_{ic} \cdot post_t + \boldsymbol{X_{ict}\beta_2} + \alpha_i + \gamma_{ct} + \epsilon_{ict} \tag{1}$$

where y_{ict} refers to either the number of reviews or average price of restaurant i in grid cell c during quarter t. The variable $post_t$ is a dummy variable that takes the value of 1 starting from the first quarter of 2013 (i.e., the quarter right after the introduction of 8PR). The vector $\boldsymbol{X_{ict}}$ captures a time-varying restaurant-level characteristic – distance to the nearest subway station, to tease out the confounding effect of improved public transit over time, which could have allowed diners to more easily access more distant locations. The fixed effects α_i control for time-invariant differences across restaurants. The cell-by-year-quarter fixed effects γ_{ct} capture unobserved neighborhood-specific patterns, such as differential growth in Dianping users, restaurant location choice, and changes in within-city amenities that may drive restaurant consumer spending patterns. We cluster standard errors by grid cell to account for any arbitrary within-cluster correlation.

We first estimate the impact of the 8PR across different distances from the power centers using a spatial gradient model, where $location_i$ represents the distance from restaurant i to the nearest government office. This helps us understand the geographic reach of the impact. Based on the results from the spatial gradient model, we conduct a spatial differences-in-differences analysis by using $location_i$ as a treatment dummy variable. This variable takes a value of 1 if restaurant i is within a certain distance from its closest government bureau (treated) and zero otherwise (untreated).

Our primary parameter of interest is β_1, which we expect to have a negative sign due to the downward pressure on customer demand and average prices following the anti-corruption crackdown. However, any observed differential trends between affected and unaffected restaurants could result from within-restaurant effects, as well as reallocation of demand across restaurants (e.g., demand shifts to lower-end restaurants or those farther away from the city center), which could potentially bias our estimates. To disentangle the impact of the policy intervention from these other factors, we include store establishment fixed effects to adjust for pre-existing location-specific differences and to absorb any effect due to demand reallocation. Additionally, cell $\times$ year-quarter fixed effects help us account for year-to-year fluctuations and area-specific shocks to consumer spending behaviors.

Our key identification assumption is that restaurant consumer expenses followed similar trends before the implementation of 8PR, regardless of their proximity to power centers. This assumption is bolstered by the fact that the implementation of 8PR was largely unexpected and there were few, if any, rumors circulating prior to its announcement. As a result of the policy shock's random nature, it is unlikely that the relative location of restaurants to power centers influenced the pre-treatment dynamics of demand and supply within the city. Establishment fixed effects account for any persistent spatial differences in restaurant characteristics. Our within-city approach also controls for any cross-city differences in underlying economic fundamentals that may drive the distribution of economic activity, captured by the constant term β_0. Therefore, any differences in the trends of restaurant consumer expenditures across locations relative to political power centers after the implementation of 8PR can be attributed to the differential impact of the policy intervention, rather than pre-treatment differences in the spatial distribution of economic activity. We will empirically test this assumption using our data.

5 Results

5.1 Baseline Results: Online Reviews

We start by looking at the impact of 8PR implementation on customer traffic (as proxied by the number of online reviews) and expenditures per customer (as captured by expenditures reported in those reviews). Our first key result is shown in Figure 1, which displays, in semiparametric fashion, the spatial gradient estimates for the effects of the anti-corruption campaign on those outcome variables in a series of 200-meter buffer rings around the nearest government office. Specifically, we use a set of dummy variables indicating each of the 200-m buffer rings to replace $location_{ic}$ in equation (1) and interact them with the post-policy dummy variable. We find that restaurants located within approximately 1.5 kilometers of their nearest government office experienced a statistically significant decline in customer traffic and average price after policy implementation. In contrast, the anti-corruption campaign did not have a significant impact on restaurants situated beyond this 1.5-kilometer threshold. These findings rule out the possibility that the observed negative impact on restaurants close to political power centers is due to a spatial shift in extravagant consumption from the vicinity of power centers to areas on the periphery where government oversight is less stringent.

To get a sense of magnitudes, we turn to the parametric specification in equation (1), using the distance from each restaurant to its nearest office as the treatment variable of interest (Table A.7 in the Online Appendix). Our preferred specification, which controls for distance to the nearest subway station, shows that a 10% decrease in the distance between a restaurant and its nearest government bureau leads to a 0.2% decrease in customer reviews and a 0.1% decline in average price after the 8PR.[10]

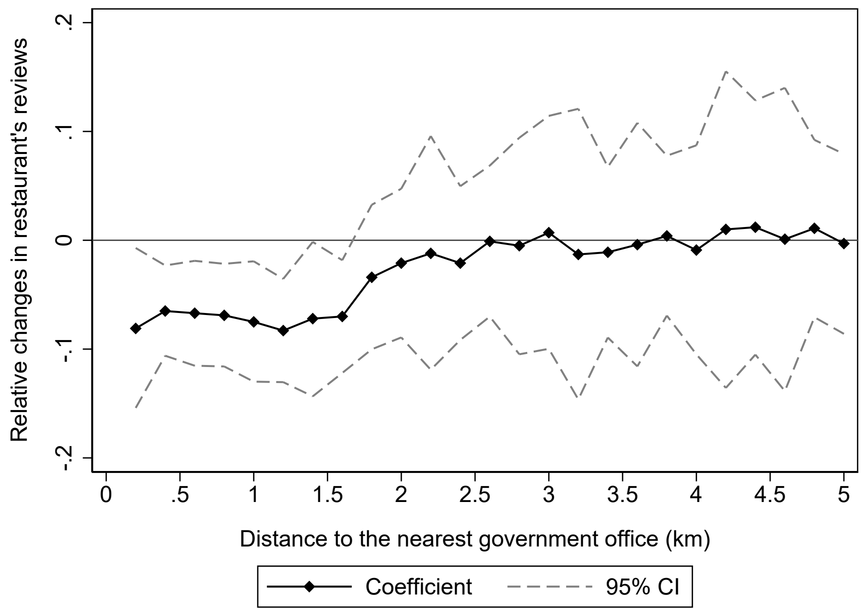
We then move on to the spatial differences-in-differences approach. Based on the non-parametric results, we set the binary treatment variable as equal to 1 for restaurants located within 1.5 km of any government office, and 0 otherwise. We summarize the key patterns in Figure 2, using an event-study approach. Panels (a) and (b) show the trends in customer traffic and average expenditure for treated and untreated restaurants, respectively. The vertical lines in both panels denote the time of policy implementation (December 2012), with Period -1 corresponding to the last quarter of 2012, Period +1 to the first quarter of 2013, and so forth. Panels (c) and (d) then plot the net difference in the trends between treated and untreated restaurants. [11]

It is immediately clear from visual inspection that, there was no apparent difference in customer traffic and expenditure trends prior to the implementation of 8PR. This is reassuring with respect to our key assumption for causal identification. After implementation, a noticeable gap emerged, with a relative drop in the treated restaurants located near po-

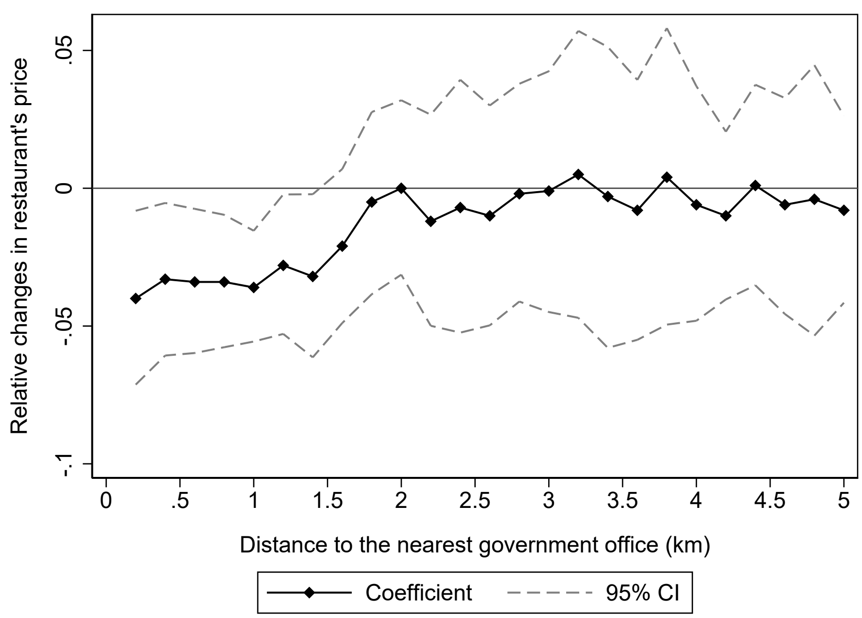
[10]The analysis also finds that the distance to subway stations does not significantly explain changes in restaurant consumption patterns. This suggests that improved public transit did not lead to a significant spatial reallocation of restaurant consumption to more distant locations.

