Corruption and the Allocation of Business Activity in Brazil

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Abstract: It is well known that corruption is harmful to the economy, reducing investment and entrepreneurial activity. Corruption's effect on the allocation of economic activity, however, is comparatively understudied. We examine the relationship between corruption and sector allocation in Brazilian municipalities. More specifically, we test whether the allocations of employees and establishments across sectors are influenced by the amount of corruption in the area. We also test whether sectors are more concentrated in general using an employment share weighted HHI measure. We find that there are larger shares of employment and establishments in the relatively non-corrupt agricultural sector in highly corrupt areas and, likewise, lower shares of employment/establishments in sectors that are relatively corruption-prone (e.g., construction). This result implies that individuals are trying to avoid the problem of corruption by participating in sectors that are less vulnerable. We also find that public administration employment and establishment shares are higher in more corrupt areas, suggesting bureaucratic bloat. Our strongest evidence of the impact of corruption is shown through concentration, where concentration is higher (implying less competition) in more corrupt municipalities across every sector.

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1. Introduction

There are many proposed mechanisms through which corruption is hypothesized to reduce growth and harm the productive capacity of an economy. These mechanisms range from uncertainty (Wei 1997; Campos et al. 1999; Bologna Pavlik 2018)[1] to a weakened property rights system (Klitgaard 2000; Hogdson and Jiang 2007) and a misallocation of resources, broadly construed.[2] Our focus is on this last mechanism – resource allocation – in the context of business activity. On the one hand, the potential for illegal rents may attract entrepreneurs to sectors prone to corruption.[3] In this sense, we may expect more business activity to take place in sectors that are particularly susceptible to corruption. Boudreaux et al. (2018) find evidence of this in the U.S. However, corruption may also limit entry and monopolize these sectors – as monopolized rents yield the highest return (Bliss and Di Tella 1997; Ades and Di Tella 1999; Emerson 2006). Moreover, if corruption does *not* grease the wheels of economic growth, we may see firms and/or individuals avoiding these particularly corrupt sectors altogether. In the language of Baumol (1990), corruption could be attracting unproductive (or potentially destructive) entrepreneurs while simultaneously deterring productive entrepreneurship, making the net effect of corruption on sector-specific business activity an empirical question.

In this paper, we study how corruption affects the allocation of business activity in the context of Brazil. We first examine whether corruption is attracting more (or fewer) labor resources to specific sectors by analyzing how corruption influences the share of total employment across nine

[1] More specifically, these authors argue that the reason corruption is more harmful than other governmental activities, such as taxation, is because of the uncertainty involved.
[2] Aidt (2016) parallels the waste created from corruption to the rent-seeking costs famously highlighted in Tullock (1967). Shleifer and Vishny (1993) theorize that one cause of bureaucratic in efficiency in corrupt countries is that jobs tend to be allocated via bribery. Weaver (2021), using a novel dataset, shows that the efficiency effect from corrupt job allocations depends on the correlation between wealth and quality. Suktankar (2015) empirically analyzes corruption's misallocating effect on the wireless-communications market in India, finding no impact. This author argues that the lack of an effect in this case is due to the specific nature of the market in India that limit the deleterious effects of corruption. Thus, the potential misallocating effects of corruption are far ranging.
[3] This could be true on both the supply (entrepreneur/firm) and demand (politician) side. Liu and Mikesell (2014) find that the ten most corrupt U.S. states have governments that both spend more overall than the average state ($1,300 per capita), spend less on social services, and more on sectors that are more likely to be "bribe-generating" like construction, highways, and borrowing. Our focus is on the former.

sectors. Four of these sectors (wholesale, manufacturing, construction, and transportation and communication) are known to be prone to corruption internationally. The first – wholesale – is identified by Colonnelli and Prem (2022) as one of the top sectors experiencing corruption in Brazil. The latter three are cited in the Organization for Economic Development and Cooperation (OECD) Foreign Bribery Report (2014) as being particularly corrupt globally. The next four sectors (education, health, professional services, and agriculture) are generally considered to be non-corrupt (Boudreaux et al. 2018; Colonnelli and Prem 2022), though there is reason to believe there is room for corruption in the first three in Brazil.[4] The final sector is public administration. Whereas the first eight sectors are focused on tangible good/service producing activities and *can* include government providers[5], the latter sector is focused on the less tangible administrative services of government alone (e.g., defense, social security, etc.). If corruption is pushing resources towards this last sector, it could suggest bureaucratic bloat. We calculate employment shares using the *Relação Anual de Informações Sociais* (RAIS) – a dataset containing the universe of formal firms in Brazil.[6]

As a second step in our analysis, we also study how corruption affects establishment shares in these same nine sectors. While correlated with employment shares, this gives us a better idea of the types of establishments in an area and is more indicative of entrepreneurial activity. A key result of the Colonnelli and Prem (2022) article is that following an exogenous reduction in corruption, the number of firms in government-dependent sectors increases while the other sectors are unaffected. In terms of our analysis, this would imply that highly corrupt areas have a smaller share of establishments in these corruption-prone sectors. This would be suggestive of corruption-induced

[4] Boudreaux et al. (2018) only consider education and professional services as non-corrupt sectors in their paper. Details concerning corruption in Brazil, and the corruption measures used in this paper, are given in Section 3.

[5] For example, a public school would appear in our data as an establishment in the education sector along with private education providers.

[6] Our corruption measure is focused on corruption in the formal sector, making RAIS an appropriate dataset. However, we also test if there is any difference when studying formal versus informal employment shares using Census data. These latter results are similar, but less accurate due to the nature of the Census data. These results are available upon request.

resource misallocation in the sense that not enough resources are being invested in these vulnerable sectors and perhaps too many resources are flowing toward the non-corrupt sectors.

Lastly, we construct a Herfindahl–Hirschman Index (HHI) using each establishment's employment share – as opposed to the standard market share – for each sector in each municipality. This is an important part of our analysis because even if we find that there is less employment or a smaller share of establishments (or both) in certain sectors, it may be that these sectors are more concentrated. This is also a form of resource misallocation, but it is of a slightly different focus. Rather than suggesting that resources are misallocated across industries, it could suggest that resources are underutilized in general. There would also be less room for small-scale entrepreneurs to compete with these bigger firms. Of course, both types of misallocations could be present. For example, if only "corrupt" sectors are concentrated, while the other sectors tend to be more competitive that would be consistent with both types of misallocations.

Our primary corruption measure comes from Avis, Ferraz, and Finan (2018). In their paper, they measure corruption across all Brazilian municipalities that were selected for a corruption audit between 2006 and 2013. This audit program relied on the random selection of municipalities, focused on auditing the (mis)use of federal transfers, and publicized the results of each audit so that the public would be made aware of any malfeasance.[7] They utilize the 2006 – 2013 audit reports to calculate the number of instances corruption was uncovered; the audits themselves cover multiple years of transfers and thus this is best interpreted as a cross-sectional measure for our analysis. Because municipalities vary drastically in size, we take this number and divide it by the municipality's population for a measure of "corruption per capita". This measure is available for 935 municipalities.

Our main results show that employment shares across seven of the eight good/service producing sectors are lower in municipalities with higher levels of corruption. Of these eight, the

[7] The details of this program are discussed in Section 3.

only sector that sees higher employment shares is agriculture. We also see that public administration shares are larger. Likewise, for establishment shares, most sectors experience a reduction in their share except for agriculture and public administration. These results hold both with and without controls aiming to capture the general level of development in the municipality (GDP per capita, size of informality, density, etc.); all estimates also include state and audit fixed effects.

That agricultural shares increase in response to more corruption is consistent with a "sand the wheels" effect of corruption in Brazil. In analyzing this same audit program, Colonnelli and Prem (2022) identify the top-50 most corrupt and least corrupt sectors. Agricultural activities frequently appear in their top-50 *least* corrupt list (e.g., grape growing, raising of large animals, and saltwater fishing). However, activities in the other seven good/servicing producing sectors all appear at least once in the *most* corrupt list: e.g., wholesale of pharmaceutical products, construction of road and railroad, manufacture of medicines, road passenger transport, hospital care activities, school transportation, and credit card management. Thus, we see more firms and more employees operating in the agricultural sector and less in the more corruption-prone sectors. We also see more resources being allocated to public administration, suggestive of unnecessary increases in bureaucratic size. This is evidence of resource misallocation across sectors.

Our strongest evidence, however, points to resource misallocation overall. We find evidence that all nine sectors are more concentrated, using our employment share HHI. This effect is strongest for the professional services sector (40% increase in HHI), the wholesale sector (39% increase in HHI), and the manufacturing sector (36% increase in HHI) – all three of which are potentially corrupt in Brazil.[8] But the HHI index is also predicted to increase by 33% even in the agricultural sector. This suggests that even if resources tend to flow *away* from corruption-prone

[8] These numbers are all calculated using a 0.067 (one standard deviation) increase in corruption per capita and for regressions that include all controls.

industries, there are no sectors that are entirely immune to the effects of corruption. Moreover, this sector-wide increase in concentration is suggestive of a reduction in small-scale entrepreneurial activity, the kind that is most likely to be productive to society (Baumol, 1990).

In addition to the standard robustness checks (e.g., alternative datasets, controls, and time periods) these latter results are robust to an instrumental variable analysis where we instrument for corruption per capita using measures of political participation (number of local councils and the number of appointed local councils) and a measure of management capacity.[9] These measures all date back to 1998, several years prior to the audit program. The first two instruments aim to capture the degree to which the local population is engaged in government affairs, with the idea that increased engagement of the voting population can reduce corruption. The last instrument is essentially a management capacity indicator. It captures the extent to which a municipality has districts, subdivisions, zoning plans/laws, and other building codes/codes of conduct. The laws and plans included in this management indicator are relatively complex and signify that the local government is relatively well-functioning, likely with less corruption. Thus, all three instruments are likely strong, negative, predictors of corruption per capita, and we indeed find that this is the case.

We also believe that these three indicators are plausibly exogenous to the extent that they only impact concentration through their effect on corruption. First, in terms of reverse causality, these instruments were in place well before the audits occurred. We are using data from 1998 and thus if the corruption uncovered did encourage the creation of new councils and/or management rules, we are not capturing that here. Second, it is difficult to see how the existence and activity of local councils – on its own – could impact sectoral concentration. These councils exist for the purpose of citizen engagement in government affairs. The management indicator is perhaps suspect

[9] We also conduct the same instrumental variable analysis employment and establishment shares. The results are largely robust and are discussed in Section 5.2 and available in **Appendix E.**

as certain sectors may be more sensitive to zoning laws/codes. However, we note that controlling for acts of *mis*-management – constructed from the same Avis et al. (2018) dataset – seems to have little to no effect on our corruption coefficient for HHI measures.[10] This mismanagement measure captures instances of misconduct, such as not filling out a document properly, without any evidence of corruption. Thus, corruption is an important predictor even after controlling for a more rule-based measure of misconduct. Nevertheless, as with all instrumental variables analyses, these results should be interpreted with caution. We instrument for corruption using each indicator separately and then together, finding our most robust estimates to be remarkably stable across the four specifications.[11]

The remainder of this paper is as follows. A review of the literature is given in Section 2 and an overview of the audit program and corruption in Brazil is given in Section 3. Data are discussed in Section 4. Section 5 summarizes the empirical method and results. Section 6 concludes.

