Local Corruption and Misreported Income: Evidence from the Earned Income Tax Credit

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Abstract

We study the relationship between local corruption and income misreporting in the context of the EITC program. Using a newly assembled dataset of corruption at the MSA level, we observe that public officials' corruption predicts more than 70% of the variation in bunching in the distribution of EITC-eligible self-employed workers' reported income. Using a research design that exploits exogenous variation in institutional accountability, we find that a one standard deviation rise in our corruption measure causes sharp bunching among self-employed to increase by 0.60 to 0.83 standard deviations. This is consistent with a behavioral model that embeds social stigma.

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A fish rots from the head down.[1]

1 Introduction

There is consensus among economists that institutional corruption is central in determining macroeconomic outcomes like growth and investment (e.g., Mauro, 1995). We show that institutional corruption in the United States has an impact on the microeconomic behavior of taxpayers. In particular, we show that living in a Metropolitan Statistical Area (MSA) with a higher number of public officials involved in district court appeals against the federal government increases the share of self-employed workers eligible for an Earned Income Tax Credit (EITC) who report earnings close to the subsidy-maximizing point of the EITC schedule.[2] In the literature on tax evasion, the broad phenomenon of misreporting income just enough to have the most favorable treatment in terms of taxes and subsidies is often referred to as *secondary* tax evasion (Slemrod, 1985; Schmidt and Werner, 2005); as opposed to *primary* tax evasion, which is underreporting earnings in order to pay less income tax, when the tax schedule is a continuous increasing function of income (Slemrod, 1985).

Using a stylized model mostly based on Benabou and Tirole (2006), we propose a theoretical framework in which as institutions get more corrupt, citizens start to underestimate the seriousness of their fraudulent actions and put less weight on the potentially negative consequences of their misbehavior. In other words, we argue that corruption of local institutions affects the behavior of the rest of the population in a certain area by changing the perceived social norms. Notable evidence of the relationship between corruption and social norms is offered by Fisman and Miguel (2007), who observe the parking behavior of UN diplomats in Manhattan and show that officials from highly corrupt countries accumulated a significantly higher number of unpaid parking violations.

A robust body of research in behavioral economics has shown that norm violation can be contagious. Keizer et al. (2008), for example, perform six field experiments to test whether

[1] According to Grant (2005), the Latin version of this saying—*Piscis primum a capite foetet*—is to be attributed to Desiderius Erasmus Roterodamus.

[2] Throughout the paper, we will refer to the phenomenon of clustering around the refund-maximizing point in the distribution of reported income as *bunching*. See Kleven (2016) for a broad review of the general phenomenon of bunching and recent developments in the literature.

knowledge of petty crime fosters more criminal behavior. They find that when people observe violations of norms, they tend to engage more in unlawful behavior, possibly because they may lower their expectations of the likelihood of being punished or may update their beliefs of what is socially acceptable based on their observation of other people's behavior (see, for example, Cialdini et al., 1990). Diekman et al. (2015) show that the latter mechanism plays a central role in determining the tendency to cheat in a lab experiment. Participants were asked to throw a die without supervision and anonymously report the result through a computer, knowing that each number is associated with a specific monetary payoff that is known to all. The authors find that participants who are shown the cheating behavior of other participants become more likely to report the number with the highest payoff. More recently, Schulz and Gächter (2016) perform the same (single-round) experiment in 21 countries and show that cheating is positively correlated with a measure they call Prevalence of Rule Violations (PRV), which is based on country-level data on fraudulent politics, tax evasion, and the World Bank's measure of corruption.

The main contribution of this paper is threefold. First, we build a novel dataset of corruption in the US at the MSA level. We do this by analyzing 20,593 appeals related to cases filed in US Appeal Courts between 2000 and 2010, in which the federal government is the plaintiff. We select those in which one or more public officials are involved and assign them to geographical areas based on their jurisdiction. This measure of corruption closely mirrors the one commonly used in the corruption literature (i.e., number of public officials convicted by the federal government) and maintains the same desirable properties, such as a common set of laws for all the officials. To the best of our knowledge, ours is the first paper in which corruption in the US is estimated at a geographical level of disaggregation finer than the state level.

Second, we show that the corruption of authorities affects tax compliance. We find that self-employed workers are more likely to report a subsidy-maximizing income in areas with higher corruption. This relationship is economically relevant and robust to adding various controls to the regression model. Moreover, by using an instrumental variable approach, we show that the link is causal. Based on the intuition provided by Campante and Do (2014) that institutions are more accountable if they are less isolated from the rest of the population, we build a measure of institutional isolation for each MSA and use it as an instrument for local corruption. We find that increasing our corruption measure in a given MSA by one standard deviation induces an increase of bunching by up to about 83% of one standard deviation.

Third, we contribute to the literature on labor supply responses to tax policies by offering further evidence that a substantial part of the variation in sharp bunching documented in recent studies and used as an identifying variation (see, for instance, Saez, 2010 and Chetty et al., 2013) is likely to be due to misreporting instead of actual labor supply responses. This result is in line with Chetty et al. (2012), who use audit data from the 2001 National Research Program to show that almost one third of the observed bunching disappears when using post-audit earnings.

Based on the idea that if misbehavior is contagious, then the contagion is stronger when information about other individuals' misbehavior is more easily available, we build a measure of news coverage and estimate the extent to which the effect of public corruption is channeled through the spreading of information. Intuitively, we would expect that in MSAs in which newspapers cover corruption cases more closely, people would engage in more unlawful behavior due to their increased awareness. Therefore, following Saiz and Simonsohn (2013), we build a measure of news coverage as the ratio of the number of news articles related to a given MSA appearing in Newsbank, an online repository of news articles, that include the word "corruption" to the total number of Newsbank articles related to that MSA. We build the measure at the city level and aggregate it to the MSA level. When we add this variable to our baseline specification, the coefficient that captures the impact of corruption on tax evasion shrinks by almost 10%. Moreover, the interaction term shows that as the coverage of corruption increases, a higher local corruption measure is associated with higher sharp bunching. This suggests that news coverage helps decrease the perceived social stigma of corruption by making people aware of the corrupt behavior of community leaders around them.

The rest of the paper is structured as follows. Section 2 provides an overview of the EITC program and explains why we expect misreporting of income according to its subsidy schedule. Section 3 describes the data and explains in detail how we assign every appeal to a geographical area. Section 4 introduces the conceptual framework used to motivate the empirical model specifications and to interpret the estimates. Section 5 presents the identification strategy and discusses the estimates. Section 6 shows robustness checks. Section 7 explores the news channel as one possible mechanism driving the main results of the paper. Section 8 concludes.

2 Misreporting earnings in the context of the EITC

The EITC is a tax credit distributed in the form of tax refunds to low-income households, especially those with young children. We use the bunching rate at the first kink of the refund-maximizing locus (sharp bunching) in the EITC schedule as a measure of earned income misreporting. We do this for two reasons. First, EITC is the biggest tax credit program in the United States, and therefore is a perfect candidate to study the broad behavior of taxpayers. In 2010, 27.4 million tax filers received a total of $59.6 billion in EITC payments (Chetty et al., 2013). Second, there is some evidence that the bunching around the refund-maximizing incomes observed in the data might be mainly due to misreporting. Chetty et al. (2012) compare the bunching of self-employed people around the refund-maximizing points pre- and post-audit. Using data from the 2001 National Research Program the authors show that when using post-audit data, more than one third of the bunching disappears. This suggests that a big portion of the observed bunching among self-employed people is due to income misreporting.

[Figure 1 approximately here]

Figure 1 reports Figure 1a in Chetty, Friedman, and Saez (2013) and depicts the EITC schedules for tax filers with one qualifying dependent and two or more qualifying dependents,[3] as well as the percentage of self-employed tax filers who report a certain income. We see clearly that self-employed workers tend to report incomes around the two kinks of the schedule. It is interesting that people tend to bunch more around the first kink than the second one, possibly because the effective marginal tax rate for people on the left-hand side of the first kink is negative. Therefore, tax filers with an income below the first kink might be tempted to overstate their income, whereas people to the right of the kink (where the marginal tax rate is positive) to understate it. On the contrary, at the second kink only one of these forces is at work: people with an income below the second kink do not have any incentive to overstate their income.

