Fiscal Capacity and Execution at the Local Level: New Evidence from Brazil*

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Abstract

This paper introduces a new disaggregated and harmonized dataset on public procurement and budget execution by Brazilian subnational entities, which covers half of Brazilian municipalities and spans the years 2003-21. This dataset provides key information that was previously unavailable from aggregate data, such as the identities of suppliers, details on purchases of goods and services, and granular information on the life cycle of each expenditure action. It then uses these data to provide new stylized facts about local public finance. First, it shows that about one-quarter of government purchases are locally procured and discusses implications for efficiency. Second, it demonstrates that close to 15 percent of payments exceed the 30-day threshold and that payment timeliness is systematically correlated with the income level of the municipality. Finally, it shows that municipalities where mayors have reelection incentives systematically employ more non-competitive tenders and buy more from local suppliers.

Keywords: Subnational Public Finance; Procurement, Budget Execution
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1 Introduction

The last decades have seen a remarkable expansion in the number of subnational units across the world and their roles in providing public services (Gadenne and Singhal, 2014; Grossman and Lewis, 2014; Dahis and Szerman, 2025). As their role in service provision increased, so did their economic relevance – in Brazil, municipal procurement was equivalent to approximately 3% of GDP between 2002 and 2019, or about 25%-30% of total purchases by all levels of government – federal, state, and municipal (Thorstensen and Giesteira, 2021).

Data on local governments are often only available at an aggregate level, e.g. the total amount of purchases of goods and services, the total amount spent on health services, and the total amount of accrued liabilities. Consequently, many simple yet important questions related to the public finances of these units remain unanswered. Which are the suppliers of local governments, and what are their characteristics (e.g., size, location)? What is the share of purchases that happen through competitive tenders versus non-competitive methods? When competitive auctions take place, what is the degree of competition?

Another crucial dimension of local governments' finances is how they execute their budgets. While aggregate commitment and spending amounts are easier to come by, we know little about the details of the budget execution. For instance, how long does it take to pay suppliers after deliveries are recognized? Is there a large variability in the payment timeliness across purchases within the same government? Do governments treat suppliers equally regarding payment timeliness? Answers to these questions can shed new light on the effectiveness of local governments and on their interaction with other economic agents. Similarly, when facing liquidity constraints, do governments prioritize the payment of some government functions at the expense of others? Payment delays impose several costs on suppliers and might affect the provision of public goods (Flynn and Pessoa, 2014). The importance of this issue is reflected in several recent regulations and initiatives that governments implemented in an attempt to shorten payment terms.[1] Yet, the scarcity of granular data on the stages of the budget execution renders the answers to these questions elusive.[2]

In this paper, we introduce a new dataset on municipal public finance in Brazil (MiDES, *Microdados de Despesas de Entes Subnacionais*) that allows researchers to answer several of these questions.[3] We collect, clean, and harmonize microdata on public procurement and

[1]Examples include the QuickPay initiative, launched in 2011 in the United States; Regulation 113 of the Public Contracts Regulations, passed in 2015 in the United Kingdom; and the introduction of the Centralized Payment Platform (PPC) in 2020 in Chile.

[2]According to Potter et al. (1999): "For the fiscal economist seeking to monitor budget execution, choosing which stage(s) of the expenditure management procedure to monitor is often constrained by information availability. In principle, the data given at the verification stage may be particularly relevant because they measure the actual liability of the public entity and thus the accrued account liability. For example, if bills are verified promptly when they arrive, it allows a good measure of the potential arrears, where strict cash limits constrain the amounts available to make payments. But such information is rarely available."

[3]The English translation of *Microdados de Despesas de Entes Subnacionais* is Subnational Entities' Expenditure Microdata.

budget execution that covers more than half of the total municipalities of Brazil and represents over 40% of the country's population. Our procurement dataset allows researchers to see information on specific tenders, such as the number, reserve price, and description of items being sold, the number of participants in competitive tenders, and the identity of participants and winning parties. On the budget execution side, the data includes information on each commitment, verification (an important step in the budget spending when buyers recognize that a good or service was delivered), and payments, again allowing researchers to see the identity of payees and the amount and dates of each step of the budget execution. In particular, we can compute the time to pay a particular transaction by using the time elapsed between the verification and payment stages.

The dataset we build is fully and publicly available on the Data Basis (*Base dos Dados*) platform (Dahis et al., 2022).[4] The platform provides high-quality data at scale, with tools such as a curated search engine and an SQL-powered data lake where tables share a unified schema. The platform allows users to seamlessly query and merge hundreds of tables, across a variety of themes, directly on Google BigQuery.[5] All code used to generate our dataset is publicly available on GitHub.

We collect our data from State Audit Courts (*Tribunais de Contas dos Estados*, TCEs). These courts are independent institutions that supervise the public finances of the municipalities of their states. One important concern is the quality of the data – are municipalities providing accurate information on procurement and budget execution, or are they providing incomplete and selective information? We test the quality of our budget data by generating aggregates from our microdata and comparing them with information from the Brazilian Public Sector Accounting and Tax Information System (*Sistema de Informações Contábeis e Fiscais do Setor Público Brasileiro*, SICONFI), a dataset maintained by the National Treasury to "facilitate the production and analysis of accounting and tax information, standardize consolidation mechanisms and increase the quality and reliability of accounting information, financial and fiscal statistics received from municipalities, states, the Federal District and the central government." We show that our aggregates closely match those of the SICONFI, not only at the municipality-year level but often at the more disaggregated level of function, which is a classification that groups expenditures according to their purpose (e.g., health, education, security). We also provide quality checks on the procurement data, showing that key features observed in federal procurement microdata, such as bunching below the maximum value threshold for competitive tender waivers, also replicate in our municipal dataset.

We exemplify possible uses of our data with three applications. First, we evaluate the extent to which local governments buy from suppliers located in the same municipalities. García-Santana and Santamaría (2025) show compelling evidence of home bias in the Euro-

[4]Available as the *Microdados de Despesas de Entes Subnacionais* (MiDES) dataset at https://data-basis.org/dataset/d3874769-bcbd-4ece-a38a-157ba1021514.

[5]In Appendix B, we illustrate how the dataset can be seamlessly queried to perform descriptive analyses using R.

pean Union and discuss its implications for the value-for-money of public procurement. We show how our microdata allow us to identify each government supplier and identify their location using publicly available data from *Receita Federal*. We then document that approximately 25% of suppliers of local governments are located in the same municipality, but with wide variation across entities. Local purchases are less prevalent in smaller municipalities, which could be driven by the scarcity of local suppliers, and more prevalent when suppliers are selected through non-competitive procurement methods. For a smaller subset of municipalities, we can also use publicly available data on federal purchases to compare the prevalence of local suppliers between municipal governments and federal entities based on those municipalities (e.g. compare purchases from the government of Porto Alegre with those of the Federal Military Hospital of Porto Alegre). Consistent with the findings of García-Santana and Santamaría (2025), we also find a much higher share of local purchases from municipal buyers, within the same municipality.

Second, we document the extent of delays in payments to suppliers across municipalities in the country and how it correlates with municipal characteristics. Payment delays are considered one of the key barriers to the participation of small and medium-sized enterprises (SMEs) in public procurement since they often have less access to working capital loans and are unable to wait for longer periods of time before being paid by their clients (Barrot and Nanda, 2020; Breza and Liberman, 2017; Barrot, 2016; Conti et al., 2021). By law, public entities in Brazil are mandated to pay their clients in less than 30 days as a rule.[6] However, late payments are common – we document that 15% of all payments to suppliers of goods and services in recent years are made in more than 30 days, and 20% of municipality-year observations have an average payment speed over 30 days. Payment timeliness is also systematically correlated with local per capita GDP, with higher-income municipalities paying faster on average. The granularity of the data allows us to show that aggregate quantities, such as the average payment speed, might hide a strong variability in payment timeliness across suppliers and types of purchases. This is an instance in which microdata is crucial for a proper assessment of the quality of the budget execution process of a municipality.

Third, we show how our newly available measures of purchases via non-competitive methods and the share bought from local suppliers correlate with mayors having reelection incentives. We estimate a regression discontinuity (RD) design comparing municipalities where the elected mayor was in their first term versus where they were in their second term and thus term-limited. We find that municipalities with a first-term mayor have 6 p.p. more non-competitive tenders and 3.5 p.p. more purchases from local suppliers. These findings help connect two strands of literature, one studying rules versus discretion in public procurement (e.g., Szucs, 2024; Fazio, 2025; Decarolis et al., 2025) and one studying reelection incentives

[6]Public procurement in Brazil was primarily governed by Law No. 8,666/1993 until 2021. Article 40 of this law established the rules regulating payment conditions. In 2021, Law No. 8,666 was revoked and replaced by Law No. 14,133/2021, which introduced a new legal framework for public procurement and administrative contracts.

and governance (e.g., Ferraz and Finan, 2011; Dahis et al., 2025a). One possible explanation is that first-term mayors strategically use public procurement to build local networks of support, channeling resources through less competitive tenders and local suppliers who may, in turn, provide electoral backing. Another possible explanation is that first-term mayors bring in new bureaucrats, who have less experience with public procurement and who default more frequently to discretionary purchases. We leave this and other questions – now unlocked by the availability of new data – for future research.

The remainder of this paper is organized as follows. In Section 2, we provide further institutional details on procurement and budget execution in Brazil and present some statistics from our datasets. We then proceed to validate the quality of our budget execution and procurement data in Section 3, producing metrics of internal consistency as well as comparing aggregates constructed from microdata to information available at SICONFI. In Section 4, we illustrate two applications of this new dataset. Finally, we conclude in Section 5 by discussing other avenues of research using these new data.

2 Institutional context and data

Municipalities in Brazil are the lowest levels of government administration, after the federal and state governments. As of 2024, there were 5,569 municipalities across 27 states. The typical municipality is small, with a median population of approximately 11,000 individuals; while the 15 largest municipalities had populations above 1 million, including São Paulo with over 11 million inhabitants. The Brazilian Constitution assigns to municipalities the responsibility for specific service provision, including access to basic health, primary education and other local services such as garbage collection, sanitation and street lighting (Dahis and Szerman, 2025). These priorities are reflected in how municipalities allocate their budgets: in 2023, close to 50% of municipal expenditures were towards health and education provision vs. less than 30% among Brazilian states (Tesouro Nacional, 2023).

Our dataset on public procurement and budget execution of Brazilian municipalities is constructed from data that state audit courts (TCEs) assemble. The mission of these courts is to oversee the fiscal policy of states and municipalities, which includes taxation, spending, and budget execution. TCEs are present in each of the twenty-six Brazilian states plus the Federal District.[7]

All data used to construct our dataset are publicly available, often in transparency portals provided by the TCEs.[8] The structure, coverage, and quality of the raw data vary across states and often across municipalities in the same state. For those reasons, the data require

[7]In the states of Rio de Janeiro and São Paulo, the TCEs oversee all municipalities apart from the capitals, which have their own audit court. Three states – Bahia, Goiás, and Pará – have two audit courts: one that oversees the state government and one that oversees all municipal governments within the state.