2. Literature Review

Our paper contributes to the broad literature connecting firms and entrepreneurship to corruption or institutional quality more generally. Kreft and Sobel (2005), Sobel (2008), Wiseman and Young (2013), Bologna Pavlik (2015), Bradley and Klein (2016), Bjørnskov and Foss (2008; 2016), Angulo-Guerrero et al. (2017), and Bennett (2021) all study the effect of economic freedom – simply defined as an institutional environment with a solid foundation of property rights and one that is conducive to voluntary exchange – on entrepreneurship. The methods used across these

[10] This is found first by comparing **Table 5** (our main results) with the results of **Table D3** (main results with the additional mismanagement control); and second by comparing **Table 6** (main IV results) and **Table 7** (IV results with the additional mismanagement control).
[11] We also instrument for corruption using the political competition indicators along with a distance to the federal capital measure in place of the management indicator, finding the results to be robust. Because we are looking at federal transfers, it makes most sense to focus on the distance to the federal capital, Brasília, as opposed to state capitals. These results are in **Appendix D**.

studies vary widely and the scope of coverage ranges from cross-country and/or cross-sectional to more micro level analyses within the U.S. (e.g., state level or even metropolitan statistical area level). However, a common finding across this group of studies is that economic freedom is an important predictor of entrepreneurial activity.

While comparatively smaller, a complementary literature has developed focused on the effects of corruption (Desai et al. 2003; Ovaska and Sobel 2005; Avnimelech, Zelekha, and Sarabi 2011; Boudreaux 2014; Farzana, Terjesen, and Audretsch 2014; Bologna and Ross 2015; Colonnelli and Prem 2022). As above, though these studies vary widely in their scope of coverage and empirical method, all find evidence that corruption reduces entrepreneurship and/or business activity. However, there is some debate as to whether it could be beneficial when there are excessive formal barriers to operation (Dreher and Gassebner 2013; Dutta and Sobel 2016), known as the "grease the wheels" debate.

Our paper most closely follows the studies of Boudreaux et al. (2018) in the study of establishment shares; and Bologna and Ross (2015) and Colonnelli and Prem (2022) in the context of Brazil. For the former, Boudreaux et al. (2018) study the effect of corruption convictions per capita on establishment shares across the U.S. states. They find that states with higher levels of convictions per capita have a higher percentage of firms concentrated in the construction sector, and less in the non-profit and education sectors. These results suggest that corruption is *attracting* business activity in certain more corrupt-prone sectors, while our results suggest the opposite. We believe there are two potential explanations for this. First, the corruption measure used in Boudreaux et al. (2018) is heavily dependent on the U.S. legal system's ability to both identify and prosecute corruption. This is perhaps easier to do in states with a significant amount of construction activity. Our corruption measure is more comprehensive, as discussed in the following section, and more insulated from this type of bias. Second, as noted in Schneider and Dreher (2010), corruption in high income countries like the U.S. is likely to be less coercive – a bribe perceived as "unfair" could result in the official being taken to court. In Brazil, that is less likely to be the case. This would imply that while it may be a fruitful activity (for the rent-seeking entrepreneur) to engage in corruption in the U.S., this experience may not be the same elsewhere. Indeed, the findings of Bologna and Ross (2015) and Colonnelli and Prem (2022) support this idea.

In the context of Brazil, Bologna and Ross (2015) utilize a similar (cross-sectional) corruption measure coming from the random audit program and estimate corruption's effect on the number of establishments within Brazilian municipalities, finding corruption to be harmful to business activity. Colonnelli and Prem (2022) take a different approach and study the effect of the audits themselves on the number of establishments in each municipality. This latter study finds that the audits, which could be interpreted as a (future) reduction in corruption, increased the number of establishments in "government dependent" sectors and had no effect elsewhere. Thus, both find that corruption reduces the *number* of establishments in Brazilian municipalities. Our focus is different – we want to know whether corruption pushes resources into or out of certain sectors relatively speaking. As famously noted in Baumol (1990), while the number of entrepreneurs may vary across societies, the variance in the types of activities they pursue is perhaps more important. If establishment shares are higher in corruption-prone sectors, this would suggest that there are more "unproductive" or even "destructive" entrepreneurs according to the Baumol (1990) terminology. But because these shares are lower, this suggests that corruption is pushing "productive" entrepreneurs into alternative industries. We also want to know how concentrated these sectors area. A reduction in the number of firms is suggestive of increased concentration, but it is unclear how business activity is distributed across remaining establishments. Our results suggest that corruption pushes resources away from potentially corrupt sectors and towards sectors that have been shown to involve little corruption. They also show that *all* sectors tend to be more concentrated. This latter finding suggests that all industries might have less room for the productive entrepreneurs that Baumol (1990) envisioned.

3. Brazil's Random Audit Program & Corruption Background

Following the Federal Constitution of 1988 and the transition to democracy, Brazil became an extremely decentralized country. Its nearly 5,600 municipalities receive millions in federal transfers each year and the local mayor has the discretion to use these funds to provide public services. The allocation of these transfers is constitutionally mandated and based on population thresholds (Brollo et al. 2013). However, this discretion led to significant corruption at the municipal level (Ferraz and Finan 2008; Ferraz anad Finan 2011; Avis et al. 2018).

In 2003, the federal government created the Office of the Comptroller General (*Controladoria-Geral da União* (CGU)) as part of a larger anticorruption initiative. Of relevance to our study is the CGU's launch of the *Programa de Fiscalização por Sorteios Públicos* in 2003. We refer to this as the Random Audits Program. While the details of the program vary through time, it essentially involves selecting municipalities via a lottery and auditing their expenditures of federal transfers.[12] The CGU then publishes the results of the audit in a report for the public to see. From 2003 through 2015, there have been 2,241 audits across 1,949 municipalities and 40 lotteries (Avis et al. 2018). Only the largest municipalities (those with greater than 500,000 in population) and state capitals are excluded from the program, as these municipalities have their own monitoring mechanisms.

The audits focus on the (mis)use of federal transfers to municipal government. Once selected, the CGU collects information on all federal funds transferred to the municipal government from three-four years prior to the present. They send 10 – 15 auditors to the municipality to conduct

[12] For further details concerning the audit program, see Avis et al. (2018) and Colonnelli and Prem (2022).

detailed inspections of specific government projects – called service orders (Avis et al. 2018).[13] Auditors also consult the residential population through councils on any complaints of misconduct. The goal of the auditors is to uncover any irregularities associated with the projects. This includes the examination of accounts, the verification of the existence and quality of public construction, and the verification that certain public services were delivered as agreed. This information is collected and organized into a report and made available to the public.

The audit program launched in 2003 and is still in existence today, but the program is no longer random. In 2015 the program was renamed the *Programa de Fiscalização em Entes Federativos* (*Inspection Program in Federative Entities*) and now utilizes non-random forms of selection, including the use of a "Vulnerability Index". Our paper uses the corruption measure constructed by Avis, Ferraz, and Finan (2018) and includes corruption occurring between 2004 and 2012 uncovered by audits conducted between July of 2006 and March of 2013. Thus, this measure excludes the non-random audits. It also excludes the earliest audits as the CGU only began to code the uncovered irregularities as (1) either an act of mismanagement, (2) an act of moderate corruption, or (3) an act of severe corruption in lottery 20 that occurred in 2006 (Avis et al. 2018). This dataset yields the most expansive estimates of corruption using these audits to date[14]

Using the CGU's coding, Avis et al. (2018) measure corruption as the number of irregularities categorized as either moderate or severe (areas 2 or 3 from above). They find that auditors uncovered 2.5 acts of corruption per service order on average; and only 0.88 acts of

[13] In the earlier audits, the auditors inspected all areas of federal transfers. But more recent audits involved randomly selecting specific areas of government activity within the larger selected municipalities to improve efficiency.
[14] Given the public nature of program reports, the results of this program have been used extensively to construct corruption measures and test several hypotheses related to corruption. Some examples include Ferraz and Finan 2008 (electoral incentives), Ferraz and Finan 2011 (term limits), Brollo et al. 2013 (political resource curse), and Bologna 2017 (income). The audits themselves have also been used as a treatment – Avis et al. (2018) and Colonnelli and Prem (2022) – but only the former develops a measure of corruption. Given the expansive nature of Avis et al. (2018), we rely on this data as our primary measure. But we also supplement our analysis with the data from the earliest audits used in Ferraz and Finan (2011) as a robustness check. We discuss this in more detail in **Section 4**.

mismanagement per service order. Importantly the minimum number of corrupt acts per service order in the sample is 0.285 – and not zero – implying that all municipalities have some level of corruption. The maximum value is 8.136. We discuss further details concerning this measure and the number of corrupt acts in Section 4.1 below but focus more on the content and coding of these audits throughout the remainder of this section.

Acts of mismanagement are not necessarily nefarious. As noted in Avis et al. (2018), they can be as simple as not properly filling out documents. Corruption is more intentional, but the coding between moderate and severe is not particularly clean. Avis et al. (2018) use two examples to illustrate this point. In one case – the case of Chaval, Ceará – the CGU found that when inspecting the financing of school buses, a contract was awarded to a firm that did not match the original proposal with inconsistencies in the contract value. This was coded as severe. But in another case – that of Urbano Santos, Maranhão – the auditors discovered that though a school lunch program was funded, lunches were not provided for an entire year in one school. This was coded as moderate. Despite the difference in coding, it is not clear that the former is more severe than the latter. But in both cases, it is obvious that corruption occurred. As such, Avis et al. (2018) treat categories (2) and (3) as acts of corruption and give them equal weight.

While these examples are useful in understanding the CGU's coding, and therefore the Avis et al. (2018) measure, they are also informative as to the sectors of the economy covered by these audits. The audits focus on federal transfers. These federal transfers are intended to fund a wide variety of public services. As the examples above indicate, the education sector is a major beneficiary of this funding and, as such, is susceptible to corruption. Even using earlier audits only, Ferraz and Finan (2011) discuss additional examples of misappropriation of money intended for school lunches. Through analyzing the audits, Ferraz and Finan (2008; 2011) and Avis et al. (2018) note that a significant amount of corruption in general occurs in the implementation of both education and healthcare social programs. Indeed, Owen and Funk (2020) find evidence that the audits improved specific health care and education outcomes via their corruption reducing effect in these areas.

We might then expect health and education to be particularly vulnerable and potentially lucrative for corrupt individuals. But, what about the more traditional "corrupt" sectors – extraction/mining, manufacturing, construction, and transportation/communication? In a 2014 OECD Foreign Bribery Report, analyze international bribery cases over a 15-year period (1999 through 2014), finding that 67% of these cases involved firms in these four sectors.[15] Healthcare is close behind in the OECD list – accounting for 8% of bribery cases alone – but does not make the top four. The studies of Colonnelli et al. (2022) and Colonnelli and Prem (2022) suggest that three of these four sectors are likely accounting for most of the cases in Brazil. They complete the herculean task of identifying (corrupt) firms' names in the audits and connecting these names to the RAIS database. In their supplementary data they list the top 50 sectors that had the most exposure to corruption. Manufacturing, construction, and transportation top this list. The extractive/mining industry is notably absent, despite accounting for 19% of corruption cases worldwide (OECD 2014).

The lists provided by Colonnelli et al. (2020) and Colonelli and Prem (2022)[16] confirm that three of the four traditionally hypothesized "corrupt" sectors are also the ones that seem most involved in corruption in Brazil. But the specific detail provided in the studies highlights an important nuance. Many of the sectors categorized as manufacturing, construction, and transportation involve activities related to the healthcare and education sectors. For example, "manufacture of medicines", "school transportation", and "hospital care activities" are included in the list. Thus, one cannot simply separate these sectors and treat them as independent. Given the

[15] Technically, the OECD separates the transportation/communication sector into two. We include them both as one.
[16] We utilize the list presented in the Colonnelli and Prem (2022) paper, specifically.

two-party nature of corruption, there is likely an opportunity for corrupt rents in all sectors involved.