3 Data

In this Section, we describe the data used in the empirical analysis. Throughout the paper we use MSAs as the geographic units of analysis.

[3] Qualifying dependents are relatives who are younger than 19 (24 for full-time students) or permanently disabled, and live with the tax filer for at least six months a year.

Since MSAs encompass highly densely populated places that share strong economic ties, they seem to constitute the most appropriate unit of analysis to study the impact of corruption of public officials on the behavior of economic agents living and interacting in a homogeneous area.

Summary statistics are reported in Table A1 in the Appendix.

3.1 EITC data

The sharp bunching variable is taken from Chetty et al. (2013). Following their approach, we use the share of self-employed incomes clustering inside a $[-500\$, +500\$]$ interval around the first kink of the EITC schedule as our measure of sharp bunching among self-employed workers. Chetty et al. (2013) perform their analysis at a three-digit ZIP-code (ZIP3) level. We map this variable to MSAs on the assumption that claimants are uniformly distributed in every ZIP3.[4] Figure 2 shows the geographic distribution of the measure at the MSA level.

[Figure 2 approximately here]

3.2 Demographic Data

Demographic data are mainly collected from the 2010 Census. In particular, we collect data about average household income, number of households with children below 18 and the number of people belonging to a minority. Data are collected at both the state and the MSA levels. The number of public employees is obtained from the Bureau of Labor Statistics.

3.3 Corruption Measures

State-level corruption is proxied by the number of public officials convicted by the federal government, as reported by the Public Integrity Section (PIS) of the US Department of Justice in its Report to Congress. This measure has been widely used in the literature on corruption (see, for instance, Glaeser and Saks, 2006) and has some appealing properties. First, since federal laws are the same across states, it allows us to compare observations from regions with different state legislation. Second, it can be argued that in places with high levels of corruption, law

[4] For example, if 51% of a ZIP3 area is contained in a certain MSA, we multiply the number of claimants in that ZIP3 by 0.51 and assign that number of claimants to the MSA.

enforcement officials are also more likely to be corrupt, raising endogeneity concerns. Federal laws are enforced by federal agents who should not be affected by local dynamics of corruption.

In order to estimate corruption at the MSA level, we follow the state-level measure as closely as possible. Ideally, we would like to get the text of each case in the PIS documents and assign it to an MSA, but the PIS Report to Congress only reports some selected noteworthy cases and the judge's opinions are not always readily available. However, it is easy to get access to the opinions of judges in the 12 regional appeal courts (11 circuits plus DC). Assuming that the probability of appeal is similar across states, we download the 9,674 appeals filed in the United States between 2007 and 2013 in which the federal government is the plaintiff. We analyze them by hand and select the 467 appeals (4.8% of the total) in which public officials are involved (e.g., cases of bribery) as *learning set*.[5] For each of the 467 cases, we identify key words that might help us recognize similar cases.[6] We then download all the appeals filed between 2000 and 2006 for a total of 10,919 additional appeals. Instead of going through them by hand, as we did with the learning set, we identify those that contain any of our key words as well as those referring to law 18 U.S. Code $\S$ 666 (theft or bribery concerning programs receiving Federal funds) or containing the word ”bribery”. Those appeals are then analyzed by hand and the false positives discarded. In the end, we are left with 153 additional cases involving public officials. We also apply the same approach to the learning set to check whether we misclassified any appeal in the first step of this procedure. We find 23 appeals between 2007 and 2013 that were erroneously discarded. At the end of this procedure, we are left with 643 appeals concerning public officials. To assign each selected appeal to a geographical area, we proceed as follows. For each case, we identify where the public official was in office and in what position at the time of the crime. Based on the official's sphere of influence, we assign the case to one or more MSAs. For example, a crime perpetrated by a police officer of a certain city is assigned to the MSA that contains that city (or the closest one if the city is not in any MSA),[7] whereas a crime of bribery involving a governor is assigned to every MSA at least partly contained in that state. Also, when the same appeal refers to multiple officials, we treat it as if there were multiple cases. For example, if a city's mayor and police chief received bribes in the same indictment, we assign

[5]Note that our definition of corruption, like that of the PIS, is broader than just bribery. For example, it encompasses electoral fraud and police violence. In this context, corruption should be interpreted more broadly as corrupt behavior.

[6]We list the key words in the Online Appendix.

[7]As a robustness check, we also performed the empirical analysis discarding the cities that do not fall inside an MSA. The results are unchanged.

two cases to the MSA that contains that city. A total of 816 corruption cases are distributed among MSAs.

[Figure 3 approximately here]

Figure 3 shows the distribution of our measure of local corruption. Only 14 MSAs (4% of the total sample) show 0 cases of corruption.[8] In the right tail, three MSAs stand out for number of corrupt officials.[9]

[Figure 4 approximately here]

[Figure 5 approximately here]

In Figures 4 and 5, we show how corruption is distributed throughout the US according to our measure. Darker areas correspond to MSAs with a higher concentration of corrupt public officials. As a check of the validity of this newly built measure, we aggregate it at the state level and compare it with the state-level measure calculated using the the PIS Report to Congress. Figure 6 shows the correlation between the two metrics, which is more than 0.8, significant at a 0.01% level.

[Figure 6 approximately here]

3.4 News Coverage

The data on news coverage are collected through the Newsbank database at the city level. Following Saiz and Simonsohn (2013), we compute the measure of news coverage as the ratio of the number of news stories related to a given MSA that include the word ”corruption” to the total number of news stories related to that MSA in the database. We collect data from 2000 to 2016 and aggregate them at the MSA level and over time.

[8] These MSAs are Lexington-Fayette, KY; Cheyenne, WY; Lincoln, NE; Reno-Sparks, NV; Idaho Falls, ID; Bowling Green, KY; Coeur d'Alene, ID; Owensboro, KY; Honolulu, HI; Pocatello, ID; Elizabethtown, KY; Carson City, NV; Boise City-Nampa, ID; Casper, WY.

[9] These MSAs are Washington-Arlington-Alexandria, DC-VA-MD-WV, New York-Northern New Jersey-Long Island, NY-NJ-PA and Chicago-Joliet-Naperville, IL-IN-WI, with 56, 70 and 79 cases, respectively.

4 Conceptual Framework

In this section, we develop a simple theoretical framework of group behavior, based mainly on the model by Benabou and Tirole (2006) (BT, hereafter) and its version appearing in Adriani and Sonderegger (2015) (AS). This simple model offers a conceptual framework that can be used to motivate and interpret the results obtained in Section 5. Our model differs from BT and AS in that it allows for spillovers across different social groups and focusing on stigma rather than prosocial behavior and honor.

There are two groups of agents: citizens (c) and institutions (i). In each group $g \in \{c, i\}$, individuals make a discrete choice $a \in \{0, 1\}$ that represents misbehavior (corruption for institutions and misreporting income for citizens). The utility of an individual in group g is given by the following function:

$$U(a, x) + \mu_g \mathbb{E}[x|a, g]. \tag{1}$$

The first term is the intrinsic utility from a, and it depends on the parameter x—a measure of greed—which is distributed with symmetric and full support density f_g over the interval $[\underline{x}_g, \overline{x}_g]$. The second term reflects the disutility that a group member derives from stigma. The parameter $\mu_g < 0$ is a measure of the stigma's intensity.[10] Note that while a and g are common knowledge within each group, x is only observed by the individual.[11]

Utility-maximizing agents choose $a = 1$ if the following holds:

$$v(x) \equiv U(1, x) - U(0, x) \geq \mu_g(\mathbb{E}[X|0, g] - \mathbb{E}[X|1, g]).$$

Define $\phi_g(x) \equiv \mathbb{E}_g[X|X > x] - \mathbb{E}_g[X|X < x]$. We define x_g^* as the point that in equilibrium satisfies

$$v(x_g^*) = -\mu_g \phi_g(x_g^*) \iff -\frac{v(x_g^*)}{\mu_g} = \phi_g(x_g^*) \tag{2}$$

such that every individual with $x \geq x_g^*$ optimally sets $a = 1$.[12]

[10]It can also be interpreted as the probability of being caught misbehaving or a combination of this probability and the intensity of a social stigma.