[11]Specifically, we estimate the baseline model equation (1), with the interaction terms of the dummy variable $location_{ic}$ and a set of quarter dummy variables relative to the 8PR policy start date. We plot the coefficients from our preferred specification, which includes store fixed effects and cell $\times$ year-quarter fixed effects, and a control for the distance to the nearest subway station, with standard errors clustered at the grid-cell level to account for potential spatial correlation. Table A.9 reports corresponding regression results.

Figure 1: Customer traffic and price effects by proximity to nearest government office



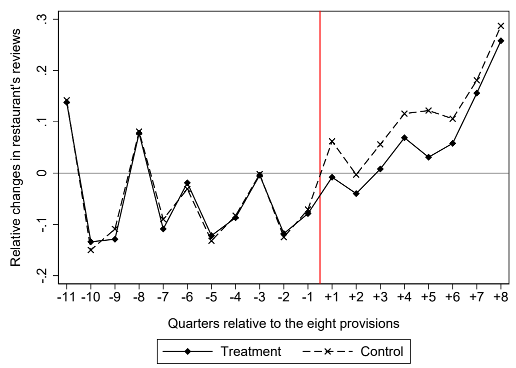
(a) No. of restaurant reviews



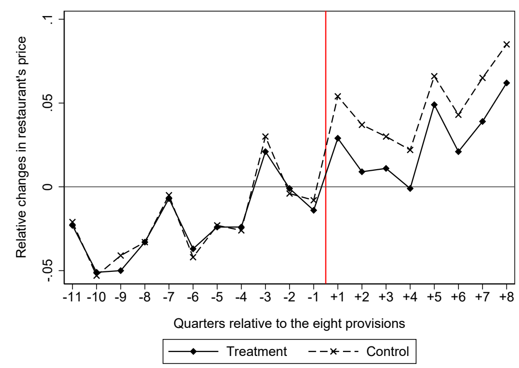
(b) Average price (RMB)

Notes: This figure presents point estimates from a spatial gradient model, as outlined in equation (1). Panels (a) and (b) depict the effects on restaurant customer traffic and prices in 200-meter buffer rings around the nearest power centers, respectively. Corresponding estimates are reported in Table A.8.

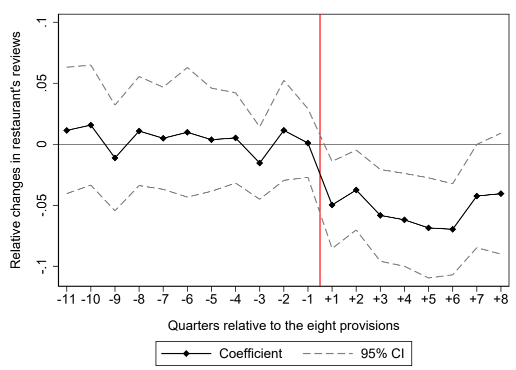
Figure 2: Differences-in-differences estimation: Event study



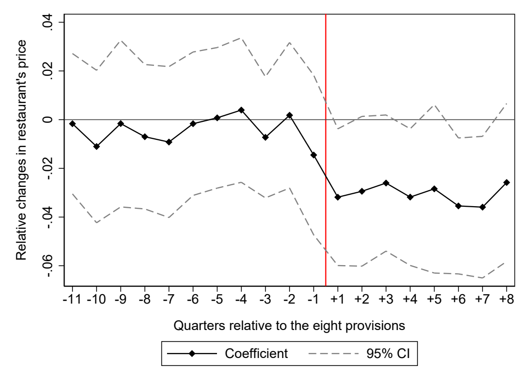
(a) Treated vs. untreated: # reviews



(b) Treated vs. untreated: Average expenditure



(c) # reviews: ATE



(d) Average price: ATE

Notes: This figure presents point estimates from our baseline DID model based on equation (1). Panels (a) and (b) illustrate trends for treated and untreated restaurants in number of reviews and average reported expenditures. Panels (c) and (d) show net differences in these trends. Table A.9 reports corresponding regression results.

litical power centers. This underscores the causal impact of 8PR in reducing the demand for those restaurants, relative to their counterparts situated farther from government offices.[12]

For magnitudes of the average effects, we estimate a basic differences-in-differences specification following equation (1), with results presented in Appendix Table A.10. Our preferred specifications show that restaurants located near political power centers experienced a 5.5% $(= 1 - e^{-0.057})$ relative reduction in the number of reviews and a 2.7% $(= 1 - e^{-0.027})$ decrease in average price after the implementation of the 8PR.[13]

Simple back-of-the-envelope calculations provide additional perspective on the magnitudes. Treated restaurants make up 60.92% of all restaurants in Beijing, according to data from Dianping. In 2012, the total revenue generated by the Beijing catering sector was 53.45 billion RMB. Applying the aforementioned numbers for expenditure per capita and customer traffic would yield a 5.6% [= (1 - 94.5% $\times$97.3%)$\times$60.92%] drop in total revenue for the affected catering businesses in Beijing. This corresponds to revenue losses of approximately 3.0 billion RMB, or roughly 488 million USD using the average exchange rate with respect to the US dollar in 2013 (6.15).

5.2 The Spatial Distribution of Establishments

Having shown the immediate impact of the implementation of 8PR on restaurants, as captured by online reviews, we turn our attention to its effects on the spatial distribution of establishments. This is important for two reasons: first, it allows us to trace the real effects of the shock on the sector over time, thereby helping us determine whether the allocation of resources is durably affected – and hence whether the pre-existing spatial distribution indeed reflected rent-seeking activities.

Second, this helps us determine whether the changes observed from online reviews

[12] It is worth noting that the difference between the two groups eventually decreases, particularly in customer traffic, after approximately two years. This may be due to longer-term adjustments in the market, particularly in terms of establishment entry and exit, which we will address in Section 5.2.

[13] Once again, we find no evidence that the estimated effects were driven by the spatial reallocation of restaurant consumer spending due to the improved metro system. Including $Ln(dis\_subway)$ in the model results in negligible differences in point estimates and R^2, and the control variable $Ln(dis\_subway)$ itself registered a small and insignificant coefficient.

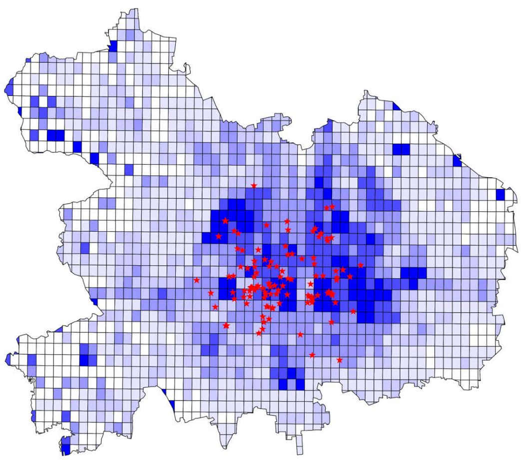
reflect changes in posting behavior, rather than actual restaurant demand. In spite of the anonymity of the reviews, one cannot rule out, in principle, that the new accountability environment could affect incentives to post reviews and report expenditures, particularly for government officials. While it is unclear why those incentives should affect restaurants differentially based on their location relative to government offices, and hence constitute systematic measurement error, it is rather unlikely that decisions on entry and exit would be driven by online reviewers' posting behavior, as opposed to an actual impact on demand and profitability.[14] As such, detecting an impact on the spatial distribution of establishments would be a strong indication that 8PR induced changes in actual consumer behavior.

Figure 3 displays the density of establishments across Beijing's six inner districts, as well as the location of government offices, in 2010, 2012, 2014, and 2016 – thus covering a two-year period before and up to four years after the implementation of 8PR. It is apparent that the distribution, which was relatively stable in the pre-campaign period, becomes substantially more dispersed relative to where the government offices are situated, especially by 2016 – unsurprisingly, as entry and exit decisions accumulate over time. A more systematic depiction is in Figure 4: there is a decline in the number of restaurants located within 3km of the nearest government office, matched by a relative increase in the number of restaurants located farther away.