Another common sector in the most corrupt category of Colonelli and Prem (2022) is wholesale trade. Again, the specific activities of this sector often seem to be related to health care and education – "wholesale of pharmaceutical products", "wholesale of machinery and equipment for dental and medical purposes", and "wholesale of office and stationery supplies". This sector is small in the OECD report, accounting for only 4% of cases, but seems important in our analysis. One sector that is notably absent on the most corrupt side and present on the least corrupt side of the Colonnelli and Prem (2022) lists is agriculture.

Our analysis therefore focuses on the eight good/service producing sectors. Six of which we expect to be vulnerable to corruption according to the Colonnelli and Prem (2022) lists: wholesale, health, education, manufacturing, construction, and transportation & communication,.[17] We also study corruption's effect on professional services and agriculture. The former is used as a "non-corrupt" comparison in the analysis of Holcombe et al. (2018). However, some of these activities fall in the "most corrupt" and/or "most government-dependent" sectors in the Colonnelli and Prem (2022) lists, thus it is unclear whether they should be considered "non-corrupt" here. Lastly, we study corruption's effect on public administration. This sector is different in nature than the first eight as it is focused exclusively on the administrative duties of government. Descriptions of the activities included in each sector are given in **Table A1**.

4. Data

4.1 Corruption Measure

[17] While we estimate results for the extractive/mining industries, we do not report them here. This sector is extremely small in Brazil, accounting for less than one percent of employees and establishments, and is not frequently cited as corrupt in the audit reports.

Our measure of corruption is cross-sectional. As discussed in the preceding section, we use the measure constructed by Avis, Ferraz, and Finan (2018) who, in turn, use data from the audit reports dating from 2006 through 2013. Their sample covers 17 lotteries and 1,020 audits and 967 municipalities. Thus, even in this restricted sample, 53 municipalities were audited twice.[18] For those 53 municipalities, we consider their average corruption score across the two audits.[19] After collapsing the data and considering municipalities where corruption scores were missing in Avis et al. (2018), we are left with 935 municipal observations. Recall that the audits cover corruption from the time of the audit through the previous 3 – 4 years, thus treating these values as cross-sectional is reasonable.

A concern with this corruption data is that it does include some information from 2010 through 2013 and our main outcomes of interest are derived from 2010 (discussed in the Section 4.2). While corruption is slow-changing and our focus is on the cross-sectional nature of it, this could introduce some endogeneity into our estimates. As a robustness check, we therefore also restrict the sample to include only audits occurring in 2009 or earlier. However, this limits our observations to 527 – these results are relegated to **Appendix B** and are largely consistent with our baseline results, which we discuss in the proceeding section.

The Avis, Ferraz, and Finan (2018) measure of corruption is the (logged) number of irregularities uncovered by the audits and coded by the CGU as either moderate or severe acts of corruption. A difficulty with this measure is that the number of irregularities is going to depend on the number of service orders issued. As noted in Avis et al. (2018), the number of service orders (i.e., inspection orders) is not equal across audited municipalities, but it is randomly determined. Thus, the variance in the number of corruption irregularities due to having many service orders is random and unlikely to be an important predictor of business activity.

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[18] The Avis et al. (2018) treatment is whether a municipality was audited multiple times. Some of these audits occurred prior to their sample date. In their dataset, of the 967 municipalities covered – 215 were "treated".

[19] If their corruption score was missing for either year, we simply took the existing year as their average.

Our interest is on the pervasiveness of corruption in each area. The municipal population varies drastically from only 1,409 to a maximum of almost 60,000.[20] One instance of corruption is going to be much more meaningful in the former. We therefore scale the Avis et al. (2018) corruption measure by the municipal's (logged) population as our main measure of corruption. This is our primary measure of corruption.[21]

An alternative option is to scale the Avis et al. (2018) number of corruption irregularities by the number of service orders. Simply looking at the share of audited items found to be corrupt is suggestive of corruption intensity. However, this measure does not give any information on how widespread this corruption is, given population size. Thus, this measure is only intended as a robustness check for comparison.

Lastly, while the Avis et al. (2018) dataset is the most expansive, it is in some ways less informative. In the Ferraz and Finan (2011) study of corruption and term limits, they use audit reports from lottery number two through eleven and assign uncovered acts of corruption a monetary value. They also place a monetary value on all resources that were audited. They then measure corruption as the share of audited resources found to be corrupt. This measure should be correlated with instances of corruption but provides more information on the severity of corruption. It is, however, only available for the initial lotteries covering 476 municipalities. We have 94 municipalities that were both audited early on and later in the program, such that we have corruption measures from both Avis et al. (2018) (henceforth, AFF) and Ferraz and Finan (2011) (henceforth, FF). Indeed, the raw correlations between the AFF and FF measures are positive; though the correlation is slightly stronger between the AFF corruption irregularities per capita measure and the FF share of audited resources found to be corrupt measure.

[20] The number of inspection orders is unrelated to population size. These variables have a raw correlation of -0.0024 in our data.

[21] Our main regressions do additionally control for the (logged) number of service orders.

Summary statistics for these corruption indicators are given in the top panel of **Table 1**. Sources and descriptions are given in **Table A2**.

4..2 Outcomes: Employment Shares, Establishment Shares, and HHI

Our outcome measures come from the *Relação Anual de Informações Sociais* (RAIS) database for the year 2010.[22] This is a universal database of formal firms and formal employment (i.e., registered with a tax identifier). Our first aim is to test whether corruption, as defined above, impacts sectoral shares in terms of employment and establishments. To do so, we categorize establishments into eight good/service producing sectors: wholesale, manufacturing, construction, transportation and communication, health, education, professional services, and agriculture.[23] We also examine public administration. Our sector categories are defined according to the *Classificação Nacional de Atividades Econômicas 2.0* (CNAE 2.0). The activities included in these sectoral definitions are given in **Table A1**. We then calculate, separately, the share of total employment in each sector and the share of total establishments in each sector. Summary statistics for these values are given for the full sample of municipalities in **Table 1**.

Focusing on the eight goods/services producing sectors first (i.e., all sectors except for public administration), we see that manufacturing comprises the largest share of total employment with approximately 14% (on average). Agriculture is the second largest (11%). The remaining six sectors only comprise between 1-2 % of total employment each. However, these numbers have enormous variance – often more than double their mean value. For example, only 2.3% of total employment can be attributed to activities in the construction sector on average. But the minimum value attributed to construction is 0% whereas the maximum is nearly 73%. Moreover, the standard

[22] We use the year 2010 as this is the latest year for which there is Census data available.
[23] There are other sectoral categories that we do not consider (e.g., retail). We choose to focus on these categories because they are particularly susceptible to corruption.

deviation is more than double the mean (at 4.8%). Thus, despite the seemingly low mean values, there is substantial variance in these shares across municipalities.

It is also important to note that while the sum of the first eight employment share means listed in **Table 1** only sum to approximately 36% of total employment, these sectors are capturing most good/service producing activity. Over 50% of municipalities have a population of less than 11,000; 25% have a population of approximately 5,200 or smaller. In these small municipalities, most employment comes from public administration jobs (greater than 50%); the average employment share across all municipalities in public administration is 46% (see **Table 1**). Activities in this sector include social security, defense, and other government administrative activities – not the sectoral activities that we are interested in. In this sense, the 36% of total employment across the first eight sectors is capturing nearly 70% of *non*-administrative activities.

Establishment shares across the first eight sectors sum to only 40% of the total. Public administration accounts for approximately 2% on average. Thus, while these nine sectors capture most employment, they do not account for most establishments in a given area. This implies that the existing establishments in these nine sectors tend to be large, while establishments in the vast majority of the excluded sectors (e.g., retail and accommodations) are small. Indeed, this fits with the idea the corruption prone sectors tend to be more concentrated because monopolized industries have more rents available for extraction. This also suggests that even small changes in the share of establishments can signify large resource flows.

Lastly, we construct an HHI measure of concentration, using employment shares in place of the traditional market shares. In other words, for each sector and for each municipality, we construct the following HHI measure:

(1) $HHI_{s,m} = \text{Employment Share}_{1,s,m,}^{2} + \text{Employment Share}_{2,s,m,}^{2} + \ldots + \text{Employment Share}_{n,s,m,}^{2}$

where *s* indicates the sector, *m* indicates the municipalities, and *1* through *n* index the establishments that exist within the municipalities. If no establishment exists within a given sector/area combination, we cannot measure concentration and the HHI value cannot be constructed. The HHI equals 10,000 when there is only one employer in the given sector within the municipality. It approaches zero as competition increases. The summary statistics of **Table 1** show that these nine sectors tend to be highly concentrated, but with substantial variance. Unsurprisingly, public administration is nearly 100% concentrated across municipalities.

4.3 Baseline Covariates

Our covariates aim to capture the general economic environment within each municipality. Given that corruption is often seen as a symptom of poverty, we are especially interested in including controls that capture development levels. These include per capita income, the size of the informal sector (measured as a share of employment), and population density. We include other demographic controls, specifically the percentage of the population that is of working age (18-65) or young (10-17) and the percent of the population that is male. We also control for the percentage of the adult population (greater than 25 years old) that completed their high school degree; and the percent that completed their college degree. The summary statistics for these variables are presented in **Table 2**. Sources and descriptions are given in **Table A2**.

4.4 Mismanagement

In addition to the corruption indicators, the Avis et al. (2018) and Ferraz and Finan (2011) studies both construct measures of general mismanagement. These acts of mismanagement are different in corruption in that they are based on irregularities associated with administrative or procedural concerns. This could involve, for example, the improper filing of documents. While this could involve corruption, it is much less egregious in nature. Our baseline estimates do not include mismanagement as a control as it is plausible to think that corruption can lead to more mismanagement, making mismanagement a "bad control" (Angrist and Pischke 2009). But we do include this variable as a control in robustness estimates presented in **Appendix C** showing that our coefficients are largely unchanged. We also include this variable as a control in our instrumental variable estimates, discussed in Section 5.2 below. For specifications with corruption per capita, we measure mismanagement as the (logged) number of mismanagement irregularities scaled by (logged) population. Similarly for corruption per-service order or per audited resource specification, we scale mismanagement by the appropriate denominator.

5. Results

5.1 Baseline Results

Our baseline regressions are estimated using OLS. Our focus is on the effect of corruption on resource allocation, and we believe this is best captured as a measure of corruption per capita. Nevertheless, for each outcome group (employment shares in **Table 3**; establishment shares in **Table 4**; and concentration in **Table 5**) we present estimates for three different measures of corruption.[24] We also present results both without and with the controls discussed in Section 4.3; all results include state and lottery fixed effects. *Panel A* of each table presents estimates without controls; *Panel B* presents estimates with controls. Lastly, as discussed above, because the number of service or inspection orders are not constant across audited municipalities, we additionally include a control for the number of inspections when corruption per capita is our corruption measure. The number and/or value of resources audited is implicitly captured in the corruption measures used in the other two measures and therefore is unnecessary as a control.

[24] Note that in these tables, the corruption measures are included in separate regressions. The tables reported are summaries of the full set of results that are available upon request.