[8]We provide links to all the raw data we use in Table A.1.

extensive upfront work to be harmonized, cross-checked, and cleaned for usage. The dataset we build is fully and publicly available on the Data Basis (*Base dos Dados*) platform.[9] This is an ongoing project that currently covers 3,076 (out of 5,570) municipalities in 7 states (out of 27), and we expect to keep expanding the data to the extent possible.[10] We provide all code used to download, clean, and produce the final datasets on GitHub. Below we provide more explanation of the institutional context and key variables related to public procurement and budget execution.

2.1 Public procurement

Public procurement is the process through which governments acquire goods and services. In the period covered by our data, procurement by all government entities (federal, state and municipal) was regulated by the same public procurement law (Law No. 8,666/1993).[11] The procurement process starts with some demand from a public entity – a typical demand in the municipalities in our dataset is to hire a firm to service the vehicles in the municipal fleet. The procuring unit will then prepare a procurement project, which will include a detailed description of the specifications of the service to be provided and an estimated value, based on market research. The next step is then to decide the purchase method. As a rule, purchasing entities in Brazil are expected to run competitive tenders when buying goods and services. The specific method used, such as reverse auctions, invitations to tender or framework agreements, will depend on the nature of the good or service to be acquired and its estimated value. In exceptional circumstances (such as when there is only one feasible supplier or during an emergency) or when purchase values are small, officials can waive tenders and directly contract with suppliers (see Table A.2 for more details on each of the available procurement methods in Brazil during our study period; see also Fazio, 2025).

Our municipal public procurement dataset is organized into three tables: *tender*, *tender-item*, and *tender-participant*.

In the *tender* table, one observation is a tendering procedure that some agency in a given municipality executes. These tenders can vary widely in nature: one tender might refer to an auction for the purchase of several different pharmaceutical products, with several bidders competing for each product; while another might refer to the direct hiring of a musician for a local concert. Tenders are often comprised of several *items*, so they should be thought of as a batch of items that are separately sold – one tender might contain, for example, ten different

[9]Available as the *Microdados de Despesas de Entes Subnacionais* (MiDES) dataset at https://basedosdados.org/dataset/d3874769-bcbd-4ece-a38a-157ba1021514.

[10]The first seven states included in the dataset were chosen due to data availability, granularity and ease of access. For some states we could not find any public data on the website of TCEs; in others, data were available for download but required complex scraping; yet others provide public data for download but the quality is low e.g. no detailed budget execution information.

[11]A major procurement regulation reform was approved in 2021 (Law No. 14,133/2021) but only enacted starting in 2024, after the period covered in our dataset.

items that are purchased from four different suppliers. Each tender observation in our dataset often includes dates related to the start of the procurement process, a general description of the items being purchased (like "purchase of cleaning goods for city hall" or "hiring of mechanical services"), classifiers for broad groups of goods and services, the modality used for the purchase, and the total estimated value for that batch. While these are information available at the onset of the tender process, in the dataset we also include the final status of the tender – if it was completed, canceled or deserted, for example. Each tender process is uniquely identified by the variable `id_licitacao_bd`.

In the *tender-item* table, each observation is an item – one of the many individual goods or services being purchased in a batch under the same specific tender. Items will often include a textual description of the specific purchase (e.g., "cleaning detergent 0.5L" or "accounting services"), quantities and prices. For the majority of cases, unit prices or total prices refer to the final awarded price to winning participants. In some cases, the item will separately describe the "quoted" prices, before the execution of the tender, and the price for the winning proposal. The item dataset also includes the name and document number of the winning entity, which can be a firm or individual. Each item is uniquely identified by the variable `id_item_bd` and can be connected to tenders by the variable `id_licitacao_bd`.

Finally, in the *tender-participant* table each observation is a participant in a given tender. Some municipalities will only provide winners in each tender, so in that case these will be the same as those listed in the tender-item table. Others will include all participants in a tender, including those that did not win any contracts. Notably, this data does not include bidding information for non-winning participants, neither on modalities where participants submit a single bid, such as invitation to tender, nor on auctions, where each participant can bid multiple times.[12] The data includes names and document numbers of each participant, as well as an indicator of whether they are winners. Each participant is uniquely identified by the pair of variables `documento` and `razao_social`, and can be connected to tenders by the variable `id_licitacao_bd`.

2.2 Budget execution

Budget execution refers to the implementation of the annual budget that is approved by the local legislature. While much of the analytical work presented in this paper focuses on budget execution of public procurement, the tables on budget execution include all activities performed by municipalities, including payment of salaries, transfers, and others.[13]

[12] As a benchmark, bid-level data exists for example for the Federal ComprasNet website, used by Ferraz et al. (2015) assess the impact of winning procurement contracts on firms' growth. The state of São Paulo also provides bid-level data on state auctions through the Bolsa Eletrônica de Compras (BEC-SP) website.

[13] Brazil adopts a budget classification system in which the economic classification of expenses (*elemento de despesa*) is comprised of 69 groups that are identified by a two-digit code (see the *Portaria Conjunta STN/SOF/ME nº 103/2021* for more details). For the analyses of the payment speed part of this paper, we restrict the data to three groups related to purchase of goods and materials: consumption material (code 30), material for free

The budget execution process in Brazil is similar to that in other countries.[14] It consists of three distinct steps: commitment, verification, and payment. The commitment (*empenho*) phase is the moment when governments set aside part of the budget appropriated to them for a specific activity, such as buying goods from a supplier or paying salaries of health workers. From a budgetary perspective, this is often seen as the moment an expenditure is recognized, since committed amounts are deducted from the budget appropriation. The second step of the budget execution is the verification (*liquidação*). It occurs when the government acknowledges that a certain service or good has been provided. This is the equivalent of recognizing a debt with a provider and is considered an expenditure from an accrual accounting point of view. In fact, if an expenditure was verified but not paid, it is recorded as accounts payable (*restos a pagar processados*), and, as with firms, increases in this amount might reflect a deterioration in the ability of governments to meet short-term obligations.[15] The final step of the budget execution is the payment (*pagamento*), when governments transfer the money to their suppliers.

Our municipal budget execution dataset is organized into three tables: *commitment*, *verification*, and *payment*.

In the *commitment* table, one observation is a commitment by one agency in a given municipality. Commitments vary from very large expenses, such as the commitment for the entire wage bill of the mayor's office in a month, to very specific commitments such as the acquisition of replacement parts for a car. Each commitment is often linked to four levels of "functional programming" that map the nature of a commitment (such as Transportation > Road Transportation > Road Recovery > Recovery of a specific road in a given street), as well as a text that explicitly describes the nature of the commitment.[16] After an initial commitment, officials can increase or decrease the amounts committed as well as annul them. Across municipalities in our dataset, the quality of tracking these actions after initial commitment varies, but we include initial, increases, annulments, adjustments, and net amounts for each commitment when these are available. Each commitment is also linked to a unique identifier (`id_empenho_bd`) that allows users to connect a commitment to verification and payments linked to them.

In the *verification* table, observations are verifications by some agency in a given municipality, which are always linked to a specific commitment. The key information available for each verification is the date when they happen, the initial value verified, any adjustments to the original value and the final value. One commitment might generate one or more verifications, so each verification is uniquely identified by the variable `id_liquidacao_bd` and can

distribution (code 32), and equipment and permanent material (code 52).

[14]For an overview of recommended budget execution practices and a cross-country comparison, see Potter et al. (1999), Chapter 4.

[15]As of December 2022, the local and state governments registered as accounts payable to suppliers of goods and services (account *Fornecedores e Contas a Pagar a Curto Prazo*) a total of R$ 75.6 billion (or 0.76% of the GDP).

[16]For a detailed discussion of expenditure functions see Manual do Orçamento (in Portuguese).

be connected to commitments by the variable `id_empenho_bd`.

Finally, for the *payment* table, each observation is a payment made to a specific entity. Payments can often (but not always) be linked back to a specific verification. The key information available in the payments table is the date of payment and values. The dataset also includes variables with the names and "document number" of payees - these are often unique national identifiers for individuals (CPF) and firms (CNPJ) but are not available for all payments or municipalities. Again, one verification event can lead to one or multiple payments, so payments are uniquely identified by the variable `id_pagamento_bd` and can be linked back to verification events by `id_liquidacao_bd` and to commitments by `id_empenho_bd`.

2.3 Coverage and descriptive statistics

Our dataset on municipal procurement and budget execution currently covers seven of Brazil's twenty-seven states, highlighted in Figure 1: Ceará (CE), Minas Gerais (MG), Paraíba (PB), Pernambuco (PE), Paraná (PR), Rio Grande do Sul (RS), and São Paulo (SP). These are large states that cover a substantial share of the total number of municipalities (55%), population (48%), and GDP (49%) of the country according to 2020 data. Notably, our dataset only covers states in the South, Southeast and Northeast regions - data from the states in the North and Center-West regions are currently not available. We display some descriptive statistics for municipalities inside and outside our sample in Table 1. The two sets of municipalities have similar average population, but we note that those in our sample are generally better off. They have higher GDP per capita, lower child mortality, higher access to public services, higher total revenues per capita, and higher local tax revenues per capita. This is consistent with our better coverage of the richer South and Southeast regions of Brazil.

We provide further details on the geographical and temporal coverage of the dataset in Table 2. Starting with geographical coverage, our budget execution tables (commitment, verification, and payment) are available for all seven states. The procurement data are less comprehensive: the dataset currently includes no procurement data for SP, and the data for PB and PE include information on tenders and participants, but not on the more disaggregated level of items. In terms of temporal coverage, most of our budget execution data starts in the early- to mid-2000s, with the exception of PE (2012), PR (2013), and MG (2014), and currently runs until 2021. Once again, data on procurement is less comprehensive and, with the exception of CE (2009-2021), starts in the mid-2010s.

In Table 3 and Table 4, we provide simple descriptive statistics from our public procurement and budget execution datasets, respectively. For procurement, across the six states covered, we observe over 2.4 million unique tenders and almost 800,000 unique suppliers. Since we observe microdata on each tender and often items, we are able to compute statistics such as the share of tenders that are deserted and/or unsuccessful (e.g., no bidders in a competitive tender) and the average number of items listed in a tender. We can also document, for example, that across states approximately 30%-40% of tenders are not competitive auctions – meaning they are directly awarded to suppliers by means other than an auction – but in terms of total purchase value these non-competitive tenders always represent less than 20% of total amounts. This is consistent with the fact that, similar to other countries, Brazilian law allows small purchases to be performed without competitive auctions (Fazio, 2025). We can also compute measures of competitiveness in tenders, such as the number of participants per tender - the average fluctuates between two and four across the municipalities in our sample. The dataset often contains unique identifiers for each supplier, which in Brazil vary if the supplier is an individual or a firm, allowing us to compute the share of suppliers identified as firms (which vary substantially across states, from less than 60% in CE and PB to over 80% in MG).