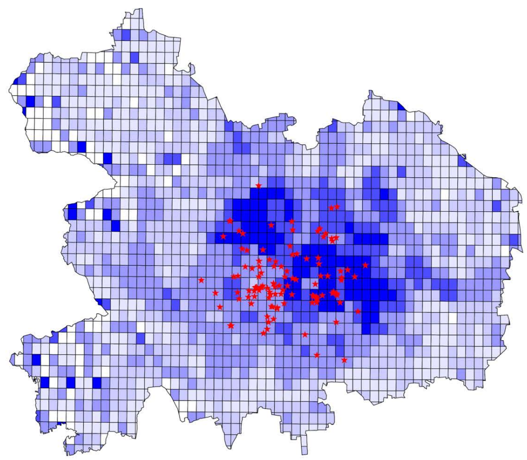
While we cannot interpret the changes in the spatial distribution of establishments as entirely driven by the implementation of 8PR, they are nevertheless consistent with the policy having triggered a reallocation in response to a relative fall in demand for restaurants located near government offices. This in turn underscores the fact that the pre-existing distribution was reflective of the rent-seeking environment at the time.

[14]To be sure, changes in online review behavior could affect profitability indirectly through an advertising mechanism. This would naturally constitute an effect of the policy implementation on actual demand, and while certainly possible, would be very unlikely to explain changes in the absence of direct effects on customer demand. Another possibility would be that restaurants could post or buy "fake" reviews to compensate for a negative demand shock. If this incentive is uniform across restaurants, it would be picked up by our fixed effects; if more affected restaurants are more likely to do so, this would entail that our estimates are underestimates of the true effect.

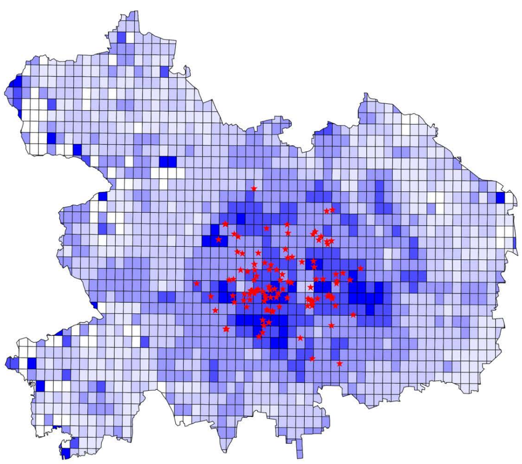
Figure 3: The number of restaurants by grid cell from 2010-2016 (relative to city average)



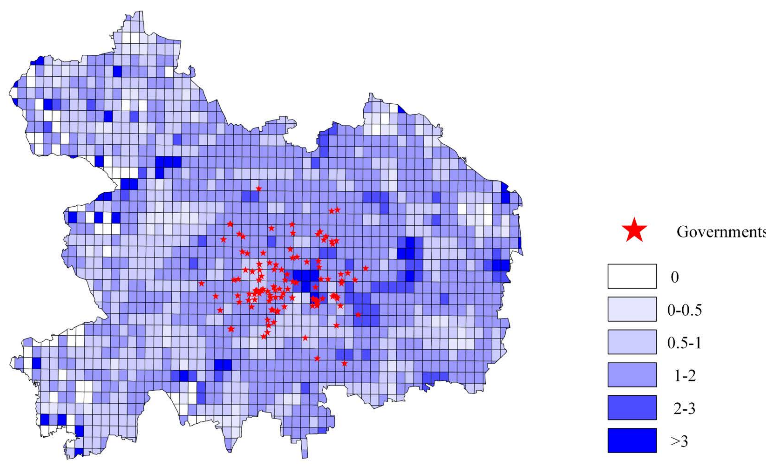
The number of restaurants in 2010



The number of restaurants in 2012



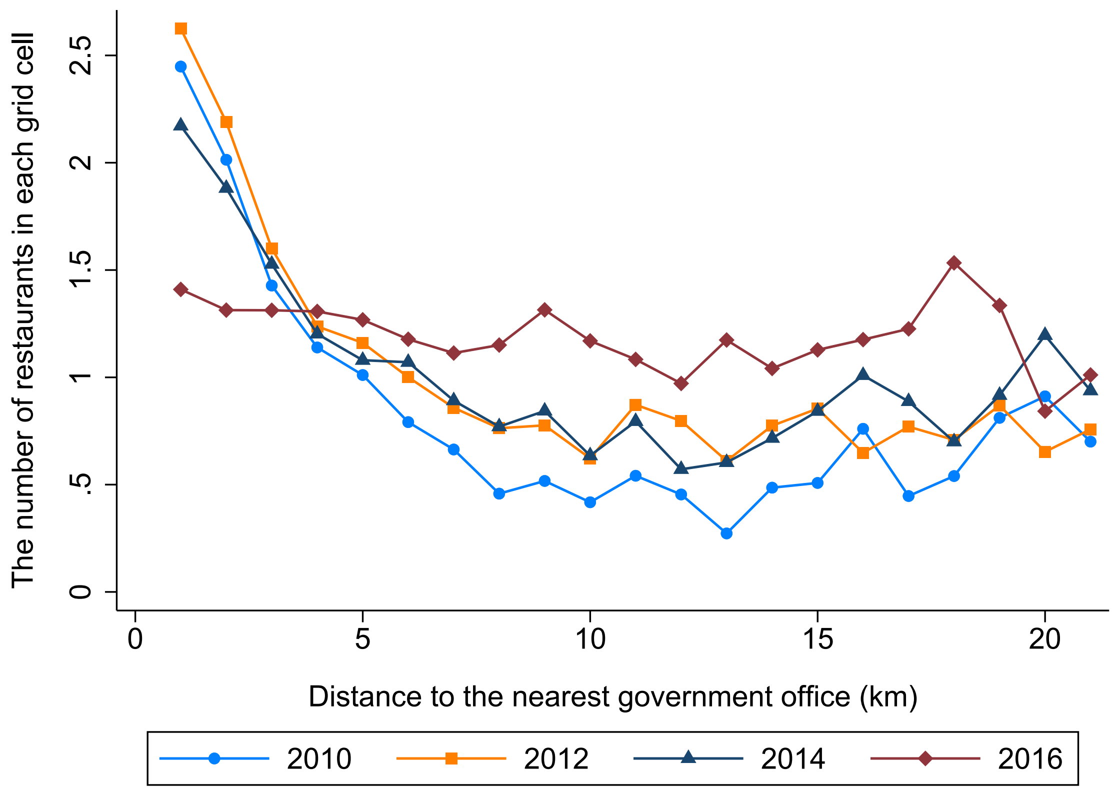
The number of restaurants in 2014



The number of restaurants in 2016

Notes: This map displays the spatial distribution of restaurants in Beijing's inner six districts from 2010-2016. The restaurant count data are presented at the level of 1 km$\times$1 km grid cells, with a darker color indicating a higher restaurant density relative to the city average in the same year. There are a total of 1,627 grid cells in our sample.

Figure 4: Restaurant gradients in Beijing, 2010-2016



Notes: This figure illustrates spatial gradients of restaurants within Beijing's inner six districts for the years 2010, 2012, 2014, and 2016. The gradient of restaurants is represented by the count of establishments in each 1 km×1 km grid cell, normalized against the city's average. This count is then plotted against the distance of each grid cell from its nearest political power center, measured in kilometers.

5.3 Heterogeneity Analysis

We can shed additional light on the nature of the shock, and its relationship to the change in the accountability environment by looking at how 8PR implementation affected different segments of the restaurant sector.

We start by examining restaurants that are included in the government's official list of 822 hotels in Beijing designated as official venues for government meetings and receptions between 2010 and 2014. We redefine our treatment dummy to include as part of the treatment group any restaurants that are situated in these hotels, under the premise that they would be particularly visible and sensitive locations. The control group now comprises establishments more than 1.5km away from the nearest government office and not in government-designated hotels.[15] The results are in Figure 5 (Panel (a)), where for convenience we reproduce the baseline results for customer traffic and expenditure per customer. Re-estimating equation (1) with the new treatment variable yields similar results for customer traffic, and an even stronger effect for expenditure per customer, in line with the idea that there is greater scrutiny over these locations under the anti-corruption campaign.[16]

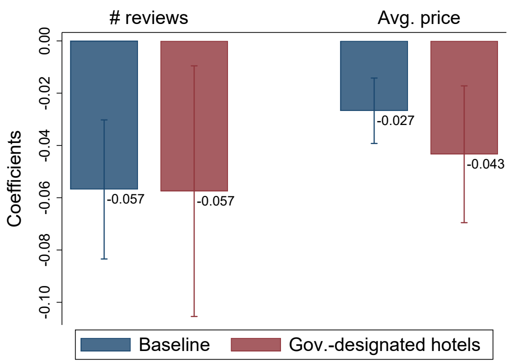
Next, we turn our attention to how the campaign affected restaurants across the quality spectrum. We categorize our sample into high-end, middle-end, and low-end restaurants based on terciles of average expenditure. Panel (b) in Figure 5 displays the coefficients from estimating the baseline differences-in-differences model in equation (1) separately for each category – again, depicting customer traffic and average expenditures side by side.[17] While we do not have enough precision to estimate statistically significant differences, our point estimates suggest that the biggest hit to customer traffic is felt by upscale restaurants, which were popular venues for government meetings and receptions prior to the anti-corruption campaign, and thus were more likely to be affected by it. Yet, mid- and lower-tier restaurants near power centers also suffered, possibly due to stiffer com-

[15] Note that the status of a hotel as government-designated varies over time, as the list is typically updated every two years.