Starting with employment shares (**Table 3**), we find that corruption irregularities per capita are a negative predictor of employment shares in seven of the eight good/service producing sectors. Only in agriculture do we find that employment share is higher in more corrupt areas. We also find that the public administration sector is larger in more corrupt areas. All nine of these coefficients are statistically significant at the 1% level for corruption per capita in *Panel A* – regressions with state and lottery/audit fixed effects, along with a service order control. While we lose some statistical significance after controlling for the general level of development within each municipality in *Panel B,* this pattern is relatively robust in that five sectors (manufacturing, transportation & communications, education, health, and professional services) still see a significant decline in their employment shares due to corruption. These results are relatively modest in size—a standard deviation increase in corruption is associated with an 8% (transportation & communication) to 18% (health) of a standard deviation decrease in the employment shares of those five sectors. These results suggest that corruption is driving resources away from corruption prone sectors. They also seem to be driving resources towards public administration and potentially the less-corrupt sector of agriculture, though this latter result is not as robust.

Moving to the other two measures of corruption in **Table 3**, where corruption irregularities are scaled by the number or value of audited items, we see little association between corruption and employment shares. The exceptions are professional services and health care. In both cases, corruption is associated with smaller employment shares in these two sectors, aligning with the results above. Nevertheless, as we will also see through the remainder of the baseline results, these alternative corruption measures highlight the importance of considering population size. While we still present these results in **Tables 4** (establishment shares) and **5** (HHI measure), our focus is therefore on corruption per capita.

Moving to establishment shares (**Table 4**), our results echo those above. There is a reduction in establishment shares across most sectors, agriculture and public administration are again the exception. The share of establishments in the transportation and communication sector also seems to increase, but this effect is only statistically significant in *Panel B* for corruption per capita– estimates with controls. Again, there is little in terms of statistical significance when scaling corruption irregularities by the number or value of audited items. Yet the significant results for corruption per capita seem to imply that corruption drives resources, whether this is measured as employment or establishments, away from most good/service producing sectors and towards the "safe" sector of agriculture and the administrative sector of the government. The latter is suggestive of bureaucratic bloat.

While these share results are important tests of resource allocation across sectors, it is important to understand whether resources are underutilized in general. Despite finding that *both* employment shares and establishment shares decline across industries in corrupt areas, we need a more precise estimate of concentration. To do so, we estimate corruption's effect on our HHI measure discussed above. These results are presented in **Table 6** and yield our most striking result. We find that corruption per capita is associated with increased concentration across *all* nine sectors. While the magnitude of the coefficient shrinks when we include our baseline set of controls, every coefficient remains statistically significant at the 1% level or better for eight of the nine sectors. For the ninth sector (public administration), the coefficient is statistically significant at the 5% level. Even using these smaller sets of coefficients, we find the corruption has a meaningful effect on concentration. For example, for the goods/service producing sectors, a standard deviation increase in corruption per capita results in anywhere from a 30% increase in firm concentration (health) to a 40% increase (professional services). Corruption even increases the concentration of the public administrative sector by 1.78%. While seemingly small, this is a relatively important effect given that most public administration sectors are heavily concentrated to begin with.[25] As above, the results are generally insignificant or inconsistent for the alternative corruption measures.

5.2 Instrumental Variable Analysis

An obvious concern with our analysis, and most analyses involving estimating the effects of corruption, is the presumed exogeneity of corruption per capita. Determinants of corruption are far ranging, and the overlap of corruption causes with causes of business activity is certainly plausible. We attempt to control for some of this using general municipal indicators for development in our baseline regressions. Nevertheless, this concern is legitimate.

In the absence of a randomized experiment, one potential solution to this endogeneity problem is the use of instrumental variables. While useful in theory, it is well-known that the problems of instruments can outweigh their benefits if their two conditions are not met: (1) instrument validity and (2) instrument exogeneity. In other words, we need to identify factors that are strongly correlated with corruption but are otherwise uncorrelated with our outcomes of interest. We propose three potential variables for this purpose: the existence of local councils, the activity of local councils, and management capacity. We believe all three are strongly correlated with corruption – condition number one. We also have reason to be believe that they are plausibly exogenous. However, given that we can never prove exogeneity, we intend these results to only be used as a robustness check.

The existence and activity of local councils is a proxy for political competition and/or local accountability.[26] These measures come from a 1998 index constructed by the *Instituto Brasileiro de Geografia e Estatística* (IBGE) aiming to capture the institutional quality of each municipality (*Indicador*

[25] Referring back to our summary statistics table (**Table 1**), the average HHI for this sector is 9,230, well above sectors like agriculture (2,364) and manufacturing (3,997), and still almost double the concentration of the second most concentrated area (health, 5,138).
[26] Carraro et al. (2016) conduct a state level analysis use the margin of victory in governor races as an instrument for corruption in their analysis of corruption and entrepreneurship. Because our corruption measure crosses multiple mayoral races, this is not a feasible instrument here.

de Qualidade Institucional Municipal – IQIM). The existence indicator simply counts the number of municipal councils in existence and puts this value into a 1 (least councils) to 6 (most councils) index scale. The activity of local councils is similar, but additionally considers if these councils were active in the sense that they had individuals appointed in positions. Municipalities with more local engagement in government is likely to have less corruption.

The management capacity indicator also comes from this same IQIM index. This measure examines whether the municipality has implemented districts or administrative regions (decentralized management), zoning plans and/or laws, building codes, and codes of conduct that establish fines for littering, licensures, operating hours, and more. The presence of such plans/laws signifies that the municipality has the capacity to implement them. We thus interpret this measure as a predictor of state capacity. While the correlation between state capacity is theoretically ambiguous (i.e., is a stronger state less corrupt?), this measure is specific enough to proxy for the ability of a municipality to carry out complex tasks. One such task might be corruption monitoring. Indeed, the raw correlation between this measure and corruption per capita is strongly negative at -0.42.

Because all three instruments are measured in 1998, this rules out the concern of reverse causality. Yet dual causality remains a concern. It is easier to argue for the plausible exogeneity of the first two instruments – the existence and activity of local councils. Local councils act as a check on corrupt behavior and impact business only through their effect on corruption. Management capacity is more of a concern as some sectors are likely more sensitive to rules/regulations than others. This is a concern for our share outcomes in that municipalities with more rules that affect a particular sector could reduce that sector's share of activity. Similarly, rules/regulations could directly impact concentration. Yet, this indicator is the strongest predictor of corruption. We therefore proceed carefully as follows.

First, we present and focus our IV results for each instrument separately: council existence, council activity, and management. We then include all three instruments together and estimate the appropriate J-Statistic, allowing us to test whether there is any evidence that our instruments are *not* exogenous (**Table 6**). Second, we repeat this analysis but additionally include a control for mismanagement. The audits not only revealed malfeasance in the form of corruption, but also included less nefarious acts of mismanagement. In this way, we can test whether corruption is still an important predictor after controlling for general inefficiencies in management. (We also include this mismanagement control in all baseline (non-instrumental variable) regressions in **Appendix C**.) Third, we replace the management instrument with a purely geographical instrument – the distance to Brasília, Brazil's federal capital. This latter idea is similar to the analysis of Boudreaux et al. (2018), but here we focus on the federal capital as the corruption is derived from federal transfers.

For brevity, our focus in this section is on the robustness of **Table 5**, results with HHI as our outcome, as this is our strongest result.[27] For all instrumental variable analyses, we only focus on corruption per capita. **Table 6** presents the set of results where we instrument for corruption with the existence of councils, appointment of councils, and management capacity – all separately in columns 1 through 3. And then include all three instruments together (column 4). As shown in the table, management capacity is by far the strongest instrument. This is also confirmed in the first stage estimates presented in **Appendix E**. The coefficients are all positive, remarkably consistent, and (mostly) statistically significant across the four columns. Corruption does seem to increase the concentration of industries.

The J-Statistic in column 4 of **Table 6** is never significant, suggesting that our instruments are potentially exogenous. But the null of the J-Statistic is that the instruments *are* exogenous. Thus,

[27] We also conduct these same instrumental variable analyses for both employment and establishment shares in **Appendix D**. These IV results largely echo the main findings: employment/establishment shares are lower in most sectors due to corruption, and higher in the agricultural and public administration sectors.

a p-value of 0.15, for example, would suggest that there is an 85% change of endogeneity, which is not reassuring. We therefore conduct several robustness checks. Our primary one, given in **Table 7**, is to additionally include the mismanagement control. The results are again robust and consistent across the four estimates. But here, the J-Statistic is generally much smaller, implying that endogeneity is less of concern.

Lastly, we replace the management instrument with the distance to the federal capital estimate. These results are available in **Table 8**. One glaringly obvious concern with this set of instruments is that they are relatively weak as a set. In addition, the J-Statistics are relatively large compared to the previous estimates. Nevertheless, again, the coefficients are all positive and statistically significant though these latter results should be interpreted with caution.

6. Conclusion

The idea that corruption is harmful to business activity is well-known. Much of the work looks at the impact of corruption on aggregate levels of output (e.g., number of establishments, incomes, overall GDP per capita). Except for Boudreaux et al. (2018), little work has examined this effect at a cross-industry level. In this study, we find that corruption is associated with a reduction in employment and establishment shares in most industries except for agriculture (which is typically seen as less corrupt) and the public administration sector (suggesting an increase in government size and scope).

These findings contrast with that of Boudreaux et al. (2018), who show that corruption *increases* establishment shares of more corrupt sectors like construction. While this difference is potentially puzzling, we note two key differences between our studies. First, our measure of corruption is different than that of Boudreaux et al. (2018). We use a measure of corruption that stems from random audits, while the aforementioned study uses federal corruption convictions.

Their measure relies on the ability of the legal system to successfully identity and prosecute corruption, which may be easier to do in areas like construction. We use a broader measure from Avis et al. (2018) that is less susceptible to legal system quality. Second, they examine the effect within the United States, which is a richer country than Brazil. In high income countries, Schneider and Dreher (2010) argue that bribes are less coercive and more likely to be the consequence of rent seeking and opportunistic behavior on part of the private sector actors. Given Brazil's differing economic performance and political institutions, it is not unexpected that engaging in bribes can be seen as a riskier endeavor, as it is less likely that the bribe would be binding. As such, we would expect individuals to stay away from corrupt sectors in Brazil (relative to the United States).

Perhaps most interestingly, we also find that corruption increases industry concentration within *every industry*, including those both those are seen as largely corrupt and those that are less so. These results hold under a variety of robustness tests, including: an instrumental variable analysis, controlling for mismanagement, and alternative samples/measures. These findings are complementary to the corruption-inequality literature, which generally shows that higher levels of corruption increase the concentration of wealth and income to a small group of elites. They are also suggestive of an entry limiting effect. Corruption seems to make all sectors more concentrated, leaving less room for entrepreneurs to thrive. Taken together, our results suggest that productive entrepreneurs are avoiding corrupt sectors and are potentially limited in number due a concentration effect.

Given our findings, we believe there are several interesting future avenues of research. First, one could examine how corruption shapes the share of production going towards workers/labor; Young and Lawson (2014) find that capitalistic institutions are associated with greater levels of labor share. To the best of our knowledge, this has not yet been studied. Second, given data availability, it would also be interesting to develop more robust measures of productive entrepreneurial activity along the lines of Sobel (2008) to test whether creative activity is indeed diminished in corrupt municipalities. Lastly, given that Brazil is a federation, one could also explore how local corruption interacts with national regulations in its effect on local business activity. Lucas and Boudreaux (2020) study a similar dynamic in national regulation versus state-level policies within the U.S.