Statistics for the budget execution dataset are presented in Table 4. Our budget execution dataset includes over 880 million observations - over 250 million commitments, around 300 million verifications and over 300 million payments. For all three stages of the budget execution, we present the total number of observations and the total number of *distinct* events – in some cases, we are unable to assess whether two commitment observations, for example, refer to the same commitment or not. In those cases, we set our respective identifier variable to missing to flag to users that we are unsure whether these are unique events that can be tracked across datasets. Using the budget classification discussed previously, we estimate that between 25%-35% of total budget commitment events are related to the procurement of goods and materials - this is a sample we exploit in more detail in the coming sections. We also show that for an overwhelming proportion of commitments values are non-zero and can be matched to some verification and payment – allowing us to track the entire cycle of budget execution. We also highlight that our dataset currently encompasses over 3.5 trillion BRL in payments (in 2021 prices) or the equivalent of 38% of GDP in 2021, made to over 9 million different unique agents (identified by national tax IDs).

We provide an illustrative example of the nature of our data in Figure 2, highlighting a case in which we can track the entire process of public procurement and budget execution. We note that this connection between public procurement and budget execution is currently only possible for the state of Parana (PR), which provides a walkthrough table connecting tender IDs to commitment IDs.[17]

In this figure we zoom in on one case involving the town hall of Abatiá – a municipality with less than 10,000 inhabitants but relatively high income in the state of Paraná – which initiated a tender to procure uniforms for basic health employees, identified by ID 1336360. The tender was officially published in November 2018, with an initial budget of 17,116 BRL. The auction took place on December 13 of the same year, during which bids were received for 23 items, comprising different types of t-shirts and bags. The tender resulted in two win-

[17] Approximately 78% of the procurement IDs and 38% of total commitment IDs can be found within this correspondence table.

ners, one for supplying t-shirts and another for supplying bags. Subsequently, the tender was officially homologated on December 18.

One day after the tender's homologation, four separate commitments were made – meaning that the local government set apart funds to pay for the purchases, once goods were delivered. Verification of delivery happened in mid-May 2019, five months after the end of the tender. Less than 30 days later, three separate payments were made to different agents that won the contracts, with total values of 11,377 BRL and 3,890 BRL. For the purchase of this relatively simple good, a total of 235 days elapsed between the tender publication and the last payment.

The example above illustrates the processes of budgeting and procurement that generates the microdata in our database. While we can only jointly track specific procurement processes and their budget for municipalities in the state of Paraná, the information on procurement and budget execution is representative of our data and suggests the potential of this newly constructed dataset in providing researchers, policy makers, and the civil society with a granular view of how local governments in Brazil acquire goods and services and execute their budgets. It also illustrates the potential for similar datasets to be developed in other countries where scattered data might exist but require upfront investment to be collected, cleaned, and harmonized.

3 Validation

In this section we investigate the quality of our datasets, benchmarking aggregates and features of the data we generated with other established data sources. For more details on the internal consistency of our data (such as the number of municipalities in each dataset across years) and limitations (such as the availability of unique identifiers that allows different states of the budget execution to be connected), see Appendix C.

3.1 Budget data validation

The flagship dataset for information on public finances in Brazil is the *Sistema de Informações Contábeis e Fiscais do Setor Público Brasileiro* (SICONFI).[18] SICONFI contains self-reported information on revenues, expenditures, and balance sheets for all levels of government, including municipalities, starting in 1989, with details on amounts per category and budget execution phase (i.e. commitment, verification, payment). These data have been extensively used and validated in empirical research using data on public finances in Brazil (Gadenne, 2017; Corbi et al., 2019; Shamsuddin et al., 2021). Moreover, the federal government performs several checks to guarantee an adequate level of quality. Our budget data is much more granular than SICONFI, measuring individual commitments, verification and payments, but once we

[18] The dataset was formerly called *Finanças Brasileiras* (Finbra).

aggregate at levels such as municipality-year we should expect to match totals from SICONFI. A natural validation of the quality of our budget dataset therefore is to compare our aggregates with those provided by SICONFI.[19]

We perform the following exercises. First, we aggregate both amounts committed and paid at the municipality-year level in our new dataset and compare these values with information from SICONFI.[20] Formally, we compute $D_{mt} = (T^{BE}_{mt} - T^{SICONFI}_{mt})/T^{SICONFI}_{mt}$, where T^{BE}_{mt} represents total expenditures for municipality m and year t as calculated from our budget execution data and $T^{SICONFI}_{mt}$ represents total expenditures as calculated from SICONFI data.[21]

In Figure 3, we present the histogram of the percentage deviation of *committed amounts* from SICONFI, across states. Our key takeaway is that for five states (CE, MG, PB, PE and SP), our aggregates are almost identical to those from SICONFI - for each state, over 75% of deviations at the municipality-year level are below 1%, and often precisely zero. For PR and RS our deviations are centered around zero but with larger mass slightly above or slightly below - in both states three-quarters of deviations are in the range [-0.5%, 5%], but with more mass for larger absolute deviations in some municipality-years. We also present the same deviations but considering total committed amounts at the municipality-year-function level, where one observation is, for example, the total amount committed by one city for the Health function in 2020. We present these results in Figure A.1, again documenting that our measures of aggregate commitments closely follow those available at SICONFI.

We also provide the distribution of deviations from SICONFI in verification and payment amounts in Figure 4 and Figure 5, respectively. Here our concordance with SICONFI is less precise – while PB and SP show very small deviations, in the remaining states we systematically *overestimate* total amounts of verification and payments. The distributions of deviations are somewhat similar across states, centered at around 5%-8% and with some mass up to 15%-20% in some municipality-years – meaning that the aggregate amount in our data exceeds that in SICONFI by that amount. As reported in Figure A.4 for the states of MG and PR, these deviations do not seem to be driven by specific municipalities or to be systematically different across years, suggesting that there are consistent differences between our measures of verification and payments and those of SICONFI. While we are unable to precisely explain those differences, we expect they are partly driven by amounts carried over across fiscal years, the so-called *restos a pagar*. In most states we are unable to assert whether payments in a given year were committed and/or verified in the previous year; furthermore, annulments of verifications and cancellations of payments can be common, and are not always precisely measured in our dataset. We believe both of these factors might drive the systematic overestimation of

[19]We note that SICONFI contains self-reported information and as a result can also contain errors. Moreover, some differences may arise due to different aggregation methods and the inclusion of government entities besides the municipal executive branch, such as state-owned companies.

[20]We use the SICONFI dataset available on the Data Basis (*Base dos Dados*) platform at https://basedosdados.org/dataset/5a3dec52-8740-460e-b31d-0e0347979da0.

[21]We are only able to compute these indicators for municipality-year observations available both in our dataset and SICONFI.

aggregate amounts in our dataset compared to SICONFI. Finally, we also highlight that results in both our dataset and SICONFI are self-reported by municipalities, meaning there could be systematic discrepancies not due to errors in one source, but due to inconsistent reporting by subnational agents.

While we document that in some states we systematically overestimate total amounts verified and paid, these deviations D_{mt} are only weakly correlated with municipal characteristics within states or years. We perform a predictive OLS exercise regressing D_{mt} on a list of observables including each municipality's log population and log GDP. For each of the three deviation outcomes, in Table 5 we report four results progressively controlling for more stringent fixed effects. All regressions include "% Procurement of goods and materials" as a control, which measures the percentage of all expenditures directed to procurement of goods and materials, as defined in Section 2.2. In columns (1)-(2), (5)-(6), and (9)-(10) we find that deviations are negatively correlated with ln(Population) and positively correlated with ln(GDP), but these explain a very small amount of the variation observed in deviations. Adding year fixed effects increases explanatory power just slightly, and exacerbates coefficients for commitment and verification, but attenuates it for payment. Adding state fixed effects in columns (3), (7) and (11) increases explanatory power significantly, particularly for verification and payment deviations (which are larger in absolute magnitude), and make correlations become much smaller in magnitude and mostly not statistically different from zero. For deviations in payment amounts, we still observe marginally significant correlations (at 10% significance level) for both population and GDP – in column (11), a one log point increase in GDP correlates with 0.46 p.p. smaller deviation in payments, or about 10.7% of the mean. A one log point increase in GDP per capita roughly corresponds to going from p25 to p75 of the distribution, so this is a small magnitude. Finally, in columns (4), (8), and (12) we include municipality fixed effects and find that correlations again are not consistent across outcomes: larger GDP predicts smaller deviations in commitments, larger population predicts smaller variations in verification, but neither predicts deviations in payment at standard levels of significance.

In sum, these results suggest that deviations from SICONFI totals in our budget execution data are partially correlated with municipalities' characteristics, although only weakly. Researchers using our data may want to control for such characteristics and combinations of fixed effects, depending on the research question at hand. For example, we include year and state fixed effects in our analysis of payment speed in Section 4.2.

3.2 Procurement data validation

Validating our procurement datasets is more challenging. Unlike SICONFI for budget data, there is no other source of information on municipal purchases that could be used as a natural benchmark. Although municipalities can use the federal *ComprasNet* portal, for the period covered by our data we see very few municipal government actively using the portal – in Table A.3, we show that less than 2% of all purchases in 2020-2021 (fewer than 2,000 tenders/year) were conducted by municipal administrative units. By 2024 (outside our sample period), this share had increased to 11% or 13,600 purchases – still representing a very small fraction of all municipal procurement activity. The new procurement law enacted in 2021 created a new National Portal of Public Procurement (*Portal Nacional de Compras Públicas* or PNCP), which became mandatory for municipalities with more than 20,000 individuals (one-third of all municipalities) in 2024 but will only be mandatory for the remaining ones in 2027. In summary, while Brazil is currently undertaking an important institutional effort to consolidate data on procurement across all spheres of the public administration, there is currently no systematic alternative sources of data on municipal procurement, making comparisons challenging.[22]

To assess the quality of our procurement data, we instead rely on the fact that procurement law applies to all spheres of government in Brazil (federal, state and municipal) and that detailed microdata on *federal* purchases is readily available. We then use well-documented features of federal procurement data to investigate whether the same patterns appear in our newly constructed municipal dataset.

Our focus are the maximum thresholds for using waivers. As previously discussed, competitive tenders can be waived for small-value purchases: since 2018, these values are R$ 17,600 as a general rule and R$ 33,000 for construction projects. These are not the only justifications for waivers, as they can also be using for emergency purposes. But if these caps are somewhat binding, we should expect both that i) at the margin, purchasing entities might adjust the estimated value of tenders so that they fall below the maximum threshold, generating a bunching pattern in the data; and ii) that the likelihood of using waivers changes discontinuously across these thresholds (Fazio, 2025). We document these two patterns for the MiDES dataset in Figure 6. First, in Figure 6a we show an excess mass of tenders with values just below the R$ 17,600 threshold, and an equivalent missing mass above - suggesting that marginal contracts that would be placed above the threshold are instead quoted at a lower value to qualify for waivers.[23] Second, in Figure 6b, we show that while waivers are used in nearly 70% of tenders for projects valued below R$17,600, this share falls sharply to around 40% for tenders with estimated values just above that level and further reduces to about 20% for those above R$ 33,000. Reassuringly, in both figures we document that these patterns are very similar to what we observe for federal purchases – the bunching pattern is very similar in both distributions, and the discontinuities in use of waivers are also similar, although federal tenders tend to use them more, conditional on estimated value. We interpret these results are

[22]One potential approach would be to compare, at the municipality-year level, the aggregate value of tenders in our procurement dataset and the total value of budget expenses that are related to procurement. However, there are fundamental differences in those quantities that make this validation far from ideal. We explore in detail this potential approach, including validations when we can connect tenders to all committed expenses related to them, in Appendix D.