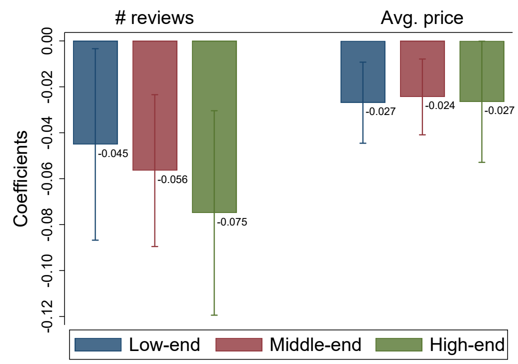
[16] Table A.11 reports the corresponding estimates for this test. Table A.12 confirms the validity of the parallel trend assumption.

[17] Please refer to Table A.13 in the Appendix for the estimation results.

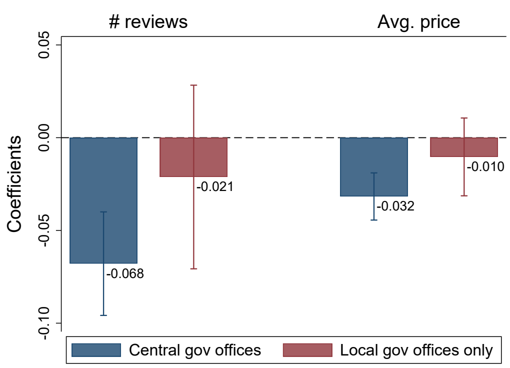
Figure 5: Baseline result, heterogeneity, and placebo test



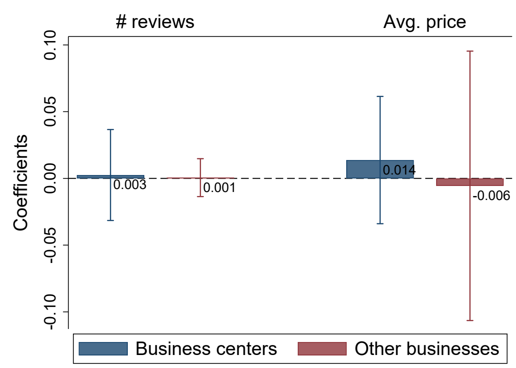
(a) Main results



(b) Heterogeneity by restaurant quality



(c) Heterogeneity by gov rank



(d) Placebo test

Notes: This figure presents the results of the baseline and heterogeneous analyses, along with placebo tests. Panel (a) shows the baseline estimates for the full sample and a reduced sample of government-designated hotels only (Tables A.10 and A.11, respectively). Panel (b) presents estimates for the heterogeneous effects by restaurant quality (Table A.13). Panel (c) shows estimates for heterogeneous effects by proximity to government offices of different ranks (Table A.14). Panel (d) depicts estimates from two placebo tests (Table A.15). The blue bars represent the point estimates from an estimation of the effects on restaurants in proximity to business centers. The red bars indicate the point estimates from an estimation that shifts focus to other businesses, including swimming pools, grocery stores, and laundromats. Bars indicate the size of the coefficients, and whiskers show the 90% confidence intervals of the point estimates.

petition from upscale restaurants downgrading to accommodate the policy shock. This finding highlights the spillover effects of the policy intervention.

It is also interesting to distinguish between different types of power centers, specifically between central government and local (municipal) government locations.[18] As much as the central government's anti-corruption campaign would also affect subnational governments, we expect the effect to be particularly visible around national-level power centers. As can be seen in Panel (c) of Figure 5, that is precisely the case: we estimate a larger effect, both in terms of both the number of reviews and average expenditures when considering proximity to central government offices.

Additional heterogeneity results consistent with our mechanism can be found in the Online Appendix. We find that our results are driven by changes on weekdays, rather than weekends (Tables A.16-A.18), as one would expect from the impact of the 8PR. The effect is also stronger for locations with a higher number of government offices or for offices with a higher number of political scandals reported after the anti-corruption campaign (Table A.14).[19]

We also conduct two placebo tests. We start from the idea that the anti-corruption campaign should not directly affect sectors not targeted by measures against lavish spending, and its effects should not hinge on locations unrelated to governments. We implement the former by aggregating information on establishments in three lines of businesses arguably unrelated to the 8PR directives: swimming pools, grocery stores/supermarkets, and laundromats.[20] We then run our basic differences-in-differences specification, defining treatment status as being within 1.5km of the nearest government office. As for the latter, we geocode 17 business centers in the inner six districts of Beijing, identified using a kernel density analysis approach from Lin et al. (2019).[21] We calculate the distance be-

[18]Beijing is a direct-administered municipality, with its local government at the provincial level, the highest subnational level in China's administrative division system.

[19]This refers to scandals reported on the website of the Central Commission for Discipline Inspection (CCDI) of the CCP, www.ccdi.gov.cn, which is collaboratively managed by the CCDI and the Ministry of Supervision of the State Council. The website regularly publishes tip-offs of corruption and breaches of party discipline, including those related to "party loyalty", "anti-graft", and "moral and behavioral expectations."

[20]We combine the three sectors to get more variation, as there are many more restaurant establishments than in each of the three. Still, we end up with relatively little variation at the cell $\times$ year-quarter level and hence control for year-quarter fixed effects instead.

[21]The 17 municipality-level business centers include Sanlitun, Wangfujing, Xidan, Zhongguancun,

tween each restaurant and its nearest business center and estimate our model based on that distance.

The results are in Panel (d) of Figure 5. In both cases, we find small and insignificant coefficients, often with the opposite sign. Interestingly, when we include both distance to business centers and that to government offices in our restaurant specifications, the coefficient on the latter remains significant and is quantitatively similar to what it was in our baseline specification.

Taken as a whole, our results suggest that the change in the accountability environment was indeed the driving force behind the effects detected in the restaurant sector.

6 Concluding Remarks

We have found that the anti-corruption campaign implemented by the Chinese government in 2012, particularly the Eight-Point Regulations (8PR) that banned lavish banquet spending by government officials, had a significant impact on spatial patterns in the Beijing restaurant sector. Using crowd-sourced online data, our findings suggest a 5.5% decrease in customer traffic (as proxied by the number of online reviews) and a 2.7% decrease in average expenditure for restaurants located in the vicinity of government offices, relative to more distant establishments. Our analysis also supports the view that this was driven by the changed accountability environment brought about by 8PR and its differential impact on the restaurants more likely to have benefited from prior largess by public officials and businesses attempting to curry their favor.

Importantly, we find that this is subsequently matched by significant changes in the spatial distribution of restaurant establishments. By 2016, the distribution had become significantly less concentrated around government offices. This highlights that the effect we detected using online data is reflective of real changes in consumption behavior. What is more, it underscores that the pre-campaign spatial distribution was meaningfully driven by the rent-seeking activities that took place at Beijing restaurants in that low-

Wangjing, Shuangyushu, Xinjiekou, Dongzhimen, Liangmaqiao, Gongzhufen, Qianmendazhalan, Chongwenmen, Chaowaidajie, Dongdaqiao, Guomao, Dawanglu, and Muxiyuan.

accountability environment.

Our findings thus establish that rent-seeking endeavors have direct real effects on economic activity and the allocation of resources, beyond their potential intentional impact on the decisions of their targets. In particular, they end up affecting unrelated sectors, such as the restaurant industry in our case. This is particularly important as it would naturally affect which sectors may be more or less supportive of corruption-fighting efforts.

Our results also speak to the real effects of the Chinese anti-corruption program and policy interventions of this kind more broadly. One skeptical view may be that the parties involved in corrupt activities may adapt through mere window-dressing, misreporting, and the like. We have documented that real economic decisions, such as the entry, exit, and location choices made by firms in the restaurant sector, are being affected.

That said, our setting does not lend itself to a full evaluation of the welfare impact of this particular policy. After all, we cannot pinpoint how the ultimate decision-making by government officials is affected and what the costs and benefits of this might be. It does underscore, however, that the welfare implications must take into account a variety of sectors and business interests, and as such, so must the politics underlying those policies.

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Figure A.1: The spatial distribution of state and Beijing government bureaus.