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Tables & Figures

Table 1: Summary statistics for main variables of interest.					
***Panel A*: Measures of Corruption**	Obs.	Mean.	Std. Dev.	Min.	Max.
Full Sample (AFF 2018)					
Corruption irregularities per capita[1]	935	0.429	0.067	0.181	0.631
Corruption irregularities per service order[1]	935	1.285	0.162	0.525	1.842
Pre-2010 Only (AFF 2018)					
Corruption irregularities per capita[1]	527	0.435	0.065	0.206	0.631
Corruption irregularities per service order[1]	527	1.252	0.152	0.734	1.678
Ferraz and Finan (2011)					
% of audited resources that are corrupt	476	0.063	0.102	0.000	0.794
***Panel B*: Outcomes (RAIS Data)[2]**	Obs.	Mean.	Std. Dev.	Min.	Max.
Employment Shares					
Wholesale	5,564	0.017	0.031	0	0.717
Manufacturing	5,564	0.143	0.175	0	0.905
Construction	5,564	0.023	0.048	0	0.728
Transportation & Communication	5,564	0.024	0.036	0	1.000
Education	5,564	0.009	0.019	0	0.495
Health	5,564	0.015	0.026	0	0.465
Professional Services	5,564	0.018	0.041	0	0.698
Agriculture	5,564	0.109	0.134	0	0.973
Public Administration	5,564	0.461	0.288	0	1
Establishment Shares					
Wholesale	5,565	0.026	0.026	0	0.476
Manufacturing	5,565	0.069	0.058	0	0.507
Construction	5,565	0.024	0.023	0	0.297
Transportation & Communication	5,565	0.043	0.035	0	0.568
Education	5,565	0.020	0.031	0	0.5
Health	5,565	0.024	0.020	0	0.333
Professional Services	5,565	0.038	0.040	0	0.721
Agriculture	5,565	0.151	0.158	0	0.896
Public Administration	5,565	0.018	0.024	0	0.438
***HHI*[3]**					
Wholesale	3,559	4,826	3,437	22	10,000
Manufacturing	4,635	3,997	3,242	5	10,000
Construction	3,683	5,042	3,528	17	10,000
Transportation & Communication	5,371	5,047	3,549	44	10,000
Education	2,939	5,410	3,409	27	10,000
Health	3,619	5,138	3,195	41	10,000
Professional Services	4,276	4,398	3,403	14	10,000
Agriculture	4,972	2,364	2,737	35	10,000
Public Administration	5,534	9,230	1,339	923	10,000

Notes: [1]The Avis et al. (2018) corruption measure is logged. We divide this value by the logged population or the logged number of service orders, respectively. [2]Relação Anual de Informações Sociais (RAIS). [3]The HHI measure is constructed using formal establishment and formal employee data only. These measures enter regressions in logged form. A municipality that lacks any activity in a specific industry is dropped from the HHI analysis as "concentration" cannot be measured.

Table 2: Summary statistics for covariates.

Covariate Name	Obs.	Mean.	Std. Dev.	Min.	Max.
GDP per capita[1]	5,564	12,605	14,721	2,262	311,882
Size of Informal Sector	5,564	0.565	0.193	0.109	0.97
Population Density[1]	5,570	108.437	572.911	0	13024.56
Share of Population Between Ages 10-17	5,564	0.154	0.024	0.043	0.235
Share of Population Between Ages 18-65	5,564	0.605	0.044	0.392	0.867
High School (%)	5,564	0.216	0.085	0.035	0.659
College (%)	5,564	0.055	0.033	0.003	0.337
Male (%)	5,564	0.505	0.016	0.458	0.811

Notes: [1]Enters regression as log.

Table 3: The effect of corruption on employment shares.

Panel A: Basic regressions with lottery and state fixed effects.

Employment Shares (RAIS)	Wholesale	Manufacturing	Construction	Transport & Comm.	Education	Health	Prof. Services	Agriculture	Public Admin.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Corruption per capita (AFF)	-0.091***	-0.773***	-0.147***	-0.113***	-0.115***	-0.121***	-0.207***	0.368***	1.955***
	(0.028)	(0.109)	(0.033)	(0.021)	(0.009)	(0.012)	(0.041)	(0.097)	(0.121)
Corruption per-service order (AFF)	-0.003	-0.046	0.013	0.003	0.003	0.008	0.003	-0.004	-0.010
	(0.005)	(0.040)	(0.009)	(0.012)	(0.005)	(0.006)	(0.012)	(0.041)	(0.062)
% of audited resources that are corrupt (FF)	-0.029	0.046	0.033	0.012	-0.000	-0.018***	-0.021**	0.063	-0.024
	(0.022)	(0.090)	(0.029)	(0.010)	(0.007)	(0.006)	(0.009)	(0.052)	(0.115)

Panel B: Regressions with lottery and state fixed effects plus additional covariates.

Employment Shares (RAIS)	Wholesale	Manufacturing	Construction	Transport & Comm.	Education	Health	Prof. Services	Agriculture	Public Admin.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Corruption per capita (AFF)	-0.033	-0.418***	-0.049	-0.043*	-0.048***	-0.071***	-0.095**	0.078	1.140***
	(0.026)	(0.113)	(0.034)	(0.023)	(0.012)	(0.013)	(0.043)	(0.096)	(0.126)
Corruption per-service order (AFF)	-0.002	-0.061	0.008	-0.003	0.001	0.006	-0.006	0.000	0.022
	(0.005)	(0.036)	(0.008)	(0.011)	(0.006)	(0.006)	(0.013)	(0.036)	(0.044)
% of audited resources that are corrupt (FF)	-0.030	0.031	0.033	0.011	-0.007	-0.021***	-0.022***	0.074	0.013
	(0.018)	(0.083)	(0.028)	(0.011)	(0.008)	(0.006)	(0.008)	(0.054)	(0.089)

Notes: *,**, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Each cell constitutes a separate regression. All regressions include lottery and state fixed effects. For corruption per capita, we also include the logged number of service orders. Regressions with controls additionally include the covariates listed in **Table 2**. Standard errors are clustered by state.

Table 4: The effect of corruption on establishment shares.

Panel A: Basic regressions with lottery and state fixed effects.

Establishment Shares (RAIS)	Wholesale	Manufacturing	Construction	Transport & Comm.	Education	Health	Prof. Services	Agriculture	Public Admin.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Corruption per capita (AFF)	-0.128***	-0.220***	-0.110***	0.015	-0.034**	-0.123***	-0.212***	0.611***	0.155***
	(0.015)	(0.024)	(0.020)	(0.019)	(0.015)	(0.013)	(0.036)	(0.175)	(0.025)
Corruption per-service order (AFF)	-0.004	-0.009	0.004	0.008	-0.005	-0.002	0.017	-0.048	0.001
	(0.004)	(0.014)	(0.006)	(0.006)	(0.009)	(0.007)	(0.012)	(0.042)	(0.004)
% of audited resources that are corrupt (FF)	-0.007	-0.011	-0.002	0.008	-0.013	-0.012*	-0.009	0.095	-0.006
	(0.008)	(0.019)	(0.009)	(0.018)	(0.012)	(0.006)	(0.009)	(0.072)	(0.009)

Panel B: Regressions with lottery and state fixed effects plus additional covariates.

Establishment Shares (RAIS)	Wholesale	Manufacturing	Construction	Transport & Comm.	Education	Health	Prof. Services	Agriculture	Public Admin.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Corruption per capita (AFF)	-0.051***	-0.120***	-0.039**	0.044*	-0.017	-0.070***	-0.038	0.264**	0.138***
	(0.011)	(0.029)	(0.017)	(0.025)	(0.022)	(0.017)	(0.034)	(0.101)	(0.028)
Corruption per-service order (AFF)	-0.005	-0.005	-0.001	0.004	-0.007	-0.002	0.003	-0.016	0.001
	(0.003)	(0.012)	(0.006)	(0.007)	(0.009)	(0.007)	(0.008)	(0.028)	(0.003)
% of audited resources that are corrupt (FF)	-0.009	-0.011	-0.002	0.007	-0.012	-0.016***	-0.012	0.110*	-0.003
	(0.006)	(0.014)	(0.009)	(0.017)	(0.012)	(0.005)	(0.008)	(0.061)	(0.007)

Notes: *,**, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Each cell constitutes a separate regression. All regressions include lottery and state fixed effects. For corruption per capita, we also include the logged number of service orders. Regressions with controls additionally include the covariates listed in **Table 2**. Standard errors are clustered by state.

Table 5: The effect of corruption on (logged) HHI measure of concentration.

Panel A: Basic regressions with lottery and state fixed effects.

HHI (RAIS)	Wholesale	Manufacturing	Construction	Transport & Comm.	Education	Health	Prof. Services	Agriculture	Public Admin.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Corruption per capita (AFF)	10.953***	9.107***	10.404***	8.172***	9.235***	8.086***	10.924***	5.644***	0.556***
	(0.750)	(0.885)	(0.767)	(0.588)	(0.740)	(0.739)	(0.640)	(0.652)	(0.128)
Corruption per-service order (AFF)	-0.489	-0.199	-0.557	-0.040	-0.750**	-0.429	-0.554	0.326	0.021
	(0.358)	(0.373)	(0.361)	(0.215)	(0.294)	(0.274)	(0.356)	(0.212)	(0.044)
% of audited resources that are corrupt (FF)	0.906	-0.200	0.290	0.152	0.438	-0.737**	0.213	0.422	0.125*
	(0.596)	(0.416)	(0.440)	(0.440)	(0.470)	(0.296)	(0.398)	(0.546)	(0.072)

Panel B: Regressions with lottery and state fixed effects plus additional covariates.

HHI (RAIS)	Wholesale	Manufacturing	Construction	Transport & Comm.	Education	Health	Prof. Services	Agriculture	Public Admin.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Corruption per capita (AFF)	5.835***	5.337***	5.237***	4.702***	5.022***	4.453***	5.996***	4.952***	0.266**
	(0.597)	(0.749)	(0.791)	(0.515)	(0.772)	(0.836)	(0.528)	(0.693)	(0.128)
Corruption per-service order (AFF)	-0.122	-0.006	-0.272	0.100	-0.580**	-0.346**	-0.318*	0.179	0.018
	(0.225)	(0.289)	(0.332)	(0.144)	(0.225)	(0.160)	(0.183)	(0.183)	(0.044)
% of audited resources that are corrupt (FF)	1.021**	-0.096	0.550	0.341	0.599	-0.560*	0.434	0.604	0.135*
	(0.488)	(0.403)	(0.382)	(0.382)	(0.440)	(0.273)	(0.336)	(0.537)	(0.073)

Notes: *,**, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Each cell constitutes a separate regression. All regressions include lottery and state fixed effects. For corruption per capita, we also include the logged number of service orders. Regressions with controls additionally include the covariates listed in **Table 2**. Standard errors are clustered by state.

Table 6: The effect of corruption per capita on (logged) HHI measure of concentration (outcomes in listed in ***bold***); instrumental variable analysis.