[11]Having perfect knowledge of a by each citizen might be considered a strong assumption. However, the assumption can be easily relaxed, as imperfect knowledge can be modeled as a small value of μ_g.

[12]Uniqueness is ensured by the following condition (see AS for a formal proof):

$$-\frac{v'(x)}{\mu_g} > \phi'(x).$$

Let us assume that μ_i and μ_c are defined in the following way:

$$\mu_c \equiv -(\theta_c + \psi(x_i)) \tag{3}$$

$$\mu_i \equiv -\theta_i, \tag{4}$$

where $\theta_g > 0,\ g \in \{c, i\}$ is an exogenous component that includes the extent of the shame arising from misbehavior and the probability that information on a is acquired by individuals, who make judgments. The function $\psi(x)$, which is assumed to be strictly positive and increasing, indicates that there are spillover effects from the institutions to the citizens, but not vice versa. The intuition behind this structure is that while the corrupt behavior of public officials is extensively covered by local media, the misbehavior of private citizens is seldom reported in the news. This implies that the mechanism of contagion is likely to be unidirectional, going from institutions to private citizens.

Now suppose that an exogenous shock reduces θ_i. This shock decreases the cost of misbehavior but does not affect its benefit. It therefore implies a decrease in the equilibrium cutoff within group i. This in turn implies that more people will perform action $a = 1$.

Now, since $\psi(\cdot)$ is stirctly increasing, we have a shift upwards in the slope of $-\frac{v(x_c^*)}{\mu_c}$, which implies a decrease in x_c^*, and consequently an increase in $1 - F(x_c^*)$. The discussion above leads to the following proposition:

Proposition 1 (i) A decrease in the stigma parameter θ_i raises the share of institutional agents who perform the action a. (ii) This increase in group i's misbehavior raises, by contagion, the equilibrium share of citizens misbehaving, $1 - F(x_c^*)$.

Proof See Appendix C.

5 Empirical Analysis

In the empirical analysis, we verify whether Proposition 1 is confirmed by the data. Consider misbehavior as income misreporting for citizens and as corruption for public officials. Part (ii) of the Proposition is our main result of interest: the one that links institutional misbehavior to income misreporting. Part (i) constitutes the theoretical ground that leads to the specification of a first stage regression, which allows us to gain exogenous variation in institutional misbehavior.

Throughout the empirical analysis, misbehaving in the group i will be measured by the logarithm of the number of corruption cases included in our dataset within a given MSA m in state s.[13] Misbehaving in group c means misreporting income to maximize the payoff from the EITC schedule. Consider the case in which equilibria such as the one described in the previous section are reached within each MSA and each local equilibrium is independent of the others. In this case, a natural test of part (ii) of Proposition 1 is a t-test on coefficient ρ in the following linear model:

$$\text{bunch}_{ms} = \rho\,\text{corruption}_{ms} + \beta_s + \boldsymbol{\delta}'\mathbf{q}_{ms} + \eta_{ms}, \tag{5}$$

where bunch_{ms} is the share of self-employed workers bunching, within MSA m and state s; $\mathbf{q}_{ms}$ is a vector of covariates that includes the share of people with an income within a 10,000 interval around the first kink of the EITC, the share of households with at least one dependent minor child, the share of minorities and the logarithm of the number of public employees, within MSA m and state s. Finally, β_s are state fixed effects.

5.1 OLS Estimates

[Figure 7 approximately here]

Figure 7 shows the cross-state relationship between sharp bunching of self-employed people and corruption. The linear fit suggests that a one standard deviation increase in state corruption is associated with an increase in sharp bunching of self-employed of about 0.65 standard deviations. Moreover the simple regression indicates that, in the state-level sample, the corruption variable alone can predict more than 40% of sharp bunching variation.

[Table 1 approximately here]

We now estimate Model (5) using simple OLS. The results are reported in Table 1. The coefficient of our measure of corruption is consistently positive and significant at a 1% level. As we progressively add controls, the coefficient maintains its statistical significance and economic relevance. We find that an increase of one standard deviation in $\log(1+\text{corruption})$ is associated

[13] In order not to lose those observations with 0 corruption cases (as noted above, they account only for 4% of the sample), we add 1 to the argument of the logarithm, using $\log(1 + corr_{ms})$ as our corruption measure.

with an increase in self-employed bunching rate by a fraction between 0.24 and 0.34 of a standard deviation.

In the following Section, we describe our identification strategy, after acknowledging the presence of a potential endogeneity bias in the OLS estimates.

5.2 Identification Strategy

There are three main factors that may bias our OLS estimates. First, since our measure of corruption is noisy, OLS estimates will probably suffer from an attenuation bias due to measurement error. Second, the mechanism of social stigma might be to some extent reciprocal between institution and citizens, so our OLS results may suffer from additional bias due to simultaneity. Third, we can have confounding factors, such as social capital, that both affect our left-hand side variable and our regressor of interest. For all these reasons, we use an instrumental variable approach that allows us to establish a causal relationship between local corruption and the share of sharp bunching.

We use a measure of isolation of the city hall of each MSA's largest city as an instrument for local corruption within an MSA. This measure is similar to the one used by Campante and Do (2014) for capital cities at the state level. Using data from the Census Bureau, we weight population-weighted densities by the logarithm of their distance (in miles) from the city hall of the MSA's largest city. More precisely, for each MSA m in state s, we weight population density in places that are k miles far from the city hall, d_k^{ms}, by the share of m's population that lives k miles from the city hall, s_k^{ms}, and the log of the ray in miles, k. Formally,

$$\text{isolation}_{ms} = \sum_{k=1}^{K_{ms}} s_k^{ms} \left(d_k^{ms} \cdot \log(k) \right), \tag{6}$$

where K_{ms} is the ray in miles of the largest circle that completely falls within the MSA m, in state s. Distances are measured from the city hall or similar municipal building of the metro area's principal city.[14] Geographical units with a high concentration of population close to the city hall receive a lower value of isolation. Campante and Do (2014) suggest that the mechanism of accountability is explained by the fact that the closer the citizens are to the capital city in a

[14] We took population-weighted densities for each circle around the city hall from www.census.gov, using data from 2000. Figure B1 depicts the distribution of population density moving out from the main city hall for the MSAs in the top first decile of the distribution of the isolation measure.

state, the more the national news will cover that state's politics. Applying the same rationale, we expect that the more isolated an MSA's city hall is, the lower the accountability of its public officials and, as a result, the higher the level of corruption. The first stage regression is specified as follows:

$$\text{corruption}_{ms} = \beta \, \text{isolation}_{ms} + \gamma_s + \boldsymbol{\gamma}' \mathbf{q}_{ms} + \varepsilon_{ms}. \tag{7}$$

A t-test on β in the above linear regression corresponds to a test of part (i) in Proposition 1. As explained below, our identification strategy relies on the fact that variation in the isolation measure is exogenous with respect to ε_{ms} in (7) and to η_{ms} in (5).

The taxpayers' response to an increase in local corruption is likely to be heterogeneous across MSAs, therefore we need to interpret our 2SLS results through the lens of Local Average Treatment Effects (LATE). That requires three main assumptions to hold, conditional on covariates. We define our assumptions by adapting our framework to the results presented by Angrist, Imbens, and Rubin (1996) (AIR, henceforth) on the identification of LATE in a context of binary treatment and binary instrument. First, the isolation measure constructed above must be independent of both *potential* misreporting and *potential* corruption. In other words, it must be that, conditional on covariates, the instrument is not correlated with the error term in both the first stage and the reduced form equation. The requirement of exogeneity in the reduced form is the usual exclusion restriction assumption, while exogeneity in the first stage (random assignment) is required for the LATE parameter to be identified. Second, we need the instrument to be relevant: the first stage must show the expected sign and strong statistical significance. Third the endogenous regressor must satisfy a monotonicity condition analogous to the binary case.