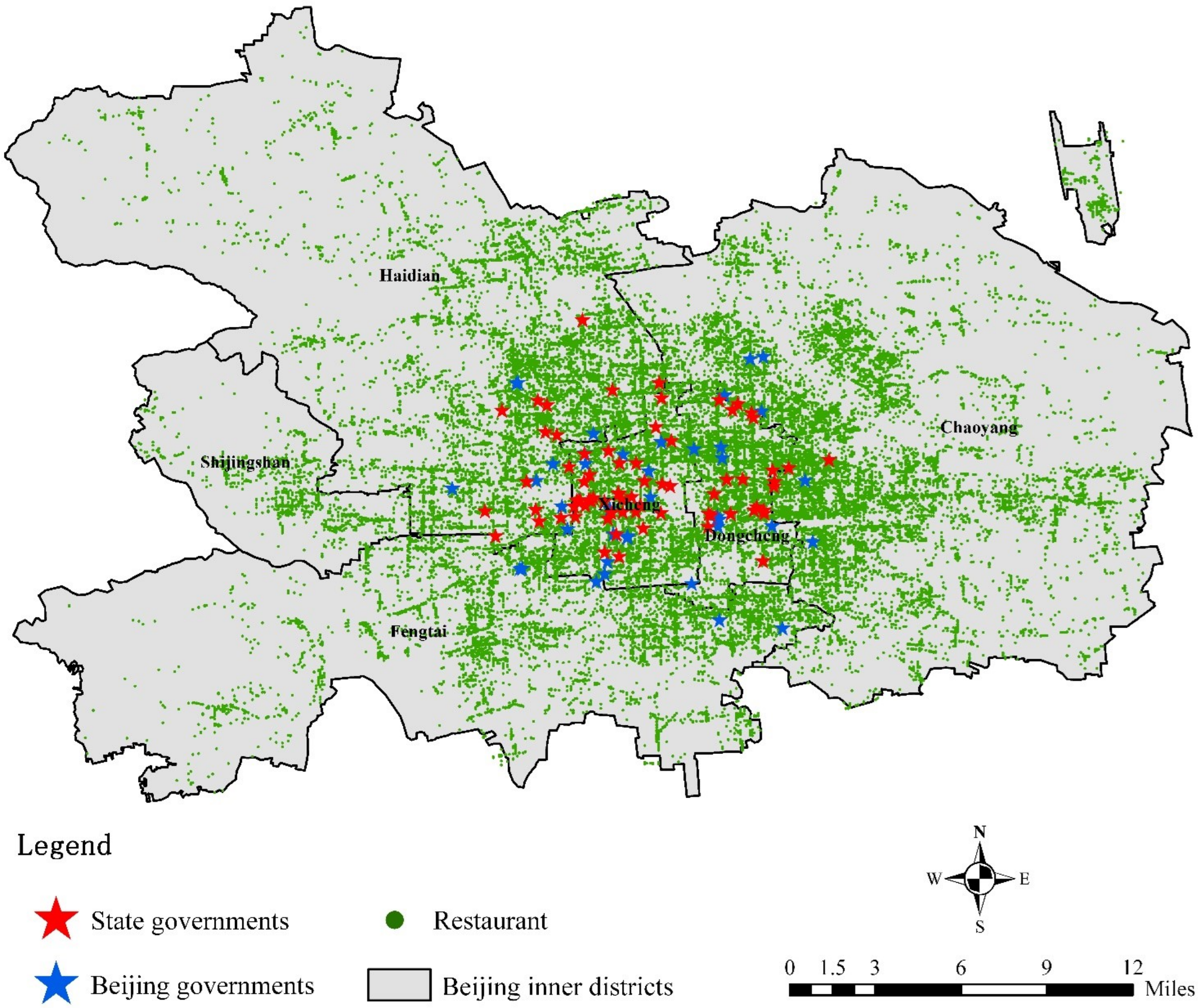

Table A.1: The impact of the corruption crackdown on household dining-out expenditures.

	(1) Dining-out expenditure per capita (RMB)	(2) Dining-out expenditure /Total expenditure	(3) Dining-out expenditure /Household income
Panel A: All			
$treat \times post$	-712.196***	-0.024***	-0.036***
	(230.632)	(0.007)	(0.009)
Household fixed effects	Y	Y	Y
County×year fixed effects	Y	Y	Y
Obs.	12,410	12,222	12,410
R^2	0.610	0.611	0.559
Panel B: Provincial capitals			
$treat \times post$	-1173.835**	-0.030***	-0.038***
	(473.033)	(0.010)	(0.014)
Household fixed effects	Y	Y	Y
County×year fixed effects	Y	Y	Y
Obs.	3,868	3,810	3,868
R^2	0.602	0.639	0.581
Panel C: Non-capital cities			
$treat \times post$	-417.967*	-0.021**	-0.035***
	(227.549)	(0.009)	(0.012)
Household fixed effects	Y	Y	Y
County×year fixed effects	Y	Y	Y
Obs.	8,542	8,412	8,542
R^2	0.615	0.597	0.549

Notes: This table reports results from estimating equation (1). The unit of observation is household by year. Robust standard errors in parentheses are clustered at the household level. * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Table A.2: government bureaus (ID: 1-30).

ID	Organization	District	Level
1	Ministry of Foreign Affairs	Chaoyang	State
2	Ministry of National Offense	Xicheng	State
3	National Development and Reform Commission	Xicheng	State
4	Ministry of Education	Xicheng	State
5	Ministry of Science and Technology	Haidian	State
6	Ministry of Industry and Information Technology	Xicheng	State
7	National Ethnic Affairs Commission	Xicheng	State
8	Ministry of Public Security	Dongcheng	State
9	Ministry of State Security	Dongcheng	State
10	Ministry of Supervision	Xicheng	State
11	Ministry of Civil Affairs	Dongcheng	State
12	Ministry of Justice	Chaoyang	State
13	Ministry of Finance	Xicheng	State
14	Ministry of Human Resources and Social Security	Dongcheng	State
15	Ministry of Land and Resources	Xicheng	State
16	Ministry of Ecology and Environment	Xicheng	State
17	Ministry of Housing and Rural-urban Development	Haidian	State
18	Ministry of Transport	Dongcheng	State
19	Ministry of Water Resources	Xicheng	State
20	Ministry of Agriculture	Chaoyang	State
21	Ministry of Commerce	Dongcheng	State
22	Ministry of Culture and Tourism	Haidian	State
23	National Health and Family Planning Commission	Xicheng	State
24	The People's Bank Of China	Xicheng	State
25	National Audit Office	Xicheng	State
26	State-owned Assets Supervision and Administration Commission of the State Council	Dongcheng	State
27	General Administration of Customs	Dongcheng	State
28	State Administration of Taxation	Haidian	State
29	State Administration for Industry and Commerce	Xicheng	State
30	General Administration of Quality Supervision, Inspection and Quarantine	Haidian	State

Table A.3: government bureaus (ID: 31-60).

ID	Organization	District	Level
31	State Administration of Press, Publication, Radio, Film and Television	Xicheng	State
32	General Administration of Sport	Dongcheng	State
33	State Administration of Work Safety	Dongcheng	State
34	China Food and Drug Administration	Xicheng	State
35	National Bureau of statistics	Xicheng	State
36	State Forestry Administration	Dongcheng	State
37	China National Intellectual Property Administration	Haidian	State
38	China National Tourism Administration	Dongcheng	State
39	National Religious Affairs Administration	Xicheng	State
40	Counsellors' Office of the State Council	Dongcheng	State
41	National Government Offices Administration	Xicheng	State
42	Overseas Chinese Affairs Office Of The State Council	Xicheng	State
43	Hong Kong and Macao Affairs of the State Council	Xicheng	State
44	Legislative Affairs Office of the State Council	Xicheng	State
45	Research Office of the State Council	Xicheng	State
46	Xinhua News Agency	Xicheng	State
47	Chinese Academy of Sciences	Xicheng	State
48	Chinese Academy of Social Sciences	Dongcheng	State
49	Chinese Academy of Engineering	Xicheng	State
50	Development Research Center of the State Council	Dongcheng	State
51	National Academy of Governance	Haidian	State
52	China Earthquake Administration	Haidian	State
53	China meteorological administration	Haidian	State
54	China Banking Regulatory Commission	Xicheng	State
55	China Securities Regulatory Commission	Xicheng	State
56	China Insurance Regulatory Commission	Xicheng	State
57	National Council for Social Security Fund	Xicheng	State
58	National Natural Science Foundation of China	Haidian	State
59	State Bureau for Letters and Calls	Xicheng	State
60	State Administration of Grain	Xicheng	State

Table A.4: government bureaus (ID: 61-90).