	Individual Instruments			*All Instruments*	
Outcome	Councils Exist	Councils Active	Management	Coefficient	J-Statistic
HHI (RAIS)	(1)	(2)	(3)	(4)	(5)
Wholesale	30.250***	35.069	26.313***	27.031***	0.219
	(10.780)	(23.599)	(6.344)	(5.623)	[0.896]
F-Statistic	7.104	2.072	14.36	7.302	
Manufacturing	25.808***	21.013***	14.568***	16.791***	2.433
	(7.279)	(6.059)	(3.889)	(3.308)	[0.296]
F-Statistic	9.124	16.07	27.70	18.11	
Construction	20.509***	17.149***	19.035***	18.927***	1.109
	(5.245)	(4.540)	(3.321)	(2.790)	[0.574]
F-Statistic	9.928	7.835	19.36	15.40	
Transportation & Communication	21.218***	19.668***	15.756***	16.966***	0.992
	(5.634)	(5.983)	(3.288)	(2.835)	[0.609]
F-Statistic	12.78	19.17	29.59	20.76	
Education	25.629***	33.855***	18.187***	19.631***	4.037
	(6.029)	(9.264)	(4.734)	(4.141)	[0.133]
F-Statistic	13.54	9.163	21.30	12.84	
Health	21.008***	23.191***	19.810***	20.239***	0.396
	(5.517)	(6.151)	(4.482)	(3.522)	[0.820]
F-Statistic	14.36	8.047	26.29	16.57	
Professional Services	39.260***	35.100***	27.394***	28.883***	1.496
	(11.392)	(10.919)	(4.195)	(3.885)	[0.473]
F-Statistic	9.860	8.023	28.68	15.37	
Agriculture	22.590***	24.504***	13.531***	15.732***	2.332
	(6.956)	(9.391)	(3.961)	(4.121)	[0.312]
F-Statistic	11.99	19.22	35.93	25.79	
Public Administration	1.879	2.181**	1.270**	1.501***	0.563
	(1.301)	(0.981)	(0.619)	(0.542)	[0.755]
F-Statistic	11.71	23.30	31.30	23.02	

Notes: *,**, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Each cell constitutes a separate regression. All regressions include lottery and state fixed effects and the logged number of service orders. All regressions additionally include the covariates listed in **Table 2**. Standard errors are clustered by state. P-values in brackets for J-Statistic. Note that each outcome has a different associated first stage F-Statistic because the number of observations differs across regressions. Because the HHI index can only be constructed when an industry exists in a municipality, there are several that get dropped depending on the sector.

Table 7: The effect of corruption per capita on HHI measure of concentration (outcomes in listed in ***bold***); instrumental variable analysis with mismanagement control.

	Individual Instruments			*All Instruments*	
Outcome	Councils Exist	Councils Active	Management	Coefficient	J-Statistic
HHI (RAIS)	(1)	(2)	(3)	(4)	(5)
Wholesale	30.398***	35.329	26.430***	27.153***	0.211
	(11.190)	(23.999)	(6.028)	(5.340)	[0.900]
F-Statistic	7.114	2.048	16.32	8.412	
Manufacturing	27.410***	21.828***	15.025***	17.394***	2.347
	(8.421)	(6.654)	(3.889)	(3.176)	[0.309]
F-Statistic	7.985	13.55	25.83	17.96	
Construction	21.260***	17.529***	19.614***	19.485***	1.098
	(6.061)	(5.255)	(3.862)	(3.301)	[0.577]
F-Statistic	8.747	6.567	16.83	11.87	
Transportation & Communication	22.105***	20.119***	15.911***	17.270***	0.972
	(6.737)	(6.693)	(3.631)	(3.180)	[0.615]
F-Statistic	11.11	15.88	25.72	20	
Education	25.552***	34.713***	17.713***	19.196***	3.997
	(6.537)	(9.888)	(4.730)	(4.064)	[0.136]
F-Statistic	12.80	8.240	20.98	12.38	
Health	19.850***	22.006***	18.833***	19.211***	0.392
	(6.005)	(6.260)	(4.244)	(3.293)	[0.822]
F-Statistic	12.88	6.534	27.57	18.57	
Professional Services	42.067***	36.352***	27.897***	29.411***	1.439
	(14.626)	(12.709)	(4.252)	(3.862)	[0.487]
F-Statistic	7.003	6.177	25.98	13.68	
Agriculture	24.213***	25.698**	13.940***	16.405***	2.189
	(7.928)	(10.421)	(4.084)	(4.308)	[0.335]
F-Statistic	10.82	15.52	33.21	24.55	
Public Administration	1.780	2.156**	1.108*	1.391**	0.666
	(1.479)	(1.055)	(0.673)	(0.592)	[0.717]
F-Statistic	10.16	20.18	27.86	23.65	

Notes: *,**, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Each cell constitutes a separate regression. All regressions include lottery and state fixed effects, the logged number of service orders, and a measure of mismanagement. All regressions additionally include the covariates listed in **Table 2**. Standard errors are clustered by state. P-values in brackets for J-Statistic. Note that each outcome has a different associated first stage F-Statistic because the number of observations differs across regressions. Because the HHI index can only be constructed when an industry exists in a municipality, there are several that get dropped depending on the sector.

Table 8: The effect of corruption per capita on HHI measure of concentration (outcomes in listed in ***bold***); instrumental variable analysis with distance to federal capital in place of management IV.

	All Instruments	
HHI (RAIS)	Coefficient	J-Statistic
	(1)	(2)
Wholesale	20.363***	1.959
	(7.332)	[0.375]
F-Statistic	5.573	
Manufacturing	17.858***	2.584
	(4.271)	[0.275]
F-Statistic	9.492	
Construction	20.349***	1.425
	(3.771)	[0.490]
F-Statistic	5.807	
Transportation & Communication	15.167***	3.086
	(4.652)	[0.214]
F-Statistic	9.191	
Education	20.604***	3.441
	(3.556)	[0.179]
F-Statistic	5.770	
Health	16.420***	3.125
	(3.314)	[0.210]
F-Statistic	6.653	
Professional Services	22.068***	5.435*
	(6.779)	[0.066]
F-Statistic	5.085	
Agriculture	14.413***	3.448
	(5.548)	[0.178]
F-Statistic	10.92	
Public Administration	1.611**	0.917
	(0.773)	[0.632]
F-Statistic	11.06	
Instruments	Council Exists, Councils Appointed, and (Logged) Distance to Capital	

Notes: *,**, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Each cell constitutes a separate regression. All regressions include lottery and state fixed effects, the logged number of service orders, and a measure of mismanagement. All regressions additionally include the covariates listed in **Table 2**. Standard errors are clustered by state. P-values in brackets for J-Statistic. Note that each outcome has a different associated first stage F-Statistic because the number of observations differs across regressions. Because the HHI index can only be constructed when an industry exists in a municipality, there are several that get dropped depending on the sector.

Appendix A: Definitions and Sources

Table A1: Sector Composition – Relação Anual de Informações Sociais (RAIS) Data Only

Sector	Activities Included
Wholesale	Wholesale Electricity
	Wholesale Biomethane and Biogas for Distribution Purposes
	Wholesale Natural Gas
	Wholesale Ambulances
	Wholesale Automobiles, Trucks, and SUV's, New and Used
	Wholesale of Commercial Trucks, New and Used
	Wholesale of Trailers and Semi-Trailers, New and Used
	Wholesale of Buses and Microbuses, New and Used
	Wholesale of Parts and Accessories for Motor Vehicles
	Wholesale of Pneumatics and Air Chambers
	Wholesale of Motorcycles and Mopeds
	Wholesale of Parts and Accessories for Motorcycles and Mopeds
	Wholesale Commercial Agents, Except Motor Vehicles and Motorcycles
	Wholesale of Agricultural Inputs and Livestock
	Wholesale of Food Products, Beverages, and Tobacco
	Wholesale of Non-Food Consumption Goods
	Wholesale of Information and Communication Products and Equipment
	Wholesale of Machines, Equipment, and Devices, Except for Information and Communication
	Wholesale of Wood, Hardware, Tools, Electrical and Construction Material
	Wholesale Specialized in Other Products
	Non-Specialized Wholesale
Manufacturing	Manufacturing of Food Products
	Manufacturing of Beverages
	Manufacturing of Tobacco Products
	Manufacturing of Textiles
	Manufacturing of Clothing and Accessories
	Leather Preparation, Manufacturing of Leather Goods, Travel Goods, and Footwear
	Manufacturing of Wooden Products
	Manufacturing of Cellulose, Paper, and Paper Products
	Printing and Reproduction of Recordings
	Manufacturing of Coke, Oil Derivates and Biofuels
	Manufacturing of Chemical Products
	Manufacturing of Pharmochemicals and Pharmaceuticals
	Manufacturing of Rubber and Plastic Products
	Manufacturing of Non-Metallic Mineral Products
	Manufacturing of Metal Products, Except Machines and Equipment
	Manufacturing of Computer Equipment, Electronic and Optical Products
	Manufacturing of Electrical Machines, Appliances, and Electrical Materials
	Manufacturing of Machines and Equipment
	Manufacturing of Motor Vehicles, Trailers, and Bodies
	Manufacturing of Other Transport Equipment, Except Motor Vehicles
	Manufacturing of Furniture
	Manufacturing of Miscellaneous Products
	Maintenance, Repair, and Installation of Machines and Equipment
	Maintenance and Repair of Computer and Communication Equipment, Personal and Domestic Objects

Table A1 (continued): Sector Composition – RAIS Data Only

Construction	Construction of Buildings Infrastructure Works Specialized Construction Services
Transportation & Communication	Land Transportation Water Transportation Air Transportation Storage and Auxiliary Activities to Transportation Mail and Shipping Activities Telecommunications Travel Agencies, Touristic Operators, and Booking Services
Education	Education
Health	Human Healthcare Activities Human Healthcare Activities Integrated to Social Assistance, Including Providers at Collective & Private Residences Non-Residential Social Assistance
Professional Services	Informational Technology Service Provision Activities Information Service Provision Activities Financial Services Activities Insurance, Reinsurance, Supplementary Pension, and Health Insurance Auxiliary Activities to Insurance, Reinsurance, Supplementary Pension, and Health Insurance Real Estate Activities Legal, Accounting, and Auditing Activities Consulting and Corporate Management Activities Architecture and Engineering Services; Tests and Technical Analysis Research and Scientific Development Advertising and Market Research Other Professional, Scientific, and Technical Activities Surveillance, Security, and Investigative Activities Services to Building and Landscaping Activities Services to Offices, Administrative Support and Other Services Provided to Companies
Agriculture	Agriculture, Livestock, Hunting, and Related Services Forest Production Fishing and Aquaculture
Public Administration	Public Administration, Defense and Social Security

Notes: We use definitions according to the *Classificação Nacional de Atividades Econômicas* (CNAE). For comparison purposes, we also construct analogous employment share measures using the 2010 Census; these data are categorized according to the 5-digit CNAE-Domiciliar 2.0. The wholesale category, however, requires the more granular 7-digit classification from the CNAE Subclasse 2.0 and thus cannot be constructed using Census data. Results using the Census data are presented in Appendix B. We also construct alternative measures of Construction and Professional Services that are equivalent to those of Boudreaux, Nicolaev, and Holcombe (2018) and the North American Industry Classification System (NAICS). Construction (NCAIS 237) includes only construction of utilities and infrastructure, being equivalent to CNAE Division 42; it excludes construction of buildings (NCAIS 236/CNAE 41). Professional, Scientific, and Technical Services (NCAIS 541) is equivalent to CNAE Section M, Divisions 69 to 75. Results using these alternative measures are available upon request.

Table A2: Data descriptions and sources for corruption variables.

Measures of Corruption	Brief Description	Source
Full Sample		
Corruption Irregularities per capita	Logged corruption irregularities divided by logged population.	AFF[1]/Census[2]
Corruption Irregularities per service order	Logged corruption irregularities divided by logged service orders.	AFF[1]
Pre-2010 Only		
Corruption Irregularities per capita[1]	Logged corruption irregularities divided by logged population.	AFF/Census
Corruption Irregularities per service order[1]	Logged corruption irregularities divided by logged service orders.	AFF
Ferraz and Finan (2011)		
% of audited resources that are corrupt	Share of total resources audited that were found to be corrupt.	FF[3]

Notes: *Notes*: [1]Avis, Ferraz, and Finan (2018); [2] Instituto Brasileiro de Geografia e Estatistica (IBGE) 2010 Census; [3] Ferraz and Finan (2011).