The first set of assumptions cannot be tested. However, we believe that random assignment is a reasonable assumption for our measure of isolation.[15] Moreover, the exclusion restriction is supported by an argument similar to that made by Campante and Do (2014). Isolation matters exclusively for the accountability of institutions and does not affect the accountability of individuals, whose income misreporting would not be covered by any news source in any case, regardless of the distance from the city hall. The second assumption can be tested in the first

[15] This amounts to believe that the location of the city hall in an MSA's largest city is not chosen based on their level of corruption. Formally—referring to the AIR framework of potential outcomes and treatment—we assume that, conditional on the covariates included in the model, isolation is independent of "potential" corruption (our treatment).

stage regression and is supported by the high value of F-statistics on the instrument's coefficient. The third assumption cannot be tested directly and is less easily interpretable in a context of nonbinary treatment as the one we are analysing. Nevertheless, we provide suggestive evidence in support of it below.

5.3 2SLS Results

The unconditional first stage is plotted in Figure 8, where we plot a binned scatter plot of the raw measure of local corruption against the measure of isolation. We present the linear regression results in Table A2,[16] where we substitute the raw measure of corruption with $\log(1+\text{corruption})$ and we regress it on the measure of isolation and the whole set of covariates we used in the OLS specification above. Both Table A2 and Figure 8 confirm the relevance of our instrument.

[Figure 8 approximately here]

The coefficient of interest is statistically significant and has the expected sign. Given the exogeneity assumption that we made on the instrument with respect to the first stage equation, we can interpret the estimate as the causal effect of isolation on the corruption measure. In particular, a one standard deviation increase in isolation causes the measure of corruption to increase by 0.25 standard deviations. As a further validation of the strength of the first stage, we notice that the Cragg-Donald F-statistics is about 16.

[Figure 9 approximately here]

Figure 9 gives suggestive evidence that the instrument is monotonic; that is, conditional on covariates, a high measure of isolation is likely to be associated with a high level of corruption everywhere in the distribution. To produce Figure 9, we compute the residuals of the regression of the measure of corruption and of the instrument on state fixed effects to isolate within-state variation. We then discretize the (residual) instrumental variable, making it a dummy equal to

[16] As it is usually done in empirical studies, we assume linearity throughout the paper. To check whether this assumption is a sensible one, Figure B2 in the Appendix plots the parametric and semiparametric relationships between the instrument and the endogenous regressor, conditional on covariates. Figure B3 does the same for the second stage, plotting the parametric and semiparametric relationships between the dependent variable and the fitted values of the endogenous regressor, conditional on covariates.

1 if the value is above the median and 0 otherwise. We plot the cumulative empirical distribution of the (residual) endogenous regressor for the subsample of observations below and above the (residual) instrumental variable's median. The empirical cumulative distribution of the endogenous regressor at values above the residual instrument's median stochastically dominates the one computed at values below the median.[17]

[Table 2 approximately here]

Table 2 shows the results of the second stage estimation. The estimates are consistently statistically significant and the magnitude of the effect of a one standard deviation increase in corruption ranges between about 0.60 and 0.83 standard deviations of the dependent variable, depending on the specification. The IV estimates in the Table are to be interpreted as the causal effects of corruption on the subsample of MSAs—which we can refer to as *complier* MSAs, in reference to the AIR framework—whose level of the endogenous variable is affected by changes in the instruments.

6 Robustness: Social Capital Placebo Test

One of the main concerns of the previous analysis is that the effect of corruption on sharp bunching is driven by the corruption's effect on some sort of local civic capital. In order to rule this possibility out, we run a set of 2SLS placebo regressions, substituting our dependent variable with the share of census respondents in 2010 as a proxy for social capital (e.g., Martin and Benjamin, 2015). We also include this variable as a control in our preferred specification. The results are shown in Table 3. Two results are worth mentioning. First, the coefficient of $\log(1 + \text{corruption})$ decreases in magnitude and loses statistical significance when we perform our preferred regression analysis using census respondents in 2010 as a dependent variable. Second, the coefficient does not suffer any change in significance or any major change in magnitude when the social capital proxy is included in the usual preferred specification as a control. This suggests that the effect of corruption captured by our empirical specification is not driven by unobserved heterogeneity related to social capital.

[Table 3 approximately here]

[17]As a further validity check, we run the second stage using the median indicator as an instrument. The results keep the expected sign and maintain statistical significance.

7 Information Mechanism

Having established the causal connection between corruption and sharp bunching, we investigate the mechanism one possible mechanism through which institutional quality affects our dependent variable. We believe that information is one channel through which the social stigma cost is influenced.

In line with the intuition sketched in Section 4, we expect that, being aware that institutions in the area are misbehaving, citizens perceive a decrease in social stigma and are more likely to misbehave themselves. We investigate the channel of newspaper coverage of corruption, which is one way information is spread. We expect the coefficient of news coverage to be positive when included as a regressor in a model with sharp bunching on the left-hand side. If news is indeed an intermediary, we expect the coefficient of corruption to decrease in magnitude. This would suggest that part of the effect previously detected is captured by newspaper coverage. We reestimate (5) by substituting $\log(1 + \text{Corruption})$ with our measure of news coverage, then adding news coverage to the linear model in Equation (5) and finally by including an interaction between the two variables. Results are presented in Table 4. The coefficient of our measure of corruption decreases by almost 10% when we add the measure of news coverage of corruption cases. Moreover, the positive coefficient on the interaction term suggests that the higher the coverage, the more corruption is associated with higher sharp bunching.

[Table 4 approximately here]

8 Conclusions

We provide evidence that corrupt institutions affect the micro behavior of self-employed workers across Metropolitan Statistical Areas. We do this by using a newly assembled dataset of corruption at the MSA level, which allows us to control for state-specific fixed effects. Using a research design that exploits variation in the accountability of local institutions, we find that a one standard deviation increase in our measure of local corruption increases the likelihood of observing sharp bunching in the EITC data among the self-employed by 0.6-0.83 standard deviations. Robustness checks rule out the possibility that our results are driven by confounding factors such as local social capital.

We interpret these results through the lens of the behavioral literature. In particular, we argue that an individual's likelihood of misbehaving in the context of tax compliance depends on a social stigma cost which is decreasing in the misbehavior of public officers in the same area. In line with this insight, we expect that the misbehavior of citizens is fostered by information on institutional corruption. We explore this channel by looking at how news coverage of corruption affects income misreporting. As suggested by the theoretical framework, we find that news coverage is indeed a channel through which local corruption affects the share of sharp bunching. When the variable that captures news coverage is included in the empirical model, the coefficient of corruption decreases by about 10%.

Our empirical results contribute to the literature on labor supply responses to government tax credit programs by showing that bunching at the kink of the EITC refund schedule is associated with—and in fact caused by—the quality of local institutions and not only by labor supply responses.

Finally, we contribute to the literature on corruption by shedding light on this rather unexplored channel through which corruption creates welfare costs and by building an estimate of local corruption at the MSA level.