[23]The distribution also presents clear excess mass at round numbers, suggesting that estimates are rounded up or down.

evidence of the quality of MiDES procurement data.[24]

4 Applications

4.1 Local firm contracting in public procurement

Using our newly created dataset on local public procurement in Brazil, we investigate how much geographical variation exists in the location of government suppliers. According to García-Santana and Santamaría (2025), government purchases are highly locally concentrated worldwide. This phenomenon may occur due to supply factors such as regional economic specialization and lack of a diverse local production sector, or frictions such as transportation costs, geography or information asymmetries. It may also be explained by demand factors such as buy-local policies. These policies are ubiquitous across countries, but there is limited evidence regarding whether governments unofficially favor local suppliers even if a formal buy-local policy does not exist. García-Santana and Santamaría (2025) provide compelling evidence that regional governments in Spain and France (equivalent to states in Brazil) present home bias, i.e. they favor local suppliers.

In this section, we document the prevalence of local suppliers across Brazilian municipalities. No such information exists currently in Brazil due to the lack of consistent data on the identity of municipal government suppliers – an information gap we fill with our dataset. We merge the identity of around 350,000 corporate suppliers in local contracts with information on which municipality they are registered in - given by the *Cadastro Nacional de Pessoas Jurídicas* (CNPJ), a dataset provided by the Brazilian tax authority (*Receita Federal*). We consider a firm local if it operates within the municipality, regardless of whether it is a headquarters or a branch.

In Figure 7, we present the distribution of the share of local suppliers – defined as those located in the same municipality as the purchasing entity – in each state, pooling all purchases from 2014 to 2021.[25] PR and MG are the states in which local contracting is higher on average - close to one-quarter of suppliers of goods and services in these municipalities are local. The remaining states – RS, CE, PB and PE – register averages in the range of 16% - 22%. However, it is worth noting that, within states, we still observe a large variation in the levels of local contracting. Take MG, for example, a state with more than 800 municipalities. According to our data, municipalities such as *Baldim* and *Ibirité* had less than 10% of suppliers located in the same municipality, whereas municipalities like *Almenara* and *Taiobeiras* registered over

[24]See Appendix E for additional comparisons between municipal and federal procurement, including on the prevalence of similar goods and services being purchased.

[25]We replicate all results in this section considering the share of total local purchases instead of the share of local suppliers, i.e. we presented results weighted by the contract amount, in Figure A.7 - Figure A.12. When doing so, we lose all observations for the states of Pernambuco (PE) and Paraíba (PB), for which no data on item value is available. Nonetheless, we find broadly similar results when looking at this subsample and considering the weighted version of local contracting.

60% local suppliers' participation.

We then explore two sources of heterogeneity in the prevalence of local suppliers across municipalities. We first consider the purchase modality. In general, purchases can be divided into competitive and non-competitive tenders (see Table A.2 for more details). The literature showing the effects of discretion on procurement outcomes documents that it may have potential negative impacts on efficiency and corruption (Baltrunaite et al., 2021; Decarolis et al., 2020; Palguta and Pertold, 2017). One explanation is related to favoritism, once lack of competition may favor government bureaucracy to engage in opportunistic behavior for private benefit by awarding contracts to local and/or connected firms. These suppliers may not be the most efficient, leading to overpricing and other inefficiencies. Using Brazilian federal procurement data, Fazio (2025) finds evidence that although public agencies use discretion to purchase higher-quality products, they also use it to favor firms that are politically connected, located in the same municipality as the government agency, larger, and older.[26]

Second, to provide insights on the role of supply-side factors, we investigate the relationship between local purchases and the size of municipalities. Within smaller municipalities, the range of economic activities tends to be narrower and less diverse. This likely translates to a scarcity of local businesses available to adequately address the requirements of the local government. In addition, even if there is a supplier for some purchase, smaller municipalities might lack local competition, which can result in higher prices being charged by local suppliers in comparison to suppliers located in more competitive markets. So it is possible that policy-makers in those small municipalities might actually encourage the participation of firms from other areas.

In Table 6, we present correlates of the probability that a tender is awarded to a local supplier. Focusing on column (3), where we include year and state fixed-effects, we show that a 10% increase in municipality population correlates with a 0.5% increase in the likelihood of having a local supplier and that probability is 7.4 p.p. higher in non-competitive tenders.[27]

While previous results provide novel patterns on the prevalence of local suppliers across Brazilian municipalities, they are not evidence that municipal buyers directly favor local suppliers - i.e. they present home-bias. We provide additional evidence that home-bias might be a driving pattern of the results above by comparing, within the same-municipality, the

[26]In the Hungarian context, Szucs (2023) finds a similar result - winners of high discretion procedures are more likely to be domestically owned. On the other hand, contracts in high discretion procedures tend to be awarded to younger and smaller firms.

[27]The simple correlation between the share of local suppliers and municipality size can be seen on Figure A.5, where we document that larger municipalities have a larger share of local suppliers – going from a population of 5,000 to 500,000 increases the average share of local supplier by approximately 10 percentage points. The correlation with purchase modality is less clear in the raw data: in Figure A.6, we present the distribution of the share of same-municipality suppliers by competitive and non-competitive tenders separately. The average share of local suppliers is approximately 20% for both modalities. We do observe more dispersion in non-competitive tenders: while the distribution for competitive ones shows concentration around the mean, in non-competitive tenders we observe both a larger share of municipalities for which almost no suppliers are local and also a larger share with large participation of local suppliers.

prevalence of local suppliers among municipal agencies vs. federal agencies located in the same municipality. Our key evidence is presented in Figure 8, where we plot municipalities according to the share of local suppliers among local buyers and federal buyers in 2021. The vast majority of municipalities are located below the 45 degree-line, indicating that municipal buyers use more local suppliers than federal buyers. We quantify these effects in Table 7. In column (1), we show that, when comparing all purchases, municipal buyers are just 2 p.p. more likely to use local suppliers and that effect is not statistically significant. But once we control for modality of purchase and municipality fixed-effects, we show that municipal buyers are almost 13 p.p. more likely to use local suppliers. This is a large effect comparing the overall mean of 21% of local suppliers. One caveat in interpreting our finding as evidence in favor of home bias is that we are unable to control for the nature or quality of goods and services being bought, so our results might be partially driven by municipal and federal buyers acquiring different products. A more thorough investigation of the available evidence to confirm or challenge these results is a promising avenue for additional research.

4.2 Timeliness in government payments

Another important dimension of procurement practices is the timeliness of payments. Stretched payment terms increase the length of time between the payments for inputs and the receipt of cash from customers, increasing the working capital needs and financial expenses of suppliers. Previous research has documented the importance of trade credit terms for the performance of firms (Checherita-Westphal et al., 2016; Breza and Liberman, 2017). In extreme cases, late payments can lead to default and bankruptcy.

Governments across the world often take long to pay their suppliers: procuring entities take on average 100 days to pay firms, with vast variation across countries (Bosio et al., 2022). This has several important implications. First, government purchases are a large share of the economy and a substantial revenue source for firms, affecting their future growth and employment trajectory (Ferraz et al., 2015). When governments take long to pay their suppliers, they impose an additional financial cost on firms deciding to supply, and potentially exclude small and medium-sized firms that are more likely to be liquidity constrained (Barrot and Nanda, 2020). Second, if firms understand these additional financial costs, firms may avoid competing for government contracts or, upon deciding to compete, only accept higher prices that make up for the additional liquidity necessary to finance themselves. In either case, that may reduce the cost-effectiveness of public purchases and/or lead to worsening of the quality of goods and services procured. Some government have explicitly introduced reforms to accelerate payment to suppliers: Barrot and Nanda (2020) discuss the impact of *QuickPay*, which decreased the payment speed from 30 to 15 days for small business in the U.S. in 2011; and Chile introduced the Centralized Payment Platform (PPC, Spanish acronym for *Plataforma de Pagos Centralizados*) in 2020, which centralized payments from purchasing units to the

Treasury and started to enforce a 30-day limit to payments.

In this section we document payment timeliness across Brazilian municipalities using our new dataset. We highlight this exercise is only possible by using microdata on the entire budget executing process. In an ideal scenario, we would be able to connect each payment to a single verification, and then compute average payment speed at the verification level. In practice, the majority of payments are connected to one commitment, but not to a verification. We instead compute payment speed at the commitment level – in cases where one commitment is linked to more than one verification and more than one payment, we compute amount-weighted-dates for verifications and payments, and then determine payment speed as the difference between these two dates.[28] We restrict our sample to procurement-related commitment, to focus on speed to suppliers, and further restrict it to the purchase of goods and materials – since verifications of services are often more complex and numerous.

Procurement law in Brazil determines that payments should be made no later than 30 days after the verification, with a shorter limit of 5 days for bid waiver processes (*dispensa de licitação*). In Figure 9 below, we present the distribution of the average payment speed at the municipality-by-year level, where average speed are calculated using the total amount of committed funds as weights (so it can be interpreted as the average speed to pay 1 BRL). In Figure 9a, we show the histogram of our speed measure – the distribution is centered around 15 days, showing that in the majority of municipality-year observations the average payment speed is well below the 30 day limit. We also document, nonetheless, a large right tail of observations with average speed well above 30 days: in Figure 9b, we show that approximately 20% of municipality-years have an average payment speed above 30 days, and many are above 45 or even 60 days. Overall, approximately 15% of the total amount paid in the procurement of goods and materials in recent years is made in more than 30 days.

In Figure 10, we present a map of the regions in Brazil included in our paper and color municipalities according to their average payment speed in 2018. Consistent with the distributions we plot above, we see that the majority of municipalities are paying their suppliers on average below 30 days, which are represented in dark and light green colors. Slow paying municipalities are often spread across the geography, but some clusters are clearly seen - the northeastern part of MG, for example, in the upper part of the "Southeast and South" region, is home to several municipalities that pay on average in more than 30 days.[29] This is also a region of lower-income municipalities, which suggests that perhaps payment speed are consistently correlated with local income – either because these are areas of lower state capacity or because local governments face budget constraints, for example.

We first document that, in that raw data, this relationship seems to be present: in Figure 11, we document a negative correlation between a municipality's per capita GDP and

[28]Details on the methodology to compute speed in complex situations, when one commitment is linked to several verifications and several payments, are discussed in Dahis et al. (2025b).