Table A3: Data descriptions and sources for covariates

Variable	Brief Description	Source
GDP per capita	Gross domestic product per capita	IBGE/IPEA
Size of Informal Sector	Share of workers aged 18 plus that are informal.	Census/IPEA
Population Density	People per square KM	Census
Share of Population Between Ages 10-17	Share of population aged 10-17	Census/IPEA
Share of Population Between Ages 18-65	Share of population aged 18-65	Census/IPEA
High School (%)	Share of population over 25 that completed high school.	Census
College (%)	Share of population over 25 with a college degree.	Census
Male (%)	Share of population that is male.	Census/IPEA

Source: Instituto Brasileiro de Geografia e Estatística (IBGE). The 2010 Census data is collected by the IBGE. Much of this data is distributed by IPEADATA (Instituto de Pesquisa Econômica Aplicada).

Appendix B: The effect of corruption using AFF pre-2010 sample only.

Table B1: The effect of corruption on employment shares.

Panel A: Basic regressions with lottery and state fixed effects.

Employment Shares (RAIS)	Wholesale	Manufacturing	Construction	Transport & Comm.	Education	Health	Prof. Services	Agriculture	Public Admin.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Corruption per capita (AFF)	-0.116***	-0.804***	-0.175***	-0.116***	-0.113***	-0.126***	-0.235***	0.375**	2.052***
	(0.017)	(0.111)	(0.036)	(0.032)	(0.018)	(0.018)	(0.049)	(0.135)	(0.161)
Corruption per-service order (AFF)	-0.011	0.007	0.028**	-0.011	0.010	0.015	0.018	-0.014	-0.048
	(0.011)	(0.058)	(0.013)	(0.024)	(0.006)	(0.012)	(0.018)	(0.044)	(0.098)

Panel B: Regressions with lottery and state fixed effects plus additional covariates.

Employment Shares (RAIS)	Wholesale	Manufacturing	Construction	Transport & Comm.	Education	Health	Prof. Services	Agriculture	Public Admin.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Corruption per capita (AFF)	-0.047***	-0.491***	-0.044	-0.048	-0.041**	-0.064***	-0.093*	0.059	1.230***
	(0.016)	(0.129)	(0.039)	(0.035)	(0.018)	(0.020)	(0.048)	(0.140)	(0.211)
Corruption per-service order (AFF)	-0.016	-0.054	0.018*	-0.023	0.008	0.010	0.004	-0.002	0.042
	(0.011)	(0.047)	(0.009)	(0.022)	(0.006)	(0.010)	(0.015)	(0.045)	(0.047)

Notes: *,**, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Each cell constitutes a separate regression. All regressions include lottery and state fixed effects. For corruption per capita, we also include the logged number of service orders. Regressions with controls additionally include the covariates listed in **Table 2**. Standard errors are clustered by state.

Table B2: The effect of corruption on establishment shares.

Panel A: Basic regressions with lottery and state fixed effects.

Establishment Shares (RAIS)	Wholesale	Manufacturing	Construction	Transport & Comm.	Education	Health	Prof. Services	Agriculture	Public Admin.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Corruption per capita (AFF)	-0.143***	-0.219***	-0.106***	0.012	-0.025	-0.132***	-0.234***	0.662***	0.159***
	(0.019)	(0.022)	(0.025)	(0.026)	(0.020)	(0.015)	(0.044)	(0.203)	(0.031)
Corruption per-service order (AFF)	-0.002	-0.003	0.021**	0.012	-0.006	-0.006	0.024	-0.044	0.001
	(0.009)	(0.014)	(0.009)	(0.008)	(0.013)	(0.010)	(0.017)	(0.042)	(0.007)

Panel B: Regressions with lottery and state fixed effects plus additional covariates.

Establishment Shares (RAIS)	Wholesale	Manufacturing	Construction	Transport & Comm.	Education	Health	Prof. Services	Agriculture	Public Admin.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Corruption per capita (AFF)	-0.055***	-0.129***	-0.017	0.042	0.000	-0.069***	-0.011	0.292*	0.144***
	(0.015)	(0.035)	(0.020)	(0.037)	(0.033)	(0.023)	(0.051)	(0.142)	(0.039)
Corruption per-service order (AFF)	-0.008	-0.011	0.012	0.002	-0.008	-0.008	0.004	0.013	0.001
	(0.007)	(0.015)	(0.007)	(0.008)	(0.014)	(0.010)	(0.011)	(0.038)	(0.006)

Notes: *,**, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Each cell constitutes a separate regression. All regressions include lottery and state fixed effects. For corruption per capita, we also include the logged number of service orders. Regressions with controls additionally include the covariates listed in **Table 2**. Standard errors are clustered by state.

Table B3: The effect of corruption on (logged) HHI measure of concentration.

Panel A: Basic regressions with lottery and state fixed effects.

HHI (RAIS)	Wholesale	Manufacturing	Construction	Transport & Comm.	Education	Health	Prof. Services	Agriculture	Public Admin.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Corruption per capita (AFF)	12.222***	9.097***	11.354***	8.961***	9.402***	8.302***	11.388***	5.478***	0.669***
	(1.071)	(1.196)	(1.604)	(0.645)	(1.236)	(0.987)	(0.852)	(0.723)	(0.168)
Corruption per-service order (AFF)	-0.907	-0.798**	-1.324**	-0.456	-1.247**	-0.746	-1.010*	-0.139	-0.017
	(0.606)	(0.365)	(0.618)	(0.298)	(0.481)	(0.447)	(0.530)	(0.369)	(0.058)

Panel B: Regressions with lottery and state fixed effects plus additional covariates.

HHI (RAIS)	Wholesale	Manufacturing	Construction	Transport & Comm.	Education	Health	Prof. Services	Agriculture	Public Admin.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Corruption per capita (AFF)	6.009***	4.505***	5.431***	4.981***	4.460***	3.868***	5.448***	4.625***	0.265*
	(0.855)	(0.990)	(1.346)	(0.700)	(0.987)	(1.125)	(0.662)	(1.086)	(0.143)
Corruption per-service order (AFF)	-0.265	-0.384	-0.729	-0.118	-0.929***	-0.449*	-0.576*	-0.464	-0.005
	(0.328)	(0.314)	(0.538)	(0.191)	(0.320)	(0.228)	(0.291)	(0.418)	(0.052)

Notes: *,**, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Each cell constitutes a separate regression. All regressions include lottery and state fixed effects. For corruption per capita, we also include the logged number of service orders. Regressions with controls additionally include the covariates listed in **Table 2**. Standard errors are clustered by state.

Appendix C – Main Results with Mismanagement as an Additional Control

Table C1: The effect of corruption on employment shares.

Panel A: Basic regressions with lottery and state fixed effects.

Employment Shares (RAIS)	Wholesale	Manufacturing	Construction	Transport & Comm.	Education	Health	Prof. Services	Agriculture	Public Admin.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Corruption per capita (AFF)	-0.083***	-0.747***	-0.143***	-0.114***	-0.106***	-0.111***	-0.205***	0.375***	1.858***
	(0.029)	(0.105)	(0.031)	(0.019)	(0.010)	(0.014)	(0.043)	(0.097)	(0.130)
Corruption per-service order (AFF)	-0.002	-0.038	0.017**	0.007	0.004	0.009	0.007	-0.013	-0.041
	(0.005)	(0.042)	(0.008)	(0.014)	(0.005)	(0.006)	(0.012)	(0.038)	(0.061)
% of audited resources that are corrupt (FF)	-0.039	0.129	0.007	0.025	0.001	-0.021**	-0.018	0.102	-0.103
	(0.027)	(0.110)	(0.023)	(0.018)	(0.008)	(0.008)	(0.011)	(0.072)	(0.138)

Panel B: Regressions with lottery and state fixed effects plus additional covariates.

Employment Shares (RAIS)	Wholesale	Manufacturing	Construction	Transport & Comm.	Education	Health	Prof. Services	Agriculture	Public Admin.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Corruption per capita (AFF)	-0.030	-0.402***	-0.050	-0.045**	-0.046***	-0.067***	-0.099**	0.094	1.097***
	(0.027)	(0.113)	(0.034)	(0.021)	(0.013)	(0.013)	(0.044)	(0.100)	(0.123)
Corruption per-service order (AFF)	-0.002	-0.062	0.010	-0.001	0.001	0.006	-0.003	-0.007	0.008
	(0.005)	(0.039)	(0.007)	(0.013)	(0.005)	(0.006)	(0.012)	(0.033)	(0.045)
% of audited resources that are corrupt (FF)	-0.042*	0.071	0.002	0.018	-0.006	-0.025***	-0.021	0.135*	-0.026
	(0.021)	(0.102)	(0.024)	(0.017)	(0.008)	(0.007)	(0.013)	(0.077)	(0.108)

Notes: *,**, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Each cell constitutes a separate regression. All regressions include lottery and state fixed effects. For corruption per capita, we also include the logged number of service orders. Regressions with controls additionally include the covariates listed in **Table 2**. Standard errors are clustered by state. Mismanagement is included as an additional control; for regressions with corruption per capita (AFF) it is divided by population, for corruption per-service order it is divided by (logged) service orders, for share of audited resources that are corrupt it is included as the analogous percentage.

Table C2: The effect of corruption on establishment shares.									
Panel A: Basic regressions with lottery and state fixed effects.									
Establishment Shares (RAIS)	Wholesale	Manufacturing	Construction	Transport & Comm.	Education	Health	Prof. Services	Agriculture	Public Admin.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Corruption per capita (AFF)	-0.121***	-0.214***	-0.111***	0.011	-0.036**	-0.118***	-0.203***	0.558***	0.147***
	(0.015)	(0.023)	(0.020)	(0.017)	(0.017)	(0.015)	(0.032)	(0.154)	(0.025)
Corruption per-service order (AFF)	-0.002	-0.006	0.007	0.009	-0.004	0.000	0.019	-0.051	-0.001
	(0.004)	(0.014)	(0.006)	(0.007)	(0.009)	(0.006)	(0.012)	(0.041)	(0.004)
% of audited resources that are corrupt (FF)	-0.006	-0.002	-0.002	0.016	-0.018	-0.012*	-0.013	0.118	-0.003
	(0.010)	(0.022)	(0.009)	(0.026)	(0.015)	(0.007)	(0.011)	(0.082)	(0.010)
Panel B: Regressions with lottery and state fixed effects plus additional covariates.									
Establishment Shares (RAIS)	Wholesale	Manufacturing	Construction	Transport & Comm.	Education	Health	Prof. Services	Agriculture	Public Admin.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Corruption per capita (AFF)	-0.049***	-0.116***	-0.042**	0.042*	-0.019	-0.070***	-0.040	0.252**	0.133***
	(0.010)	(0.027)	(0.017)	(0.024)	(0.023)	(0.019)	(0.034)	(0.100)	(0.027)
Corruption per-service order (AFF)	-0.004	-0.005	0.001	0.004	-0.006	-0.001	0.005	-0.017	0.000
	(0.003)	(0.013)	(0.005)	(0.008)	(0.009)	(0.006)	(0.008)	(0.027)	(0.004)
% of audited resources that are corrupt (FF)	-0.014*	-0.016	-0.008	0.012	-0.016	-0.019***	-0.020*	0.160**	0.001
	(0.008)	(0.019)	(0.010)	(0.023)	(0.014)	(0.007)	(0.011)	(0.073)	(0.010)

Notes: *,**, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Each cell constitutes a separate regression. All regressions include lottery and state fixed effects. For corruption per capita, we also include the logged number of service orders. Regressions with controls additionally include the covariates listed in **Table 2**. Standard errors are clustered by state. Mismanagement is included as an additional control; for regressions with corruption per capita (AFF) it is divided by population, for corruption per-service order it is divided by (logged) service orders, for share of audited resources that are corrupt it is included as the analogous percentage.