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Figures and Tables

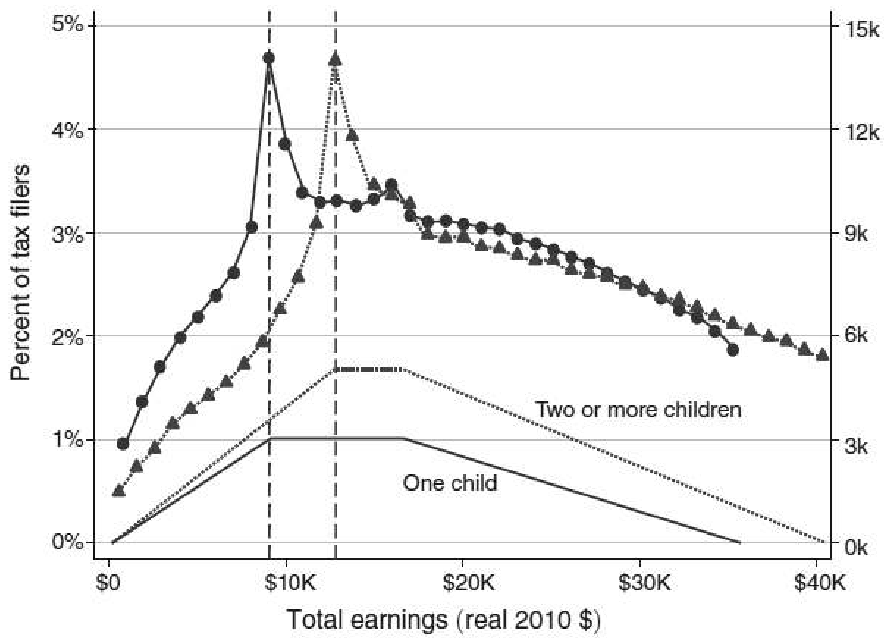

Figure 1: This figure shows the EITC schedule together with the distribution of reported income of self-employed workers. The solid line represents the EITC schedule for households with one qualifying dependent, whereas the line with circles represents the distribution of reported income of self-employed workers for the same households. The dotted line represents the EITC schedule for households with two or more qualifying dependents, whereas the line with triangles represents the distribution of reported income of self-employed workers for the same households. Source: Chetty et al. (2013).

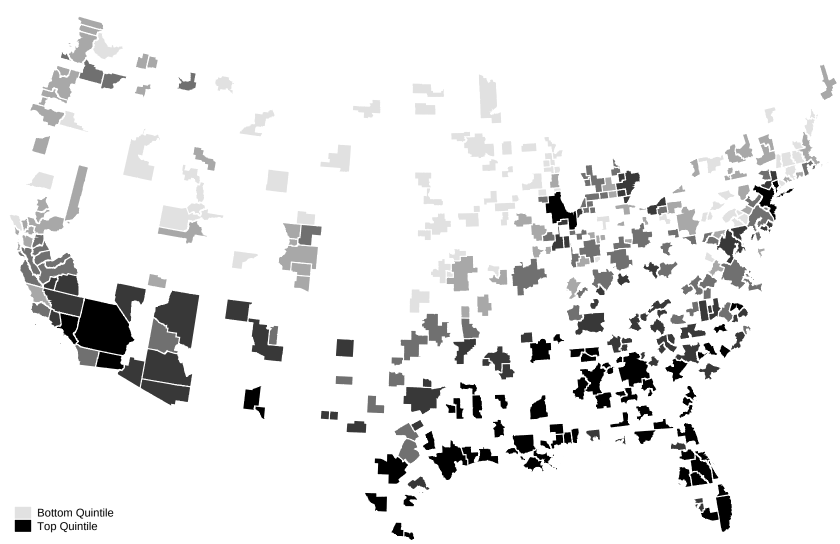

Figure 2: This map depicts the geographic distribution of self-employed sharp bunching.

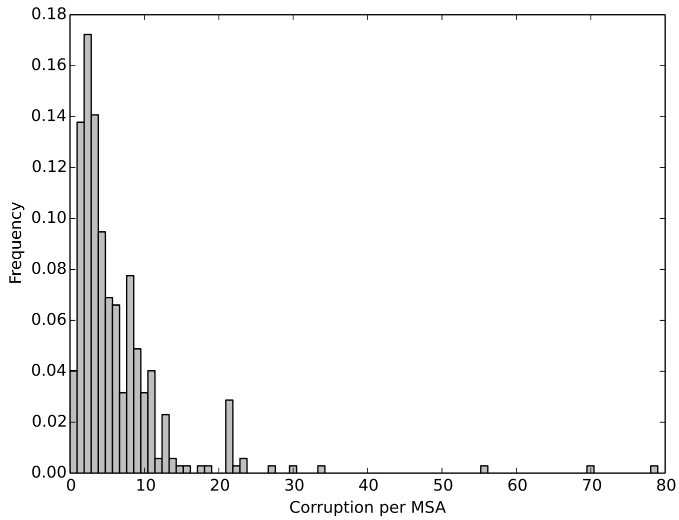

Figure 3: This plot shows the distribution of corruption at the MSA level according to the number of appeals ruled between 2000 and 2013.

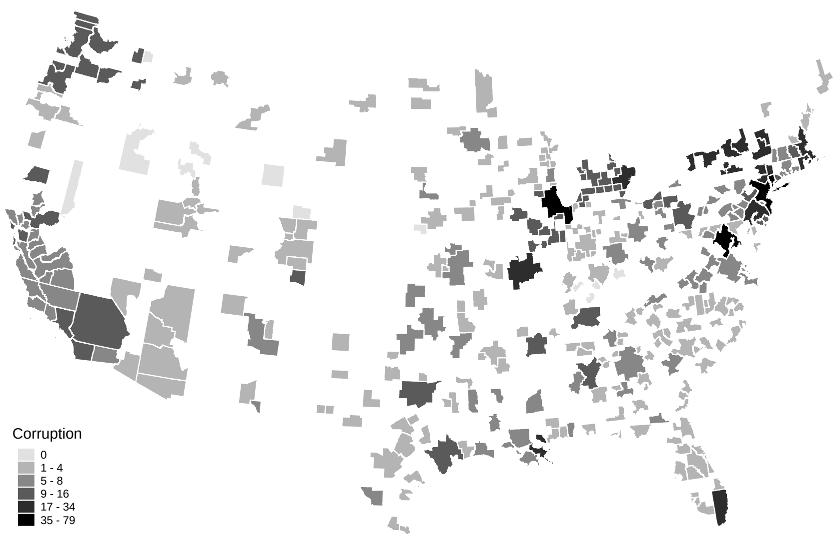

Figure 4: This map shows the geographic distribution of corruption across MSAs. MSAs are colored based on the number of appeals ruled between 2000 and 2013 that we selected—using the methods detailed in the text—because they involve a public official and show the federal government as the plaintiff.

Figure 5: This map depicts the geographic distribution of corruption per public employee.

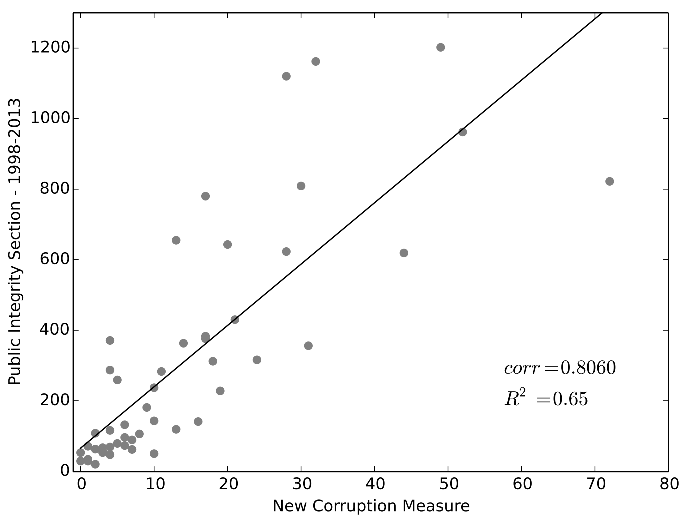

Figure 6: This graph is a scatter plot of the measure of corruption obtained using appeals from 2000 to 2013 aggregated at a state level versus the measure obtained using the PIS Report to Congress. The solid line represents the fit obtained through a linear regression. The two variables are highly correlated.