[29]We consider an alternative measure of payment delays in Figure A.13, the share of payments at the municipality level performed over 30 days, and observe a similar geographical pattern.

their average payment speed – those with higher incomes pay their suppliers systematically faster. We then present in Table 8 a series of regressions documenting that this relationship is robust to other measures of payment timeliness. In all specifications, we control for the log of population and include state and year fixed-effects. In column (1), we show that municipalities with 1 log-point higher income (which is roughly moving from the 1st to 3rd quartile in the per capita GDP distribution) pay their suppliers on average 1.7 days faster - this is approximately an 8% increase in payment timeliness when compared to the sample mean of 21 payment speed. While the average payment speed is important, it is possible that suppliers care less about averages and more about the probability of extreme events, such as being paid later than a certain number of days. In column (2), we first document that 1 log-point increase in GDP is correlated with a 3.9 p.p. decrease in the probability of being paid after the 30-days limit, compared to a 19% baseline mean. Higher income municipalities are also less likely to pay in more than 45 or 60 days, as we document in columns (3) and (4).

Overall, these findings show that, while the majority of municipalities pay their suppliers on average within the time-frame determined by law, substantial variation still exists: 15% of payments are made over 30 days and payment timeliness seems to be systematically correlated with local per capita income.

4.3 Reelection incentives and government purchases

In this section we leverage our new dataset to further study of the effects of reelection incentives on public finance. Since the work of Barro (1973) and Ferejohn (1986) the literature has asked to what extent reelection incentives discipline politicians to choose policies in line with voters' preferences and to be less corrupt. An empirical literature tests whether politicians facing reelection incentives are less corrupt (Ferraz and Finan, 2011; Bobonis et al., 2016; Dahis et al., 2025a), are less productive in the legislative (Fouirnaies and Hall, 2022), allow for more deforestation (Pailler, 2018), and much more. We extend this literature by measuring how reelection incentives correlates with procurement outcomes that are only measurable using the detailed microdata we provide.

In particular, we test whether municipalities in Brazil with a first-term mayor, who can be reelected once, rely more or less on competitive purchasing methods and local suppliers, when compared to incumbents who cannot face reelections given term limits. We implement the following local linear regression discontinuity (RD) specification:

$$y_{mt} = \tau FT_{mt} + \lambda_0 MV_{mt} + \lambda_1 FT_{mt} MV_{mt} + \gamma Z_{mt} + \alpha_{s(m)} + \alpha_t + \varepsilon_{mt} \qquad (1)$$

where y_{mt} is the outcome of interest in municipality m and term t, FT_{mt} is the indicator for first-term mayors, and Z_{mt} is a vector of mayors' characteristics. The terms $\alpha_{s(m)}$ and α_t denote state and year fixed effects, respectively. The term MV_{mt} represents the first-term candidate's margin of victory. It is specified as the difference between the vote share of the challenger receiving the largest number of votes minus the vote share of the incumbent mayor. This measure is therefore positive in municipalities where the incumbent was not reelected and a first-term mayor was elected, and negative otherwise. We weigh the regression using a triangular kernel. We choose bandwidths according to the minimum squared error (MSE) criteria by Calonico et al. (2014).

We report the results in Table 9. We find that municipalities with a first-term mayor elected by a small margin have 6 p.p. more non-competitive tenders (Column 1) and 3.5 p.p. more purchases from local suppliers (Column 4). For each outcome we include two columns with robustness tests with half or double the optimal CCT bandwidth. Visually, Figure 12a shows a clear jump to the right of the cutoff, while the patterns in Figure 12b are less clear.

Several explanations could rationalize these results. First, to the extent that discretionary purchases from local suppliers correlates with inefficient favoritism and corruption, first-term mayors could be pursuing this avenue as a substitute to other forms of illegal corruption. They may strategically use public procurement to build local networks of support, channeling resources through less competitive tenders and local suppliers who may, in turn, provide electoral backing. This would provide more nuance to the findings in Ferraz and Finan (2011) and Dahis et al. (2025a). A second interpretation could be that first-term mayors enter office with new networks of suppliers or knowledge that ultimately leads to better procurement outcomes for the municipality. This would be consistent with research documenting the positive aspects of discretion in procurement (Fazio, 2025). A third explanation could be that first-term mayors bring in new bureaucrats, who have less experience with public procurement and who default more frequently to discretionary purchases. Each possibility is interesting and deserves further study in future research.

5 Conclusion

This paper introduced *MiDES* – a new disaggregated and harmonized dataset on Brazilian local procurement and budget execution. We first described the datasets' basic properties and coverage, and then validated it against the standard public finance data sources in Brazil.

We illustrate the potential uses of this new data in three applications, uncovering new facts about local public finances in Brazil that are only measurable using the granular data we provide. First, we show that, on average, 15% - 25% of municipal suppliers are located in the same municipality. The prevalence of local suppliers is higher in larger municipalities and in non-competitive tendering. We also show suggestive evidence that this prevalence is not simply driven by local conditions by documenting a much higher share of local suppliers when the buyer is a municipal entity when compared to federal buyers located in the same municipality.

Second, we produce new descriptive evidence on speed in payments to government suppliers. We show that approximately 15% of payments are delayed, meaning they are paid over the maximum allowed limit of 30 days. Furthermore, 20% of municipality-year observations have an average speed above 30 days – suggesting they are systematically late payers. Payment timeliness is also correlated with local per capita GDP, with higher-income municipalities paying their suppliers faster. These findings open several additional research questions. For example, if suppliers know that some municipalities tend to be late payers, they might include that "financial risk" of mismatched assets and liabilities in their decisions when selling to these governments and increase prices. Some firms, particularly smaller and liquidity-constrained ones, might also decide not to sell to these governments in order to avoid that financial risk. Other possible questions are whether payment speeds are systematically different depending on government functions (are health expenses paid faster than education for example?); whether they systematically vary with the business and/or political cycles;[30] and whether some suppliers benefit from better payment terms than others (Dahis et al., 2025b). All of these have important implications for competition and value-for-money in the public sector and deserve further investigation, which is possible using the granular data we provide.

Third, we exemplify how our data can be used for causal inference with an application to the literature on reelection incentives and public finance. We compare municipalities in close elections where the elected mayor entered his or her first term versus those where the winner was the incumbent. Our results suggest that municipalities with first-term mayors rely significantly more on non-competitive tenders and buy more from local suppliers. These early findings corroborate a more nuanced reading of the literature and invite further research.

Several other research questions related to local public finances can be explored using these novel data, particularly when matched with other administrative data available in Brazil. Ash et al. (2025), for example, combine the well-known audit courts data that reveal corruption at the municipal level with aggregate data from SICONFI to predict out-of-sample corruption. The new dataset we provide could be used to compute additional measures of local budget and procurement decisions – such as payment speed or shares of purchases from local and/or politically connected firms – which could improve machine learning models used to predict mismanagement and corruption. The granular data available can also shed new light on how subnational entities adjust their expenditures throughout the business cycle, the political cycle (Foremny et al., 2018) and in response to fiscal rules that might constrain their policy choices (Carreri and Martinez, 2022). Matched with personnel data, the detailed procurement data we provide could generate new evidence on how the personal traits of state bureaucrats, such as experience and educational attainment, correlate with measures of value-for-money (Best et al., 2023; Fenizia, 2022). More broadly, we expect *MiDES* to allow researchers to engage with these and many other questions on subnational public finances.

[30]In Figure A.14, we document that the share of late payments was much higher in the 2014-2016 period, when Brazil faced a severe recession, and then improved substantially in more recent years.

Data Availability Statement

The data underlying this article are available at *Data Basis*.

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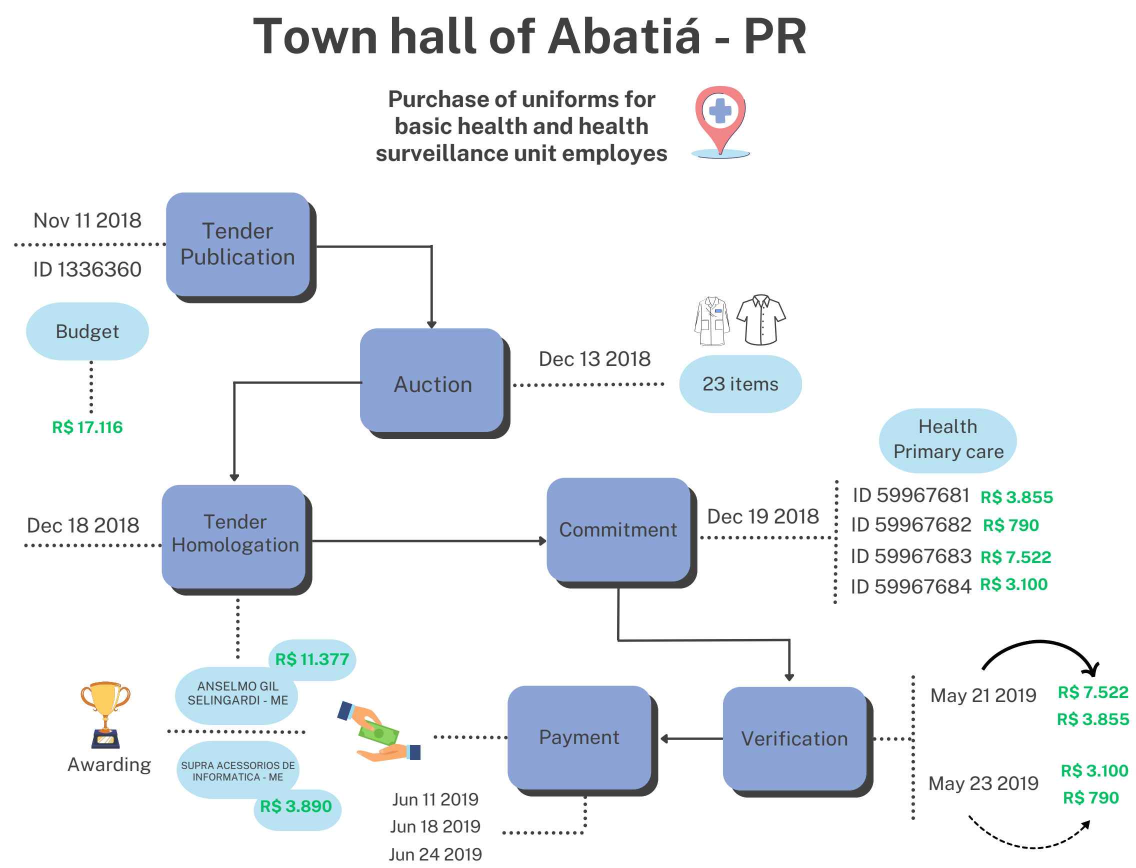
Figures and Tables