Table C3: The effect of corruption on (logged) HHI measure of concentration.

Panel A: Basic regressions with lottery and state fixed effects.

HHI (RAIS)	Wholesale	Manufacturing	Construction	Transport & Comm.	Education	Health	Prof. Services	Agriculture	Public Admin.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Corruption per capita (AFF)	10.580***	8.773***	9.916***	7.738***	8.525***	7.508***	10.123***	5.549***	0.492***
	(0.727)	(0.905)	(0.789)	(0.574)	(0.750)	(0.754)	(0.702)	(0.614)	(0.117)
Corruption per-service order (AFF)	-0.697*	-0.346	-0.679*	-0.144	-0.875***	-0.521*	-0.671*	0.233	0.021
	(0.354)	(0.364)	(0.364)	(0.219)	(0.269)	(0.284)	(0.346)	(0.214)	(0.044)
% of audited resources that are corrupt (FF)	0.498	-0.262	-0.235	0.262	0.099	-0.869**	-0.006	0.473	0.145*
	(0.858)	(0.536)	(0.611)	(0.547)	(0.608)	(0.422)	(0.514)	(0.593)	(0.079)

Panel B: Regressions with lottery and state fixed effects plus additional covariates.

HHI (RAIS)	Wholesale	Manufacturing	Construction	Transport & Comm.	Education	Health	Prof. Services	Agriculture	Public Admin.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Corruption per capita (AFF)	5.829***	5.269***	5.134***	4.535***	4.771***	4.278***	5.709***	4.880***	0.237*
	(0.604)	(0.758)	(0.795)	(0.484)	(0.761)	(0.831)	(0.573)	(0.689)	(0.129)
Corruption per-service order (AFF)	-0.262	-0.102	-0.328	0.052	-0.633***	-0.385**	-0.372**	0.105	0.022
	(0.222)	(0.295)	(0.341)	(0.151)	(0.216)	(0.171)	(0.176)	(0.186)	(0.044)
% of audited resources that are corrupt (FF)	0.995	0.164	0.347	0.595	0.550	-0.452	0.518	0.655	0.180**
	(0.709)	(0.531)	(0.638)	(0.484)	(0.646)	(0.322)	(0.440)	(0.699)	(0.083)

Notes: *,**, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Each cell constitutes a separate regression. All regressions include lottery and state fixed effects. For corruption per capita, we also include the logged number of service orders. Regressions with controls additionally include the covariates listed in **Table 2**. Standard errors are clustered by state. Mismanagement is included as an additional control; for regressions with corruption per capita (AFF) it is divided by population, for corruption per-service order it is divided by (logged) service orders, for share of audited resources that are corrupt it is included as the analogous percentage.

Appendix D – IV Analysis for Employment/Establishment Shares

Table D1: The effect of corruption per capita on employment shares (outcomes in **bold**); instrumental variable analysis.

	Individual Instruments			All Instruments	
HHI (RAIS)				Coefficient	J-Statistic
	(1)	(2)	(3)	(4)	(5)
Wholesale	0.049	0.054	-0.246***	-0.164**	3.392
	(0.159)	(0.148)	(0.074)	(0.073)	[0.183]
F-Statistic	11.94	25.35	32.31	24.21	
Manufacturing	-1.858*	-1.522*	-0.780	-0.999**	1.006
	(1.027)	(0.858)	(0.559)	(0.451)	[0.605]
F-Statistic	11.94	25.35	32.31	24.21	
Construction	-0.124	-0.082	-0.180	-0.155	0.303
	(0.325)	(0.291)	(0.181)	(0.201)	[0.859]
F-Statistic	11.94	25.35	32.31	24.21	
Transportation & Communication	-0.108	-0.199	-0.041	-0.079	0.628
	(0.174)	(0.197)	(0.132)	(0.113)	[0.731]
F-Statistic	11.94	25.35	32.31	24.21	
Education	-0.305***	-0.214**	-0.074	-0.117***	5.098*
	(0.091)	(0.101)	(0.072)	(0.045)	[0.078]
F-Statistic	11.94	25.35	32.31	24.21	
Health	-0.342**	-0.502**	-0.283***	-0.334***	3.490
	(0.160)	(0.204)	(0.092)	(0.100)	[0.175]
F-Statistic	11.94	25.35	32.31	24.21	
Professional Services	0.038	0.043	0.163	0.130	0.752
	(0.144)	(0.225)	(0.187)	(0.159)	[0.686]
F-Statistic	11.94	25.35	32.31	24.21	
Agriculture	0.909	0.579	-0.270	-0.022	2.721
	(0.679)	(0.601)	(0.314)	(0.298)	[0.257]
F-Statistic	11.94	25.35	32.31	24.21	
Public Administration	4.581***	4.917***	2.953***	3.471***	2.525
	(1.322)	(1.119)	(0.554)	(0.475)	[0.283]
F-Statistic	11.94	25.35	32.31	24.21	
Instrument	Councils Exist	Councils Active	Management	All IVs	

Notes: *,**, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Each cell constitutes a separate regression. All regressions include lottery and state fixed effects and the logged number of service orders. All regressions additionally include the covariates listed in **Table 2**. Standard errors are clustered by state. P-values in brackets for J-Statistic.

Table D2: The effect of corruption per capita on establishment shares (outcomes in **bold**); instrumental variable analysis with mismanagement control.

Establishments Shares (RAIS)	Individual Instruments			All Instruments Coefficient	All Instruments J-Statistic
	(1)	(2)	(3)	(4)	(5)
Wholesale	-0.010	-0.071	-0.264***	-0.208***	3.028
	(0.106)	(0.105)	(0.070)	(0.052)	[0.220]
F-Statistic	11.94	25.35	32.31	24.21	
Manufacturing	-0.772**	-0.498*	-0.051	-0.187	3.303
	(0.356)	(0.282)	(0.169)	(0.135)	[0.192]
F-Statistic	11.94	25.35	32.31	24.21	
Construction	-0.105	-0.070	-0.095	-0.090	0.282
	(0.084)	(0.102)	(0.087)	(0.072)	[0.869]
F-Statistic	11.94	25.35	32.31	24.21	
Transportation & Communication	0.150	0.099	0.246***	0.208***	1.135
	(0.162)	(0.142)	(0.063)	(0.066)	[0.567]
F-Statistic	11.94	25.35	32.31	24.21	
Education	-0.037	0.053	0.168*	0.132	2.436
	(0.085)	(0.176)	(0.092)	(0.088)	[0.296]
F-Statistic	11.94	25.35	32.31	24.21	
Health	-0.050	-0.241**	-0.126*	-0.147**	3.699
	(0.117)	(0.120)	(0.076)	(0.073)	[0.157]
F-Statistic	11.94	25.35	32.31	24.21	
Professional Services	-0.296**	-0.037	0.008	-0.018	1.980
	(0.135)	(0.233)	(0.154)	(0.155)	[0.372]
F-Statistic	11.94	25.35	32.31	24.21	
Agriculture	1.307	0.858	0.492	0.614*	1.362
	(0.822)	(0.694)	(0.377)	(0.365)	[0.506]
F-Statistic	11.94	25.35	32.31	24.21	
Public Administration	0.300*	0.384***	0.199***	0.245***	2.517
	(0.165)	(0.144)	(0.062)	(0.068)	[0.284]
	11.94	25.35	32.31	24.21	
Instrument	Councils Exist	Councils Active	Management	All IVs	

Notes: *,**, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Each cell constitutes a separate regression. All regressions include lottery and state fixed effects, the logged number of service orders, and a measure of mismanagement. All regressions additionally include the covariates listed in **Table 2**. Standard errors are clustered by state. P-values in brackets for J-Statistic.

Appendix E – First Stage IV Estimates

Table E1a: First stage coefficients on instruments from **Table 6**.

	(1)	(2)	(3)	(4)
	Wholesale			
Councils Exist	-0.007***			-0.005*
	(0.003)			(0.003)
Councils Active		-0.004		0.001
		(0.003)		(0.003)
Management Capacity			-0.007***	-0.006***
			(0.002)	(0.002)
	Manufacturing			
	(1)	(2)	(3)	(4)
Councils Exist	-0.010***			-0.003
	(0.003)			(0.004)
Councils Active		-0.008***		-0.005*
		(0.002)		(0.003)
Management Capacity			-0.009***	-0.009***
			(0.002)	(0.002)
	Construction			
	(1)	(2)	(3)	(4)
Councils Exist	-0.008***			-0.002
	(0.003)			(0.004)
Councils Active		-0.007***		-0.003
		(0.002)		(0.003)
Management Capacity			-0.009***	-0.008***
			(0.002)	(0.002)
	Transportation & Communication			
	(1)	(2)	(3)	(4)
Councils Exist	-0.010***			-0.003
	(0.003)			(0.004)
Councils Active		-0.008***		-0.005*
		(0.002)		(0.003)
Management Capacity			-0.010***	-0.009***
			(0.002)	(0.002)

Notes: *,**, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All regressions include lottery and state fixed effects, the logged number of service orders, and a measure of mismanagement. All regressions additionally include the covariates listed in **Table 2**. Standard errors are clustered by state.

Table E1b: First stage coefficients on instruments from **Table 6**.

	(1)	(2)	(3)	(4)
	Education			
Councils Exist	-0.009***			-0.005
	(0.002)			(0.004)
Councils Active		-0.005***		0.000
		(0.002)		(0.003)
Management Capacity			-0.010***	-0.009***
			(0.002)	(0.002)
	Health			
	(1)	(2)	(3)	(4)
Councils Exist	-0.010***			-0.005
	(0.003)			(0.004)
Councils Active		-0.007***		-0.002
		(0.002)		(0.004)
Management Capacity			-0.009***	-0.008***
			(0.002)	(0.002)
	Professional Services			
	(1)	(2)	(3)	(4)
Councils Exist	-0.007***			-0.001
	(0.002)			(0.003)
Councils Active		-0.006***		-0.004
		(0.002)		(0.003)
Management Capacity			-0.008***	-0.007***
			(0.001)	(0.002)
	Agriculture			
	(1)	(2)	(3)	(4)
Councils Exist	-0.009***			-0.002
	(0.003)			(0.004)
Councils Active		-0.008***		-0.005*
		(0.002)		(0.003)
Management Capacity			-0.010***	-0.010***
			(0.002)	(0.002)
	Public Administration			
	(1)	(2)	(3)	(4)
Councils Exist	-0.009***			-0.002
	(0.003)			(0.004)
Councils Active		-0.009***		-0.006**
		(0.002)		(0.003)
Management Capacity			-0.009***	-0.008***
			(0.002)	(0.002)

Notes: *,**, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All regressions include lottery and state fixed effects, the logged number of service orders, and a measure of mismanagement. All regressions additionally include the covariates listed in **Table 2**. Standard errors are clustered by state.