ID	Organization	District	Level
61	National Energy Administration	Xicheng	State
62	State Administration of Science, Technology and Industry for National Defense	Haidian	State
63	State Tobacco Monopoly Administration	Xicheng	State
64	State Administration of Foreign Experts Affairs	Haidian	State
65	State Administration of Civil Service	Dongcheng	State
66	State Oceanic Administration	Xicheng	State
67	State Bureau of Surveying and Mapping	Haidian	State
68	National Railway Administration	Haidian	State
69	Civil Aviation Administration	Dongcheng	State
70	State Post Bureau	Xicheng	State
71	State Administration of Cultural Heritage	Chaoyang	State
72	State Administration of Traditional Chinese Medicine	Dongcheng	State
73	State Administration of Foreign Exchange	Haidian	State
74	State Administration of Coal Mine Safety	Chaoyang	State
75	General Office of Beijing Municipal People's Government	Dongcheng	Beijing
76	Beijing Municipal Commission of Development and Reform	Xicheng	Beijing
77	Beijing Municipal Commission of Education	Xicheng	Beijing
78	Beijing Municipal Science and Technology Commission	Haidian	Beijing
79	Beijing Municipal Bureau of Economy and Information Technology	Chaoyang	Beijing
80	Beijing Municipal Commission of Ethnic Affairs	Xicheng	Beijing
81	Beijing Municipal Public Security Bureau	Dongcheng	Beijing
82	Beijing Municipal Bureau of Supervision	Fengtai	Beijing
83	Beijing Municipal Bureau of Civil Affairs	Chaoyang	Beijing
84	Beijing Municipal Bureau of Justice	Xicheng	Beijing
85	Beijing Municipal Finance Bureau	Haidian	Beijing
86	Beijing Municipal Human Resources and Social Security Bureau	Xicheng	Beijing
87	Beijing Municipal Bureau of Land and Resources	Chaoyang	Beijing
88	Beijing Municipal Bureau of Environmental Protection	Haidian	Beijing
89	Beijing Municipal Commission of City Planning	Xicheng	Beijing
90	Beijing Municipal Commission of Housing and Urban-Rural Development	Haidian	Beijing

Table A.5: government bureaus (ID: 91-120).

ID	Organization	District	Level
91	Beijing Municipal Commission of Urban Management	Xicheng	Beijing
92	Beijing Municipal Commission of Transport	Fengtai	Beijing
93	Beijing Municipal Commission of Rural Affairs	Xicheng	Beijing
94	Beijing Municipal Water Affairs Bureau	Haidian	Beijing
95	Beijing Municipal Commerce Bureau	Fengtai	Beijing
96	Beijing Municipal Commission of Tourism Development	Chaoyang	Beijing
97	Beijing Municipal Bureau of Culture	Haidian	Beijing
98	Beijing Municipal Commission of Population and Family Planning	Xicheng	Beijing
99	Beijing Municipal Audit Bureau	Fengtai	Beijing
100	Foreign Affairs Office of the People's Government of Beijing Municipality	Dongcheng	Beijing
101	Beijing Social Construction Office	Dongcheng	Beijing
102	State-owned Assets Supervision and Administration Commission	Xicheng	Beijing
103	Beijing Local Taxation Bureau	Xicheng	Beijing
104	Beijing Administration for Industry and Commerce	Haidian	Beijing
105	Beijing Municipal Administration of Quality and Technology Supervision	Chaoyang	Beijing
106	Beijing Municipal Administration of Work Safety	Xicheng	Beijing
107	Beijing Municipal Drug Administration	Haidian	Beijing
108	Beijing State-owned Cultural Assets Management Center	Dongcheng	Beijing
109	Beijing Municipal Radio and Television Bureau	Xicheng	Beijing
110	Beijing Municipal Administration of Culture Heritage	Dongcheng	Beijing
111	Beijing Municipal Bureau of Sports	Fengtai	Beijing
112	Beijing Municipal Bureau of Statistics	Xicheng	Beijing
113	Beijing Gardening and Greening Bureau	Dongcheng	Beijing
114	Beijing Financial Work Bureau	Xicheng	Beijing
115	Beijing Municipal Intellectual Property Office	Dongcheng	Beijing
116	Beijing Municipal Civil Air Defense Office	Xicheng	Beijing
117	Overseas Chinese Affairs Office of the People's Government of Beijing Municipality	Xicheng	Beijing
118	Legal Affairs Office of the People's Government of Beijing Municipality	Dongcheng	Beijing
119	Office of Letters and Calls of Beijing Committee	Dongcheng	Beijing
120	Research office of the People's Government of Beijing Municipality	Dongcheng	Beijing

Table A.6: Summary statistics.

	Obs.	Mean	Std. Dev.	P10	P50	P90
No. of reviews	348,798	10.5	32.5	1	3	22
Average price (RMB)	208,878	60	140.6	13.1	39.1	104.7
Distance to the closest gov't organization (km)	348,798	1.9	2.3	0.3	1.0	4.4
Distance to the closest subway station (km)	348,798	1.8	2.0	0.5	1.3	3.3

Table A.7: Spatial gradient model estimation results.

	Ln(# reviews) (1)	Ln(price) (2)	Ln(# reviews) (3)	Ln(price) (4)
Ln(dis_gov)×post	0.023***	0.012***	0.023***	0.012***
	(0.007)	(0.003)	(0.007)	(0.003)
Ln(dis_subway)			-0.018	0.005
			(0.014)	(0.005)
Store fixed effects	Y	Y	Y	Y
Cell × year-quarter fixed effects	Y	Y	Y	Y
Obs.	346,324	203,538	346,324	203,538
R^2	0.749	0.835	0.749	0.835

Notes: This table reports results from estimating equation (1). The unit of observation is shop by quarter. Robust standard errors in parentheses are clustered at the grid cell level. * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Table A.8: Spatial gradient model estimation results by distance buffer rings.

	Ln(# reviews)		Ln(price)	
	(1)		(2)	
dis_gov[< 0.2 km]×post	-0.081**	(0.037)	-0.040**	(0.016)
dis_gov[$0.2 - 0.4$ km]×post	-0.065***	(0.021)	-0.033**	(0.014)
dis_gov[$0.4 - 0.6$ km]×post	-0.067***	(0.024)	-0.034**	(0.013)
dis_gov[$0.6 - 0.8$ km]×post	-0.069***	(0.024)	-0.034***	(0.012)
dis_gov[$0.8 - 1.0$ km]×post	-0.075***	(0.028)	-0.036***	(0.010)
dis_gov[$1.0 - 1.2$ km]×post	-0.083***	(0.024)	-0.028**	(0.013)
dis_gov[$1.2 - 1.4$ km]×post	-0.072**	(0.036)	-0.032**	(0.015)
dis_gov[$1.4 - 1.6$ km]×post	-0.070***	(0.026)	-0.021	(0.014)
dis_gov[$1.6 - 1.8$ km]×post	-0.034	(0.034)	-0.005	(0.017)
dis_gov[$1.8 - 2.0$ km]×post	-0.021	(0.035)	0.000	(0.016)
dis_gov[$2.0 - 2.2$ km]×post	-0.012	(0.054)	-0.012	(0.019)
dis_gov[$2.2 - 2.4$ km]×post	-0.021	(0.036)	-0.007	(0.023)
dis_gov[$2.4 - 2.6$ km]×post	-0.001	(0.035)	-0.010	(0.020)
dis_gov[$2.6 - 2.8$ km]×post	-0.005	(0.050)	-0.002	(0.020)
dis_gov[$2.8 - 3.0$ km]×post	0.007	(0.054)	-0.001	(0.022)
dis_gov[$3.0 - 3.2$ km]×post	-0.013	(0.067)	0.005	(0.026)
dis_gov[$3.2 - 3.4$ km]×post	-0.011	(0.040)	-0.003	(0.028)
dis_gov[$3.4 - 3.6$ km]×post	-0.004	(0.057)	-0.008	(0.024)
dis_gov[$3.6 - 3.8$ km]×post	0.004	(0.037)	0.004	(0.027)
dis_gov[$3.8 - 4.0$ km]×post	-0.009	(0.049)	-0.006	(0.022)
dis_gov[$4.0 - 4.2$ km]×post	0.010	(0.074)	-0.010	(0.015)
dis_gov[$4.2 - 4.4$ km]×post	0.012	(0.059)	0.001	(0.018)
dis_gov[$4.4 - 4.6$ km]×post	0.001	(0.070)	-0.006	(0.020)
dis_gov[$4.6 - 4.8$ km]×post	0.011	(0.041)	-0.004	(0.025)
dis_gov[$4.8 - 5.0$ km]×post	-0.003	(0.042)	-0.008	(0.017)
Obs.	346,324		203,538	
R^2	0.749		0.835	

Notes: This table reports results from estimating the variants of equation (1). The unit of observation is store by quarter. Store fixed effects and cell × year-quarter fixed effects are included in all columns. Robust standard errors in parentheses are clustered at the grid cell level. * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Table A.9: Testing for the parallel trend assumption for difference-in-differences estimation.