Figure 1: Coverage of procurement and budget execution data

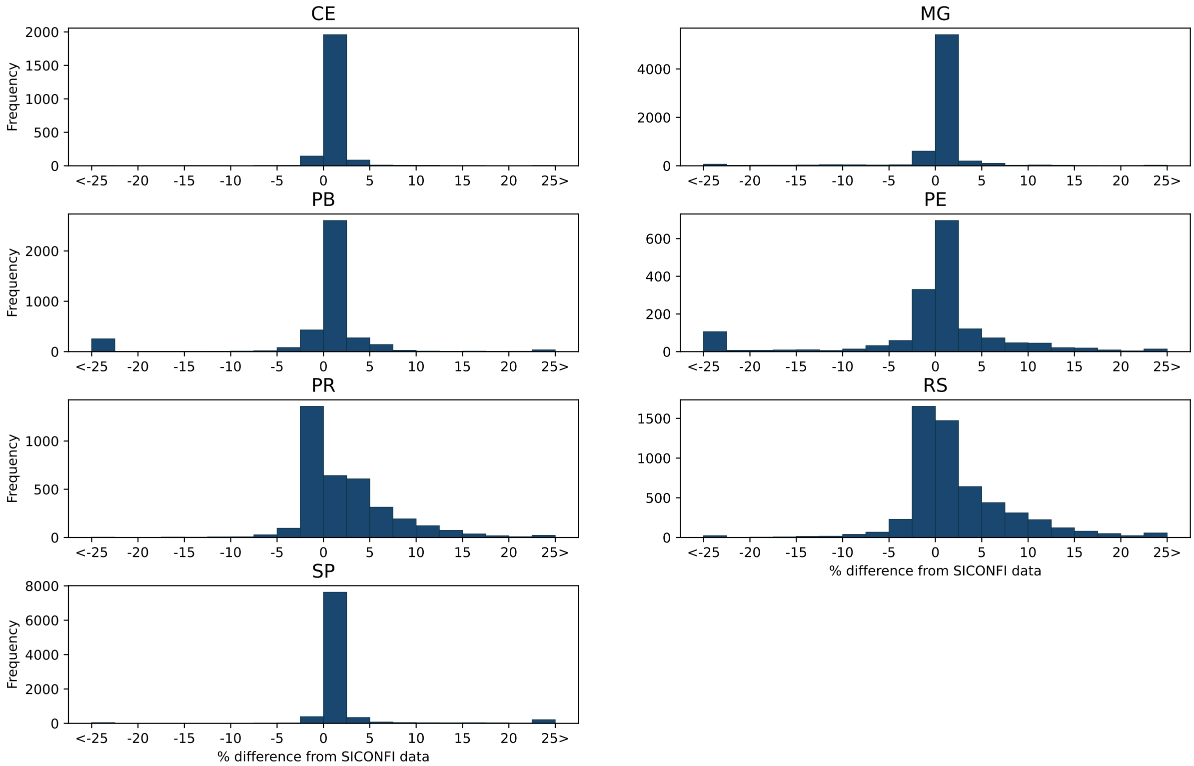
Notes: This figure presents a map of Brazil with administrative boundaries of its 27 states plus the Federal District. Blue-shaded areas represent states for which full or partial procurement and/or budget execution municipal microdata is currently available in the dataset. See Table 2 for more details on our data coverage. We do not have date for the capital of the state of SP.

Figure 2: Example of procurement and budget execution process



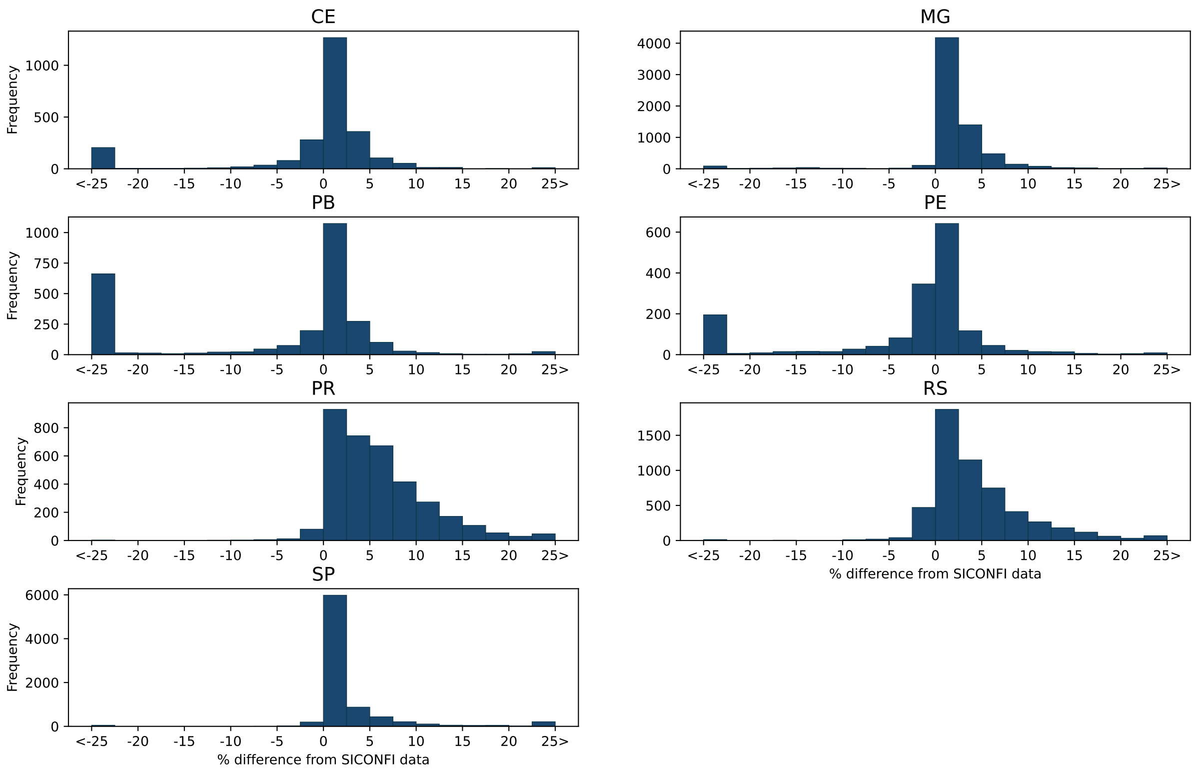
Notes: This figure illustrates the interaction between the budgeting and procurement processes, illustrated with an empirical example from the state of Paraná, where our dataset allows us to follow procurement processes from the tendering stage all the way to the payment of suppliers.

Figure 3: Validation with SICONFI data - commitment



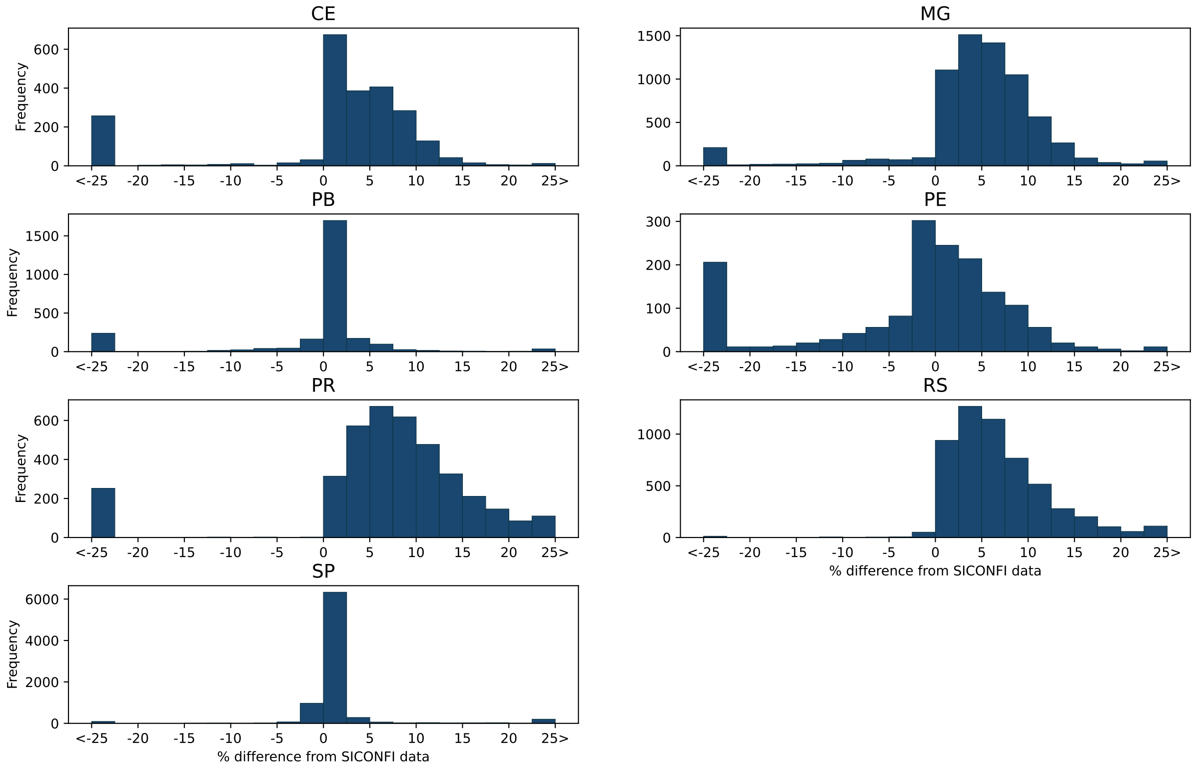
Notes: This figure presents the percentage deviation in the total amount of budget commitments, at the municipality-year level, between our dataset and SICONFI, the public finance dataset of the Brazilian Treasury. Values are positive whenever the total amount in our dataset, aggregated from individual commitments, is larger than that of SICONFI. See Table 2 for more details on our data coverage. We truncate observations at -25% to the left and at 25% to the right.

Figure 4: Validation with SICONFI data - verification



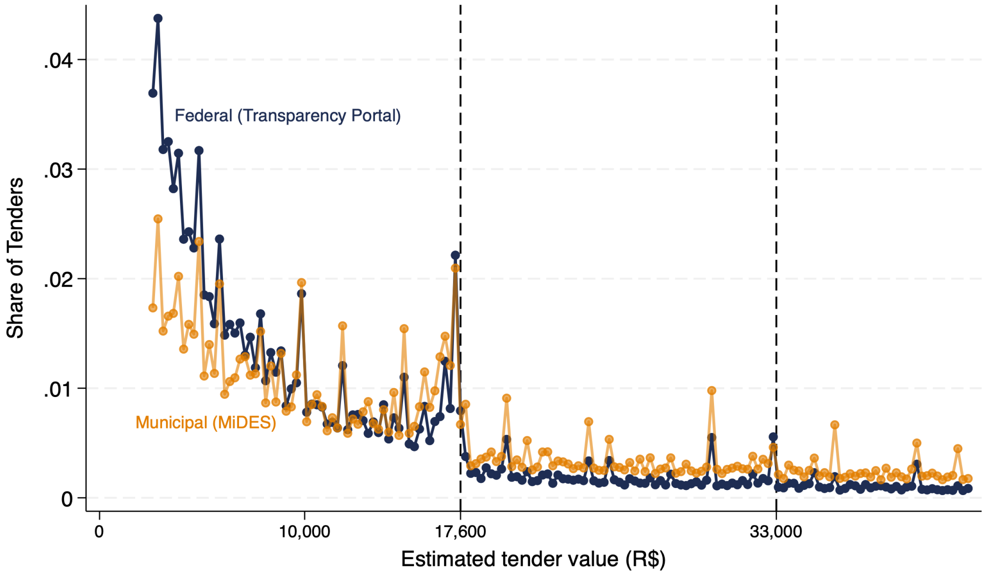
Notes: This figure presents the percentage deviation in total amount of budget verifications, at the municipality-year level, between our dataset and SICONFI, the public finance dataset of the Brazilian Treasury. Values are positive whenever the total amount in our dataset, aggregated from individual verifications, is larger than that of SICONFI. See Table 2 for more details on our data coverage. We truncate observations at -25% to the left and at 25% to the right.