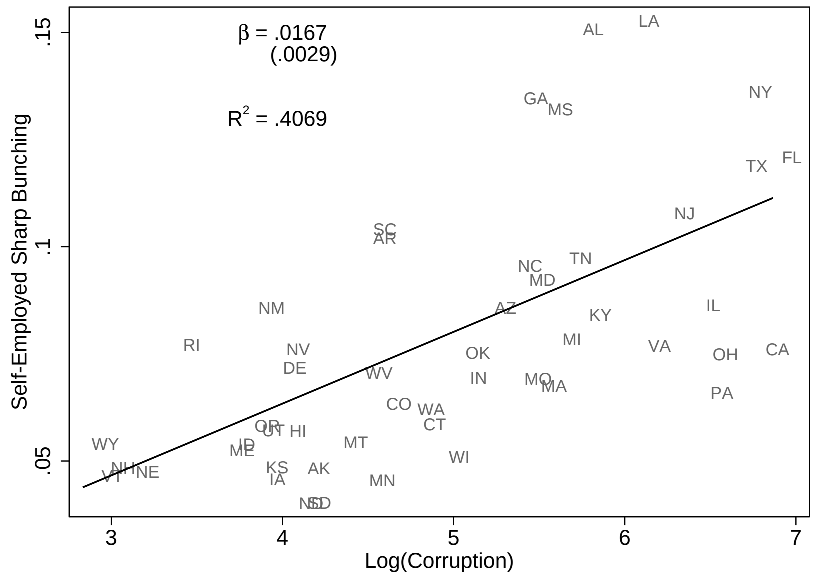

Figure 7: The figure shows the correlation between the measure of corruption at a state level as reported in the PIS Report to Congress and the level of sharp bunching. The share of sharp bunching is computed by taking the share of people in an $[-500\$, +500\$]$ interval around the refund-maximizing point of the EITC schedule for each ZIP-code and averaging it up to the state level using the number of EITC refund claimants as weights. The β coefficient is estimated through OLS in a linear model with a constant. Figure B4 in the Appendix plots an analogous graph, using corruption per public employee and the main result is unchanged.

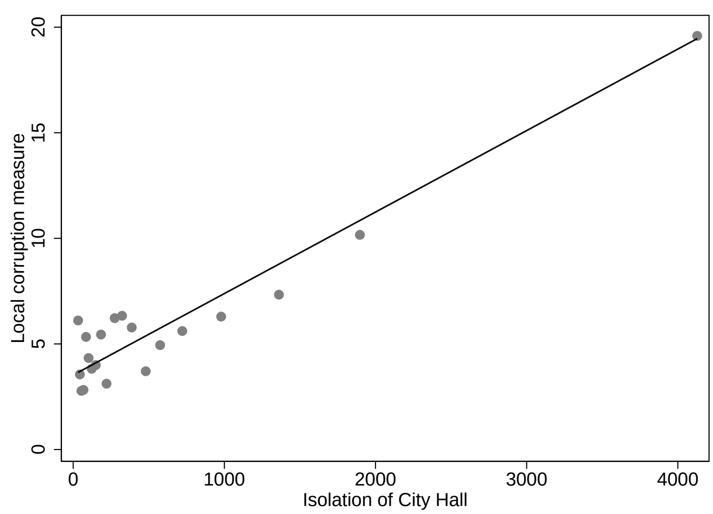

Figure 8: Binned scatter plot of MSA corruption against city hall isolation instrument. To exclude outliers, the isolation measure is constrained to be below the 99th percentile.

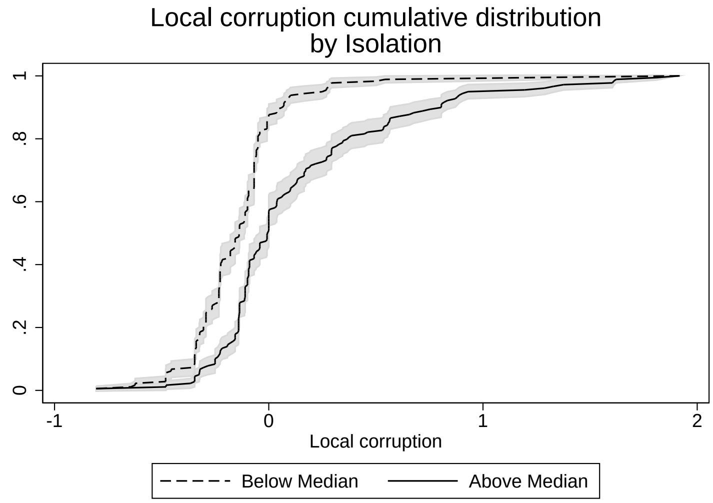

Figure 9: Monotonicity of the city hall isolation instrument. We first compute the residuals of the regression of the measure of corruption and of the instrument on state fixed effects to isolate within-state variation. We then discretize the (residual) instrumental variable, making it a dummy equal to 1 if the value is above the median and 0 otherwise. We then plot the cumulative empirical distribution of the (residual) endogenous regressor for the subsample of observations below and above the (residual) instrumental variable's median.

	Dependent variable: Share of Sharp Bunching			
$\log(1 + \text{Corruption})$	0.0132	0.0115	0.0111	0.0100
	(0.00382)	(0.00382)	(0.00294)	(0.00339)
$\log(\text{Annual Public Employees})$		0.00114	0.00189	0.00156
		(0.000755)	(0.000721)	(0.000764)
Share 10k Income Interval			0.199	0.198
			(0.0754)	(0.0795)
Children Under 18			0.161	0.147
			(0.0603)	(0.0735)
Minorities				0.0273
				(0.0185)
Constant	0.0270	0.0192	-0.0618	-0.0588
	(0.00573)	(0.00806)	(0.0324)	(0.0362)
States FE	Yes	Yes	Yes	Yes
Observations	357	357	357	357
R-squared	0.744	0.746	0.816	0.820

Standard errors clustered at the state level in parentheses

Table 1: This table reports outputs of OLS estimation of a linear regression model with the share of self-employed sharp bunching as dependent variable. All coefficients' estimates are reported except those state fixed effects. The main regressor of interest, $\log(1 + \text{Corruption})$, is the one described above in the text; $\log(\text{Annual Public Employees})$ is the logarithm of annual public employment level in 2012 at the MSA level; Share of 10k Income Interval is the share of people within the MSA whose income is included in a $\pm 10000\$$ interval around the first kink of the EITC schedule; Children Under 18 is the share of households with at least one child under 18; Minorities simply measures the proportion of the MSA's population that is an ethnic minority. As specified in the output, all specifications include state fixed effects.

	Dependent variable: Share of Sharp Bunching			
$\log(1 + \text{corruption})$	0.0236	0.0268	0.0304	0.0297
	(0.00616)	(0.00920)	(0.0106)	(0.0113)
log(Annual Public Employees)		-0.00117	-0.00101	-0.00104
		(0.00140)	(0.00162)	(0.00158)
Share 10k Income Interval			0.197	0.197
			(0.0677)	(0.0688)
Children Under 18			0.159	0.155
			(0.0455)	(0.0526)
Minorities				0.00721
				(0.0173)
Constant	0.0115	0.0175	-0.0629	-0.0621
	(0.00922)	(0.00774)	(0.0248)	(0.0264)
Observations	357	357	357	357
R-squared	0.726	0.715	0.767	0.771

Standard errors clustered at the state level in parentheses

Table 2: This table reports outputs of IV estimation of a linear regression model with the share of self-employed sharp bunching as dependent variable, using isolation of city hall as an instrument for the corruption measure. All coefficients' estimates are reported except those state fixed effects. The main regressor of interest, $\log(1 + \text{Corruption})$, is the one described above in the text; $\log(\text{Annual Public Employees})$ is the logarithm of annual public employment level in 2012 at the MSA level; Share of 10k Income Interval is the share of people within the MSA whose income is included in a $\pm 10000\$$ interval around the first kink of the EITC schedule; Children Under 18 is the share of households with at least one child under 18; Minorities simply measures the proportion of the MSA's population that is an ethnic minority. As specified in the output, all specifications include state fixed effects.

	Dependent variables:	
	Soc. Cap.	Sharp Bunching
$\log(1 + \text{Corruption})$	-0.00253	0.0237
	(0.00683)	(0.0119)
Soc. Cap.		-0.0340
		(0.0226)
Constant	0.791	0.0110
	(0.0299)	(0.0272)
Observations	353	353
R-squared	0.670	0.791

Standard errors clustered at the state level in parentheses

Table 3: This table reports outputs of IV estimation of two linear regression models with the share of Census respondents in 2010 as the dependent variable in the first column and the share of self-employed sharp bunching as dependent variable in the second column, using isolation of city hall as an instrument for the corruption measure in both specifications. In both columns $\log$(Annual Public Employees), Share of 10k Income Interval, Children Under 18, Minorities, and state fixed effects are included as controls.