	Ln(# reviews)		Ln(price)	
	(1)		(2)	
dis_gov[< 1.5 km] $\times$ 11 quarters before EP	0.011	(0.026)	-0.002	(0.015)
dis_gov[< 1.5 km] $\times$ 10 quarters before EP	0.016	(0.025)	-0.011	(0.016)
dis_gov[< 1.5 km] $\times$ 9 quarters before EP	-0.011	(0.022)	-0.002	(0.017)
dis_gov[< 1.5 km] $\times$ 8 quarters before EP	0.011	(0.023)	-0.007	(0.015)
dis_gov[< 1.5 km] $\times$ 7 quarters before EP	0.005	(0.021)	-0.009	(0.016)
dis_gov[< 1.5 km] $\times$ 6 quarters before EP	0.010	(0.027)	-0.002	(0.015)
dis_gov[< 1.5 km] $\times$ 5 quarters before EP	0.004	(0.021)	0.001	(0.015)
dis_gov[< 1.5 km] $\times$ 4 quarters before EP	0.005	(0.019)	0.004	(0.015)
dis_gov[< 1.5 km] $\times$ 3 quarters before EP	-0.015	(0.015)	-0.007	(0.013)
dis_gov[< 1.5 km] $\times$ 2 quarters before EP	0.011	(0.021)	0.002	(0.015)
dis_gov[< 1.5 km] $\times$ 1 quarters before EP	0.001	(0.014)	-0.015	(0.017)
dis_gov[< 1.5 km] $\times$ 1 quarters after EP	-0.050***	(0.018)	-0.032**	(0.014)
dis_gov[< 1.5 km] $\times$ 2 quarters after EP	-0.038**	(0.017)	-0.029*	(0.016)
dis_gov[< 1.5 km] $\times$ 3 quarters after EP	-0.058***	(0.019)	-0.026**	(0.014)
dis_gov[< 1.5 km] $\times$ 4 quarters after EP	-0.062***	(0.019)	-0.032**	(0.014)
dis_gov[< 1.5 km] $\times$ 5 quarters after EP	-0.069***	(0.021)	-0.028	(0.017)
dis_gov[< 1.5 km] $\times$ 6 quarters after EP	-0.070***	(0.019)	-0.035**	(0.014)
dis_gov[< 1.5 km] $\times$ 7 quarters after EP	-0.042**	(0.021)	-0.036**	(0.015)
dis_gov[< 1.5 km] $\times$ 8 quarters after EP	-0.041	(0.025)	-0.026*	(0.016)
Store fixed effects	Y		Y	
Cell $\times$ year-quarter fixed effects	Y		Y	
Obs.	346,324		203,538	
R^2	0.749		0.835	

Notes: This table reports results from estimating the variants of equation (1). The unit of observation is store by quarter. Store fixed effects and cell $\times$ year-quarter fixed effects are included in all columns. Robust standard errors in parentheses are clustered at the grid cell level. * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Table A.10: Difference-in-differences estimation results.

	Ln(# reviews)	Ln(price)	Ln(# reviews)	Ln(price)
	(1)	(2)	(3)	(4)
dis_gov[< 1.5 km]×post	-0.056***	-0.027***	-0.057***	-0.027***
	(0.014)	(0.006)	(0.013)	(0.006)
Ln(dis_subway)			-0.017	0.006
			(0.015)	(0.005)
Store fixed effects	Y	Y	Y	Y
Cell × year-quarter fixed effects	Y	Y	Y	Y
Obs.	346,324	203,538	346,324	203,538
R^2	0.749	0.835	0.749	0.835

Notes: This table reports results from estimating equation (1). The unit of observation is shop by quarter. Robust standard errors in parentheses are clustered at the grid cell level. * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Table A.11: The effect of the corruption crackdown on government-designated hotels.

	Ln(# reviews)	Ln(price)
	(1)	(2)
designated×post	-0.057**	-0.043***
	(0.024)	(0.013)
designated	0.770***	-0.046**
	(0.029)	(0.020)
Ln(dis_subway)	-0.019	0.007
	(0.015)	(0.009)
Store fixed effects	Y	Y
Cell × year-quarter fixed effects	Y	Y
Obs.	158,261	93,815
R^2	0.754	0.825

Notes: This table reports results from estimating equation (1). The unit of observation is store by quarter. Robust standard errors in parentheses are clustered at the grid cell level. * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Table A.12: Testing for the parallel trend assumption for government-designated hotels.

	Ln(# reviews)		Ln(price)	
	(1)		(2)	
designated × 11 quarters before EP	0.010	(0.039)	-0.006	(0.021)
designated × 10 quarters before EP	-0.031	(0.044)	0.003	(0.029)
designated × 9 quarters before EP	-0.031	(0.042)	0.007	(0.026)
designated × 8 quarters before EP	-0.003	(0.035)	-0.011	(0.022)
designated × 7 quarters before EP	-0.011	(0.032)	-0.005	(0.023)
designated × 6 quarters before EP	0.003	(0.043)	0.003	(0.023)
designated × 5 quarters before EP	-0.017	(0.043)	-0.011	(0.019)
designated × 4 quarters before EP	-0.012	(0.030)	-0.018	(0.023)
designated × 3 quarters before EP	0.011	(0.026)	-0.011	(0.021)
designated × 2 quarters before EP	-0.019	(0.032)	-0.007	(0.021)
designated × 1 quarters before EP	-0.001	(0.025)	-0.018	(0.023)
designated × 1 quarters after EP	-0.030	(0.038)	-0.037	(0.020)
designated × 2 quarters after EP	-0.071*	(0.037)	-0.051**	(0.022)
designated × 3 quarters after EP	-0.069**	(0.029)	-0.047*	(0.024)
designated × 4 quarters after EP	-0.068**	(0.033)	-0.043*	(0.023)
designated × 5 quarters after EP	-0.076**	(0.037)	-0.049*	(0.027)
designated × 6 quarters after EP	-0.088**	(0.036)	-0.050**	(0.022)
designated × 7 quarters after EP	-0.057	(0.035)	-0.067***	(0.024)
designated × 8 quarters after EP	-0.055	(0.035)	-0.059**	(0.024)
Store fixed effects	Y		Y	
Cell × year-quarter fixed effects	Y		Y	
Obs.	158,261		93,815	
R^2	0.754		0.825	

Notes: This table reports results from estimating the variants of equation (1). The unit of observation is store by quarter. Store fixed effects and cell × year-quarter fixed effects are included in all columns. Robust standard errors in parentheses are clustered at the grid cell level. * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Table A.13: Heterogeneous effects: High-end, middle-end, and low-end stores.

	Ln(# reviews)			Ln(price)		
	Low	Middle	High	Low	Middle	High
	(1)	(2)	(3)	(4)	(5)	(6)
dis_gov $[\leq 1.5\,km] \times$ post	-0.045**	-0.056***	-0.075***	-0.027***	-0.024***	-0.027**
	(0.021)	(0.017)	(0.022)	(0.009)	(0.008)	(0.013)
Ln(dis_subway)	-0.020	-0.019	-0.003	0.009	-0.017**	0.021**
	(0.015)	(0.022)	(0.021)	(0.009)	(0.008)	(0.008)
Store fixed effects	Y	Y	Y	Y	Y	Y
Cell $\times$ year-quarter fixed effects	Y	Y	Y	Y	Y	Y
Obs.	111,677	115,408	118,872	55,607	68,740	78,702
R^2	0.661	0.704	0.783	0.686	0.416	0.586

Notes: This table reports results from estimating equation (1). The unit of observation is shop by quarter. Robust standard errors in parentheses are clustered at the grid cell level. * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Table A.14: Heterogeneous effects across levels of government power.