Figure 5: Validation with SICONFI data - payment

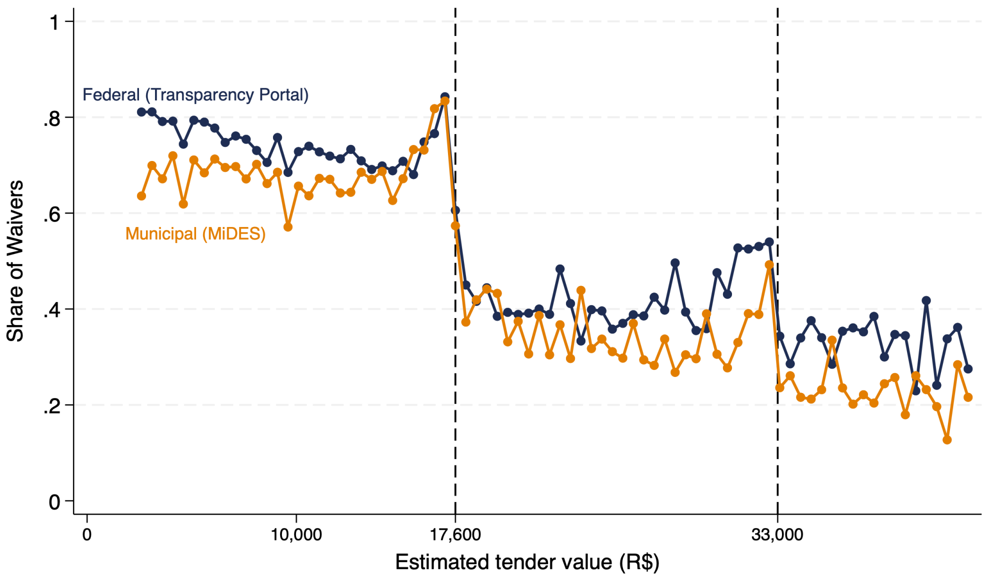


Notes: This figure presents the percentage deviation in total amount of budget payments, at the municipality-year level, between our dataset and SICONFI, the public finance dataset of the Brazilian Treasury. Values are positive whenever the total amount in our dataset, aggregated from individual payments, is larger than that of SICONFI. See Table 2 for more details on our data coverage. We truncate observations at -25% to the left and at 25% to the right.

Figure 6: Effects of tender waiver thresholds - Municipal vs. Federal data



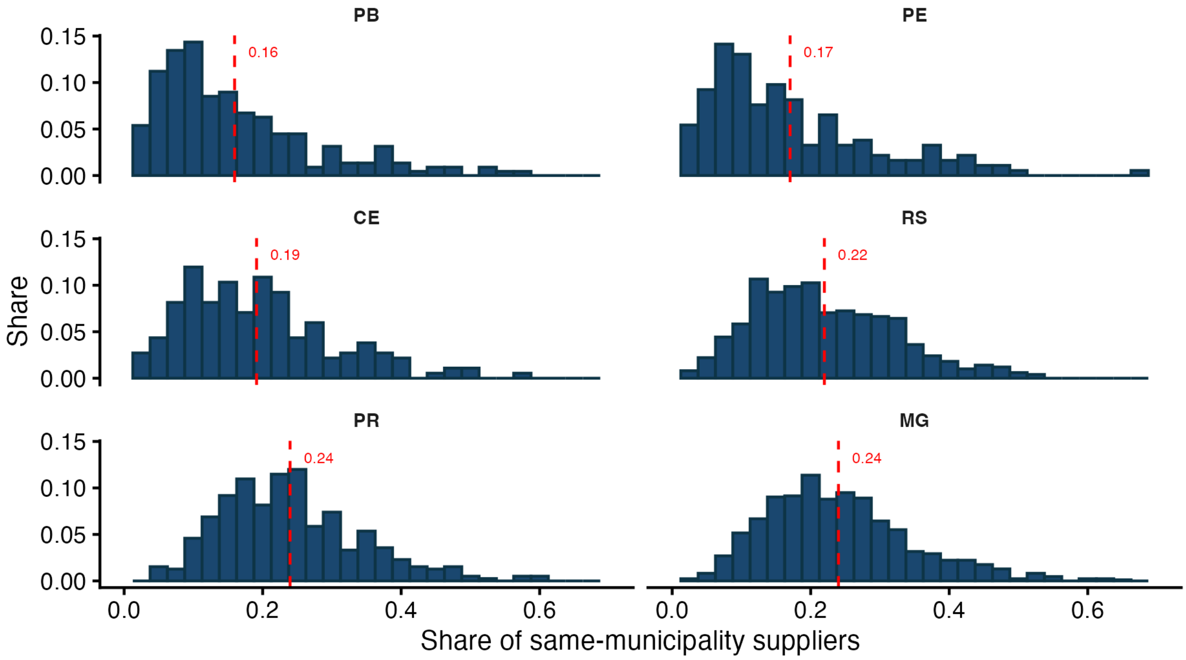
(a) Bunching below waiver threshold



(b) Share of waivers

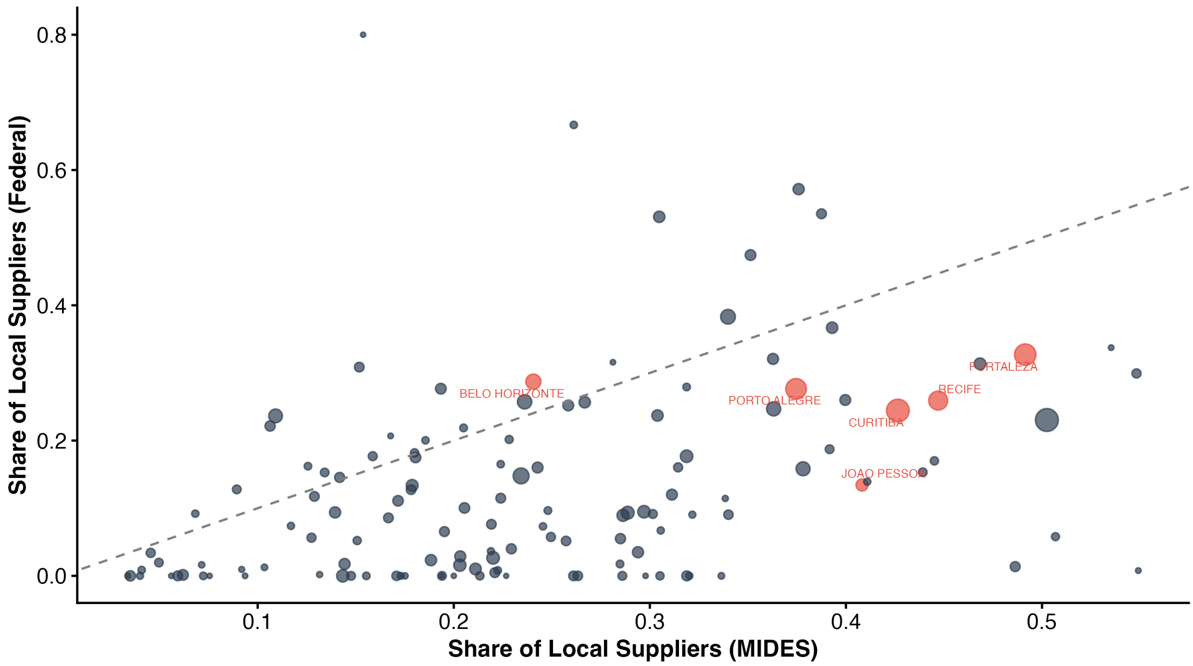
Notes: These figures present comparisons between federal and municipal purchases' characteristics around maximum thresholds for the use of competitive-tenders' waivers. Municipal data include all tenders from the MiDES dataset in 2021, while Federal data includes all tenders available in the Transparency Portal of the Federal government for 2021. For both panels we focus on tenders estimated to be in the range of R$ 2,600 - 42,600. The first panel presents the histogram of tenders' values, while the second one presents the share of tenders in each bin using waivers. Dashed lines mark the general threshold for waivers (R$17,600) and the specific threshold for construction projects (R$ 33,000).

Figure 7: Distribution of share of local suppliers across different states



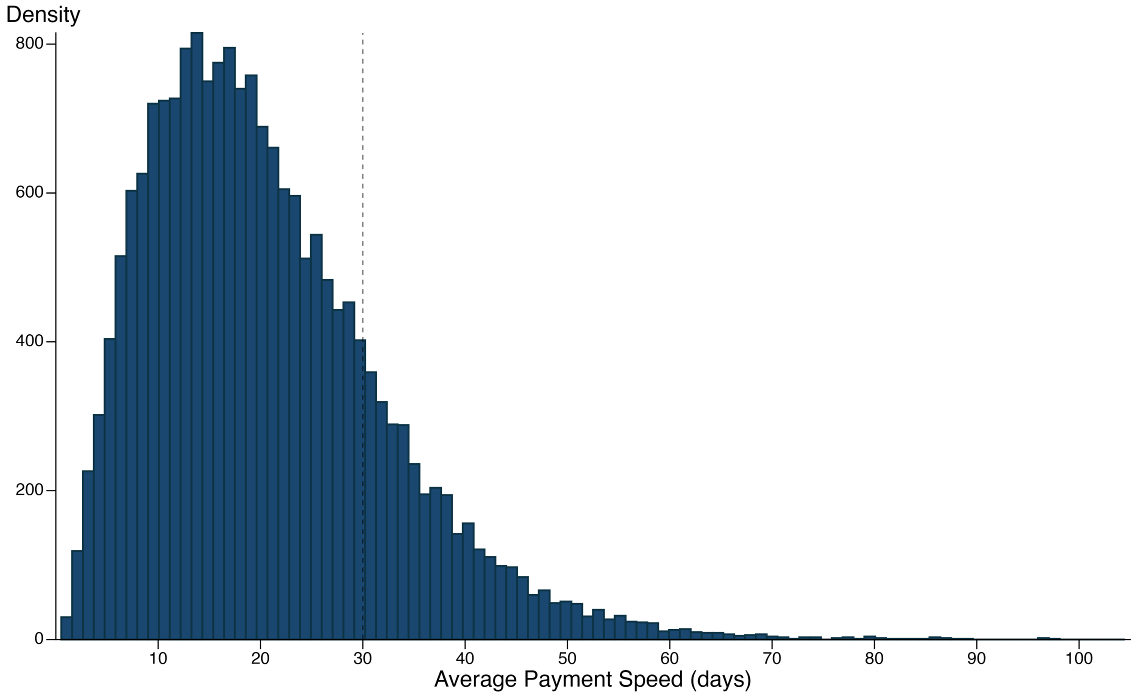
Notes: This figure presents the distribution of the percentage of suppliers located within the same municipality where the tender process occurs, regardless of whether it is a headquarters or a branch, for each state. Data are drawn from the tender-participant table, and encompass all types of purchases, including tender waivers, for both products and services. Here, we consider only the winners' (suppliers) information. We match this dataset with the *Cadastro Nacional de Pessoas Jurídicas* (CNPJ), a dataset provided by *Receita Federal* that contains information on every firm registered in Brazil (we use this information as of 2019, the earliest available year). Red dotted line marks the average value of the distribution. The temporal coverage of the data ranges from 2014 to 2021. See Table 2 for more details on our data coverage.