	Dependent variable: Share of Sharp Bunching			
	OLS	OLS	OLS	IV
$\log(1 + \text{Corruption})$		0.00846	0.00959	0.0271
		(0.00252)	(0.00297)	(0.00961)
Corruption News Coverage	0.00430	0.000298	0.00408	0.00367
	(0.00245)	(0.00309)	(0.00213)	(0.00156)
$\log(1 + \text{Corruption}) \times$ News		0.00251		
		(0.00184)		
Constant	-0.0566	-0.0568	-0.0582	-0.0611
	(0.0343)	(0.0309)	(0.0312)	(0.0230)
Observations	351	351	351	351
R-squared	0.820	0.836	0.832	0.794

Standard errors clustered at the state level in parentheses

Table 4: This table reports outputs of OLS and IV estimation of linear regression models with the share of self-employed sharp bunching as dependent variable, using isolation of city hall as an instrument for the corruption measure in the last column. In all the columns $\log$(Annual Public Employees), Share of 10k Income Interval, Children Under 18, Minorities, and state fixed effects are included as controls. The measure of news coverage has been standardized and has 0 mean and standard deviation 1.

9 Appendix

A Tables

[Tables A1 and A2 about here]

Geographic Domain	Time Span Covered	Variable	Mean	St. Dev	Min	Max	Obs.
State	1998-2013	Corruption - PIS/DOJ	313.7	326.3745	20	1202	50
	1996-2009	Self-Employed Sharp Bunching Rate	0.0774	0.0294	0.0401	0.1528	50
	1998-2013	$\log(\text{Corruption})$	5.1403	1.1164	2.9957	7.0917	50
MSA	2000-2013	Corruption	6.1064	7.8239	0	79	357
	2000-2013	Corruption per Public Employee	0.001	0.0037	0	0.0466	357
	2000-2013	$\log(1+\text{corruption})$	1.6383	0.7703	0	4.3820	357
	2000-2013	Corruption news coverage	0.0032	0.0021	0	0.0223	351
	2012	log(Annual Public Employees)	9.6746	1.3626	5.4638	13.4134	357
	1996-2009	Self-Employed Sharp Bunching Rate	0.0778	0.0302	0.0363	0.2215	357
	2010	Share 10k Income Interval	0.1933	0.0439	0.0872	0.3408	357
	2010	Children Under 18	0.2942	0.0440	0.1520	0.4881	357
	2010	Minorities	0.1996	0.1175	0.0318	0.7699	357
	2010	Isolation of MSA's City Hall	711.8463	1545.99	24.2315	16571.35	357

Table A1: Summary Statistics

	Dependent variable: $\log(1+\text{corruption})$
Isolation of MSA's City Hall	0.000122
	(3.07e-05)
log(Annual Public Employees)	0.0764
	(0.0135)
Share 10k Income Interval	0.450
	(0.604)
Children Under 18	-0.0970
	(0.986)
Minorities	0.544
	(0.323)
Constant	0.608
	(0.349)
States FE	Yes
Observations	357
R-squared	0.842
Cragg-Donald F	15.73

Standard errors clustered at the state level in parentheses

Table A2: This table reports the first stage estimations and diagnostics with the full set of controls.

B Figures

[Figures B1, B2, B3, and B4 about here]

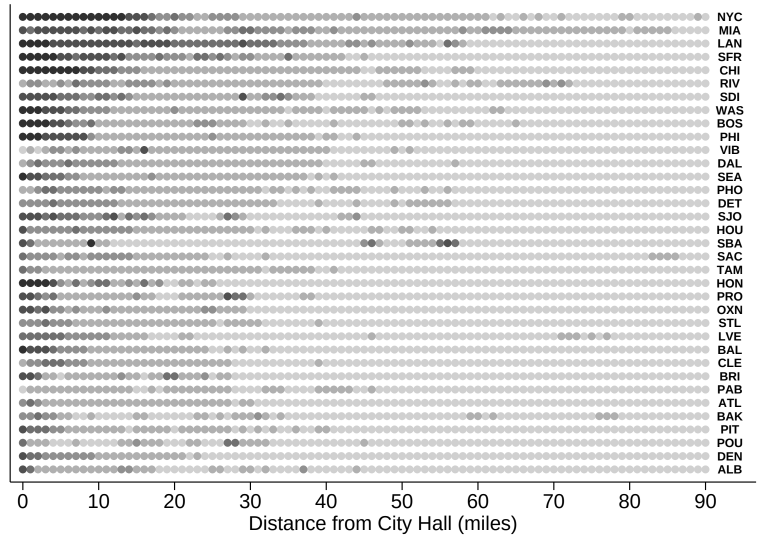

Figure B1: This graph depicts the distribution of population density moving out from the main city hall in the MSAs for the top first decile of the distribution of isolation. The x-axis shows the distance in miles from the main city hall within the MSA and each cicle represents the population density measured in one-mile distance bands radiating out from the city hall. The darker the dot, the higher the density.

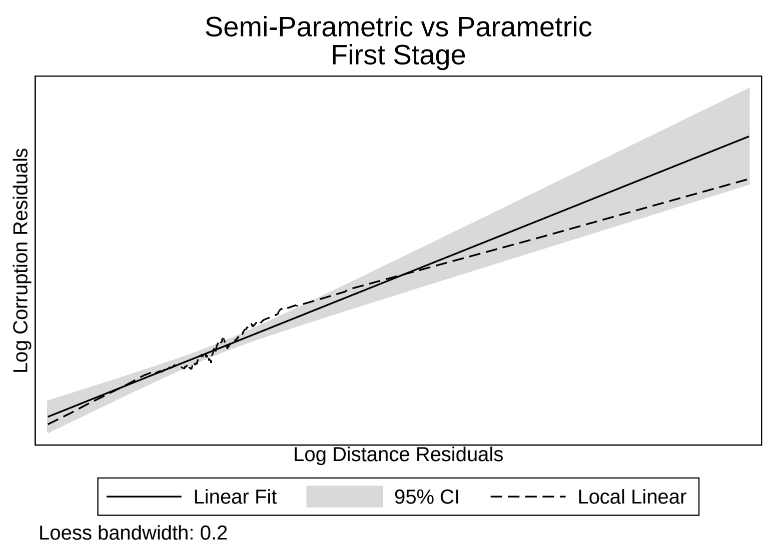

Figure B2: The graph plots the parametric and semiparametric relationships between the endogenous regressor ($\log(1 + \text{Corruption})$) and the instrument (isolation of the city hall), linearly conditioning on covariates.

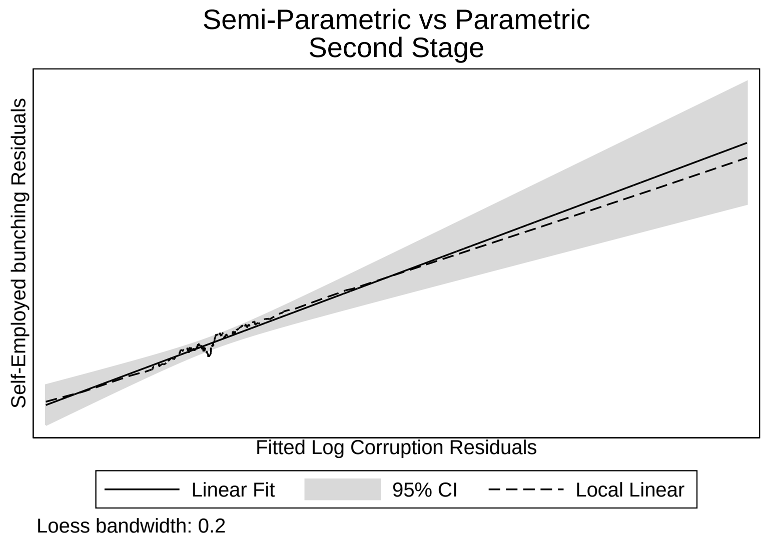

Figure B3: The graph plots the parametric and semiparametric relationships between the dependent variable (share of sharp bunching) and the fitted values of the endogenous regressor ($\log(1+\text{Corruption})$), linearly conditioning on covariates.