	Ln(# reviews) (1)	Ln(price) (2)	Ln(# reviews) (3)	Ln(price) (4)	Ln(# reviews) (5)	Ln(price) (6)
dis_gov [$\leq 1.5\,km$] $\times$ post	-0.021	-0.010	-0.016	-0.013	-0.043***	-0.023***
	(0.025)	(0.011)	(0.023)	(0.010)	(0.015)	(0.006)
dis_gov [$\leq 1.5\,km$] $\times$ post $\times$ state	-0.047**	-0.021**				
	(0.024)	(0.010)				
dis_gov [$\leq 1.5\,km$] $\times$ post $\times$ # depts			-0.004***	-0.001*		
			(0.001)	(0.001)		
dis_gov [$\leq 1.5\,km$] $\times$ post $\times$ # scandals					-0.054**	-0.016**
					(0.022)	(0.007)
Ln(dis_subway)	-0.016	0.006	-0.013	0.007	-0.021	0.004
	(0.015)	(0.005)	(0.015)	(0.005)	(0.017)	(0.005)
Store fixed effects	Y	Y	Y	Y	Y	Y
Cell $\times$ year-quarter fixed effects	Y	Y	Y	Y	Y	Y
Obs.	346,324	203,538	346,324	203,538	346,324	203,538
R^2	0.749	0.835	0.749	0.835	0.749	0.835

Notes: This table reports results from estimating equation (1). The unit of observation is shop by quarter. Robust standard errors in parentheses are clustered at the grid cell level. * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Table A.15: Estimation results of placebo tests

	Dropping stores near gov. offices		Full sample		Other businesses	
	Ln(# reviews)	Ln(price)	Ln(# reviews)	Ln(price)	Ln(# reviews)	Ln(price)
	(1)	(2)	(3)	(4)	(5)	(6)
dis_biz_ctr[<1.5 km]×post	0.038	0.001	0.003	0.001		
	(0.043)	(0.011)	(0.017)	(0.007)		
dis_gov[<1.5 km]×post					0.014	-0.006
					(0.024)	(0.051)
Ln(dis_gov)×post			0.023***	0.012***		
			(0.007)	(0.003)		
Ln(dis_subway)	-0.024	0.001	-0.019	0.005	-0.028	-0.046
	(0.016)	(0.009)	(0.015)	(0.005)	(0.022)	(0.074)
Store FE	Y	Y	Y	Y	Y	Y
Cell×year-quarter FE	Y	Y	Y	Y	N	N
Year-quarter FE	N	N	N	N	Y	Y
Obs.	142,028	80,318	346,324	203,538	11,444	6,502
R^2	0.729	0.820	0.749	0.835	0.712	0.565

Notes: This table reports results from estimating equation (1). The unit of observation is shop by quarter. Columns 1-4 report estimates from an analysis of the effects on restaurants in proximity to business centers. Columns 5 and 6 report the point estimates from an analysis that shifts focus to other businesses, including swimming pools, grocery stores, and laundromats. Robust standard errors, clustered at the grid cell level, are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Table A.16: Difference-in-differences estimation results: Weekdays vs. weekends.

	Weekdays		Weekends	
	Ln(# reviews)	Ln(price)	Ln(# reviews)	Ln(price)
	(1)	(2)	(3)	(4)
dis_gov[< 1.5 km]$\times$post	-0.058***	-0.030***	-0.016	-0.015**
	(0.012)	(0.007)	(0.011)	(0.007)
Ln(dis_subway)	-0.008	0.001	-0.015	0.010
	(0.016)	(0.005)	(0.010)	(0.007)
Shop fixed effects	Y	Y	Y	Y
Cell $\times$ year-quarter fixed effects	Y	Y	Y	Y
Obs.	346,324	176,144	346,324	113,694
R^2	0.732	0.848	0.681	0.831

Notes: This table reports results from estimating equation (1). The unit of observation is shop by quarter. Robust standard errors in parentheses are clustered at the grid cell level. * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Table A.17: Testing for the parallel trend assumption: Weekdays.

	Ln(# reviews)		Ln(price)	
	(1)		(2)	
dis_gov[< 1.5 km] × 11 quarters before EP	0.002	(0.023)	-0.001	(0.017)
dis_gov[< 1.5 km] × 10 quarters before EP	0.023	(0.024)	0.005	(0.016)
dis_gov[< 1.5 km] × 9 quarters before EP	-0.008	(0.020)	-0.005	(0.019)
dis_gov[< 1.5 km] × 8 quarters before EP	0.016	(0.021)	0.005	(0.020)
dis_gov[< 1.5 km] × 7 quarters before EP	-0.003	(0.019)	0.005	(0.015)
dis_gov[< 1.5 km] × 6 quarters before EP	0.019	(0.023)	-0.001	(0.016)
dis_gov[< 1.5 km] × 5 quarters before EP	0.009	(0.019)	0.002	(0.017)
dis_gov[< 1.5 km] × 4 quarters before EP	0.009	(0.018)	0.001	(0.017)
dis_gov[< 1.5 km] × 3 quarters before EP	-0.000	(0.014)	-0.003	(0.015)
dis_gov[< 1.5 km] × 2 quarters before EP	0.020	(0.019)	0.003	(0.017)
dis_gov[< 1.5 km] × 1 quarters before EP	-0.003	(0.014)	-0.004	(0.017)
dis_gov[< 1.5 km] × 1 quarters after EP	-0.049***	(0.017)	-0.016	(0.014)
dis_gov[< 1.5 km] × 2 quarters after EP	-0.025	(0.016)	-0.032*	(0.016)
dis_gov[< 1.5 km] × 3 quarters after EP	-0.047**	(0.018)	-0.031*	(0.016)
dis_gov[< 1.5 km] × 4 quarters after EP	-0.046***	(0.017)	-0.033**	(0.016)
dis_gov[< 1.5 km] × 5 quarters after EP	-0.074***	(0.019)	-0.034*	(0.019)
dis_gov[< 1.5 km] × 6 quarters after EP	-0.063***	(0.017)	-0.028*	(0.016)
dis_gov[< 1.5 km] × 7 quarters after EP	-0.053***	(0.020)	-0.032*	(0.016)
dis_gov[< 1.5 km] × 8 quarters after EP	-0.065***	(0.023)	-0.034*	(0.019)
Store fixed effects	Y		Y	
Cell × year-quarter fixed effects	Y		Y	
Obs.	346,324		176,144	
R^2	0.732		0.848	

Notes: This table reports results from estimating the variants of equation (1). The unit of observation is store by quarter. Store fixed effects and cell × year-quarter fixed effects are included in all columns. Robust standard errors in parentheses are clustered at the grid cell level. * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Table A.18: Testing for the parallel trend assumption: Weekends.

	Ln(# reviews)		Ln(price)	
	(1)		(2)	
dis_gov[< 1.5 km] $\times$ 11 quarters before EP	0.018	(0.022)	-0.001	(0.021)
dis_gov[< 1.5 km] $\times$ 10 quarters before EP	0.007	(0.018)	-0.003	(0.025)
dis_gov[< 1.5 km] $\times$ 9 quarters before EP	-0.006	(0.019)	-0.004	(0.026)
dis_gov[< 1.5 km] $\times$ 8 quarters before EP	-0.002	(0.015)	-0.002	(0.022)
dis_gov[< 1.5 km] $\times$ 7 quarters before EP	-0.004	(0.013)	0.001	(0.024)
dis_gov[< 1.5 km] $\times$ 6 quarters before EP	-0.005	(0.016)	-0.005	(0.017)
dis_gov[< 1.5 km] $\times$ 5 quarters before EP	0.010	(0.013)	0.001	(0.020)
dis_gov[< 1.5 km] $\times$ 4 quarters before EP	0.001	(0.013)	-0.001	(0.022)
dis_gov[< 1.5 km] $\times$ 3 quarters before EP	-0.002	(0.011)	0.000	(0.022)
dis_gov[< 1.5 km] $\times$ 2 quarters before EP	0.006	(0.013)	-0.000	(0.019)
dis_gov[< 1.5 km] $\times$ 1 quarters before EP	-0.012	(0.009)	0.001	(0.019)
dis_gov[< 1.5 km] $\times$ 1 quarters after EP	-0.014	(0.014)	-0.011	(0.018)
dis_gov[< 1.5 km] $\times$ 2 quarters after EP	-0.006	(0.012)	-0.015	(0.016)
dis_gov[< 1.5 km] $\times$ 3 quarters after EP	-0.022*	(0.012)	-0.014	(0.017)
dis_gov[< 1.5 km] $\times$ 4 quarters after EP	-0.019	(0.013)	-0.018	(0.016)
dis_gov[< 1.5 km] $\times$ 5 quarters after EP	-0.023	(0.018)	-0.017	(0.021)
dis_gov[< 1.5 km] $\times$ 6 quarters after EP	-0.012	(0.018)	-0.018	(0.017)
dis_gov[< 1.5 km] $\times$ 7 quarters after EP	-0.019	(0.019)	-0.020	(0.018)
dis_gov[< 1.5 km] $\times$ 8 quarters after EP	-0.016	(0.020)	-0.016	(0.016)
Store fixed effects	Y		Y	
Cell $\times$ year-quarter fixed effects	Y		Y	
Obs.	346,324		113,694	
R^2	0.681		0.831	

Notes: This table reports results from estimating the variants of equation (1). The unit of observation is store by quarter. Store fixed effects and cell $\times$ year-quarter fixed effects are included in all columns. Robust standard errors in parentheses are clustered at the grid cell level. * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.