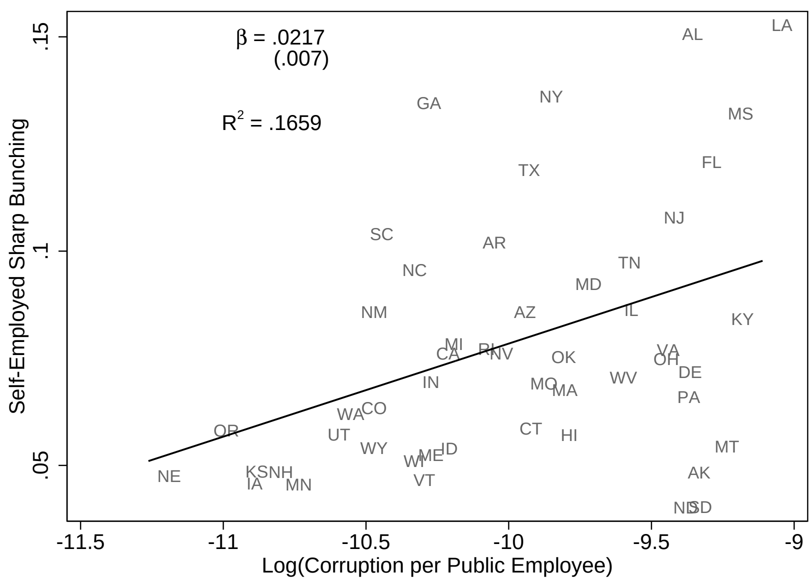

Figure B4: The figure shows the correlation between the measure of corruption per public employee and self-employed sharp bunching at the state level. The β coefficient is estimated through OLS in a linear model with a constant.

C Proof of Proposition 1

A shift downwards in θ_i clearly decreases the cutoff x_i^* above which people in group i will misbehave. To sign the derivative of x_c^*, the cutoff in the citizens group, with respect to x_i^*. We totally differentiate the equilibrium condition in (2) in group c, given the structure of the stigma parameter given by (3) in the main text.

$$
\begin{aligned}
& -dx_c^* v'(x_c^*) = dx_c^* \phi'(x_c^*)\mu_c + dx_i^* \phi(x_c^*) \frac{\partial \mu_c}{\partial x_i^*} \\
\iff & \frac{dx_c^*}{dx_i^*} = -\frac{\phi(x_c^*) \frac{\partial \mu_c}{\partial x_i^*}}{v'(x_c^*) + \phi'(x_c^*)\mu_c} = \frac{\phi(x_c^*)\psi'(x_i^*)}{v'(x_c^*) + \phi'(x_c^*)\mu_c} \geq 0.
\end{aligned}
$$

The sign of the expression above is given by the fact that (i) by definition, $\phi(x) \geq 0$, (ii) by assumption, $\psi'(x) > 0$, and (iii) by the assumption on uniqueness of the equilibrium, $v'(x_g^*) + \phi'(x_g^*)\mu_g > 0$, $\forall g \in \{i, c\}$. Given these results, it is clear that a decrease in the cutoff x_i^* will decrease the cutoff x_c^* and raise the share of misbehaving people in group c.

FOR ONLINE PUBLICATION

Keywords

former city councillor for the; bribery of a public official; public corruption offenses; working as a rural letter carrier for the United States Postal Service; former agent of the Federal Bureau of Investigation; was an officer of the [City Name] Police Department; beating of a civilian; was a police officer employed by the [City Name] Police Department; was a teacher at; was a large electrical contractor; Director of the Republican National Committee; worked as a principal at various elementary and middle schools; former FBI agent; was the [State Name] State Treasurer; formerly a police officer in the city; was a procurement officer at the United States Forestry Service in [State Name]; was a defense contractor; collected property taxes on behalf of [State Name] County; [State Name] state senator; former Governor of [State Name]; years of service in the United States Coast Guard; number of charges relating to a political corruption scheme ; embezzlement of union funds; using his position as a public official ; former [City Name] police officer; working as a life guard instructor; former FBI informant; was elected to the [City Name] Common Council; worked as a uniformed patrol officer for the; former deputy sheriff in [County Name] County; was convicted on bribery; was a [City Name] police officer; highway project fraud; as deputy liquor commissioner for [City Name]; was a member of the [City Name] City Council; was corrupt narcotics detective; former state senator in [State Name]; was corrupt narcotics detective; toiled as an elementary-school music teacher in; former mayor of [City Name]; in exchange for political favors; bribery of a public official; while stationed at; worked as a contractor; the former mayor of; was a Deputy U.S. Marshal; former Treasurer of the State of; served for many years as a city councilman; former police detective; becoming Commissioner of the Department of Streets and Sanitation; was a Special Agent of the Federal Bureau of Investigation; was the Sheriff of; former correction officer; was a local government official ; was a section chief for the U.N.; was a supervising building inspector for the City; former Senator in the [State Name]; former federal corrections officer; veteran of the [City Name] Police Department; former member of the [State Name] House of Representatives; was employed as a Federal Customs and Border Patrol officer; worked as a public defender; participating in bribery schemes; former deputy sheriff; for bribing an Immigration and Customs Enforcement; worked in the administrative offices of; honest services mail fraud; was a public information officer; honest services fraud; was a law enforcement officer; was employed as an inspector for the United States Customs; formerly a police officer; former county coroner; was an auto theft detective; conflicts of interest by public officials; mail technician at the USPS office; was a Special Agent with the U.S. Secret Service; former official of the; honest services mail and wire fraud; Air Force Staff Sergeant; was convicted of bribery; were employed at McChord Air Force Base; former state senator; formerly the Sheriff of; was a high-ranking official; was Treasurer of the City of ; former state judge; served as the treasurer for the city of ; was a police officer of; worked as a federal immigration employee; honest services wire fraud; worked as an Examinations Assistant in the United States Citizenship and Immigration Services Bureau; served as a member of the [State Name] House; the Supervisor of Building Inspectors for the City of [City Name] Department of Buildings; corrupt and far-reaching scheme; was an officer with the [City Name] Police Department; served as police commissioner; served as an elected county commissioner; working as the payroll clerk; worked for the United States Department of Housing and Urban Development; served as an Assistant City Attorney; served as mayor of the City of; was seeking reelection; at that time a detective in the narcotics unit; former [City Name] police officer; were correctional officers at; former officer in the; incumbent Sheriff of ; [City Name] City Councilman; former Governor of; constitutional violations by the; was County Commissioner of; former police officer; formerly a Commissioner for; deprivation of honest services of a public servant; a [County Name] County Corrections Officer; abetting honest-services mail fraud; was elected as a [County Name] County commissioner; was hired by the U.S. Postal Service as a letter carrier; a former officer of the Federal Protective Service; officers' subsequent conspiracy to conceal this assault; former [County Name] County Commissioner; formerly an officer of the; former zoning official for; member of the United States Army; served as the county attorney; Civil Rights of Institutionalized Persons Act; worked as law enforcement officers; worked as representatives of the; was a law enforcement officer; was the Director of the Division of Physical Services; was a senior inspector in the Air Quality Division; county-owned health-care provider; conviction for bribery and conspiracy to defraud the United States; was a political appointee; was an officer in the United States Navy; election fraud crimes; worked as a special police officer for the; section chief in the state's Bureau of Procurement; bribery of federal officials; former [State Name] Governor; work for former United States Representative; was an Alderman for ; former Chief of Staff for the mayor of; was elected as the; Director of the [State Name] Republican State Committee; the director of the Joint Apprenticeship Committee; worked at the Department of