Figure 8: Share of local suppliers - federal vs. municipal agencies

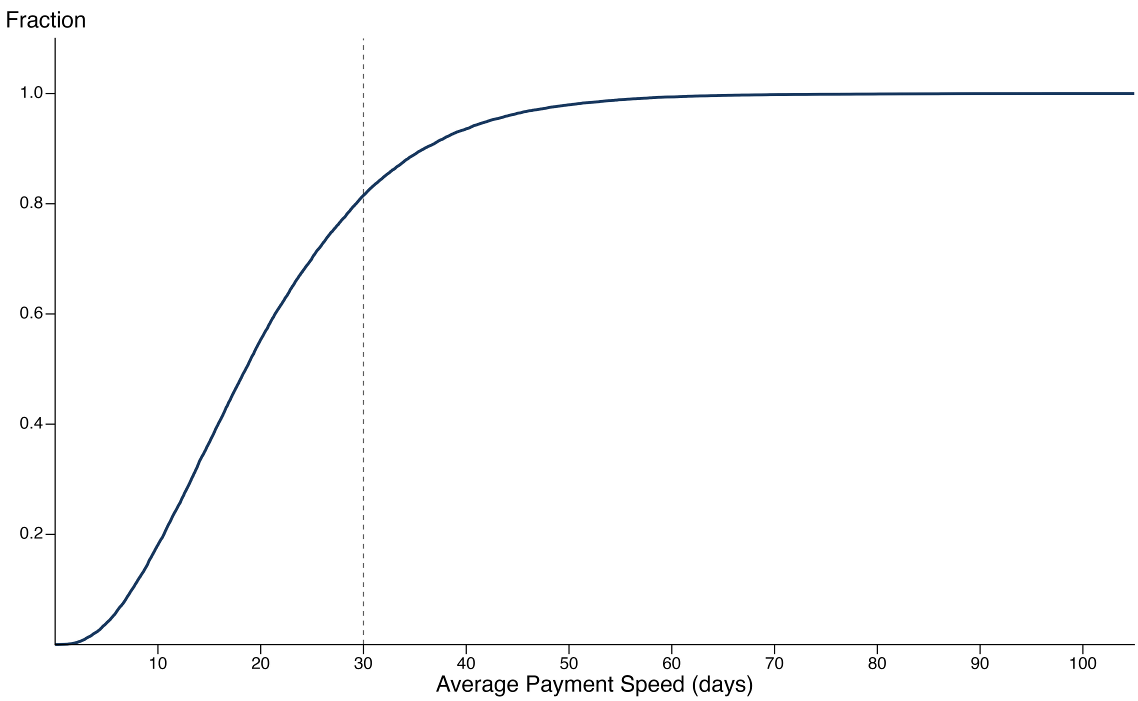


Notes: This figure presents, for each municipality, the share of local suppliers from federal agencies located in the municipality (in the y-axis) and the share of local suppliers by the municipal government (in the x-axis). The share of local suppliers is defined as the share of suppliers located in the same municipality as the buying entity, conditional on suppliers being incorporated entities (for which we can identify location). The sample includes approximately 130 municipalities for which we observe both municipal spending in MiDES and purchases from a federal agency located in the same municipality in 2021. We exclude from this figure municipalities with less than 10 purchases from local government or less than 10 purchases from a federal agency. The capitals of the six states in our sample are highlighted and labeled in red.

Figure 9: Distribution of payment speed at municipality-year level



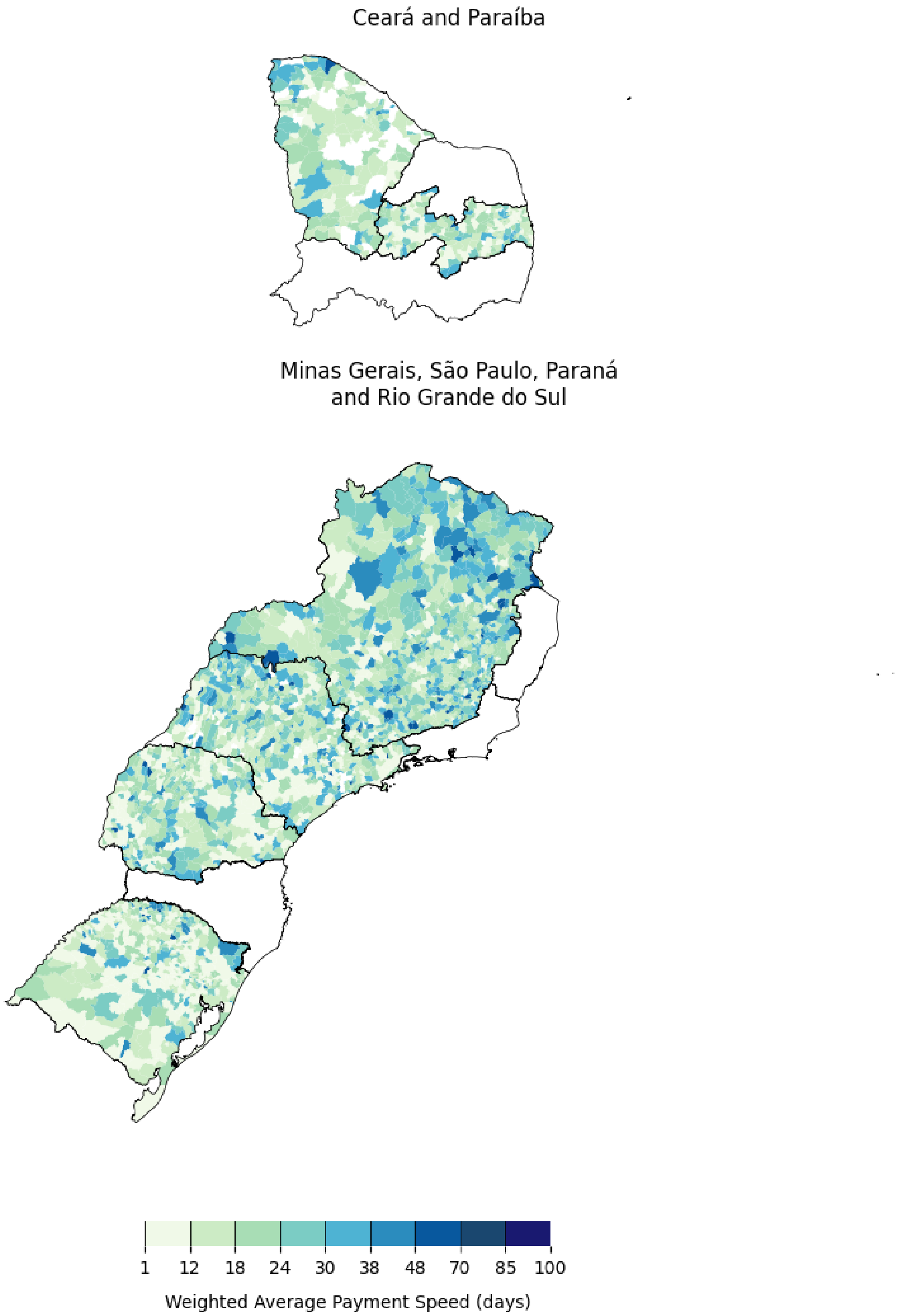
(a) Histogram



(b) Cumulative Distribution Function (CDF)

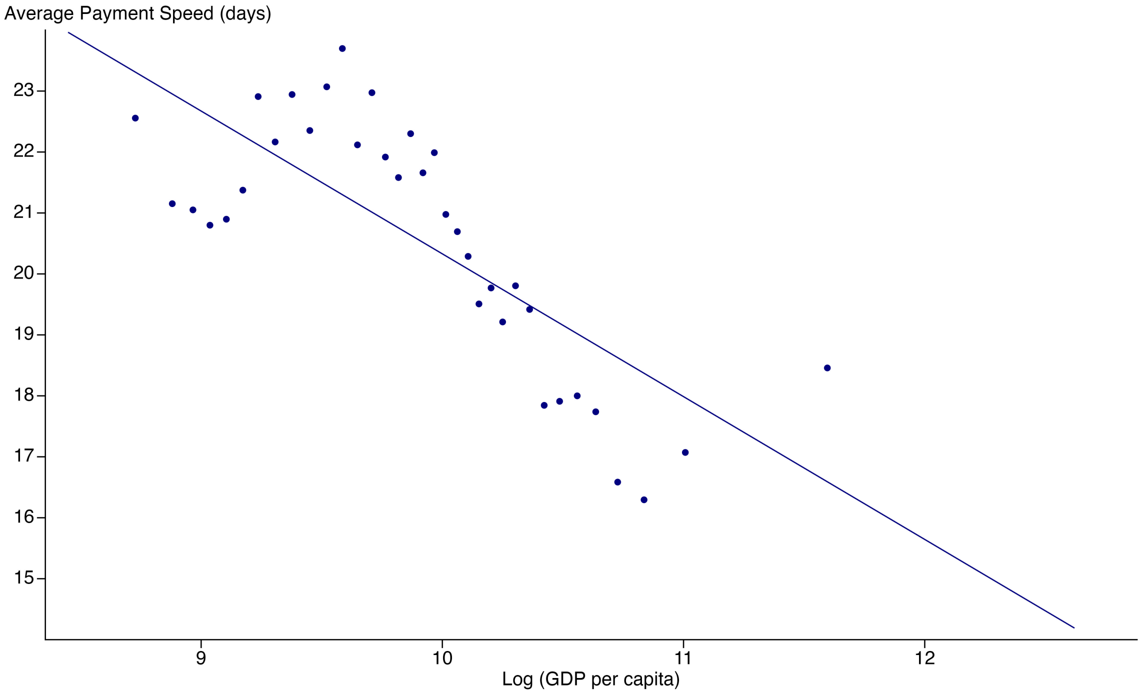
Notes: Panel (a) presents the histogram of average payment speed at the municipality-year level, where average speed is weighted by total committed amount. The dotted line marks the 30-day threshold, the maximum allowed payment speed for procurement in Brazil. The underlying data cover the 2014-2018 period and six states (CE, MG, PB, PR, RS and SP). We are unable to calculate payment speed for PE due to our inability to match payments to their respective commitments.

Figure 10: Weighted average payment speed (days)



Notes: This figure presents a map of regions of Brazil where municipalities are colored according to the average payment speed in the procurement of goods and materials. Municipality average speed are weighted by the total amount paid/committed. This indicator is available for the states of RS, PR, SP, MG, PB, CE. We only consider commitments that are fully executed within a fiscal year, that is, the amount committed is equal to the amount verified and the amount paid.

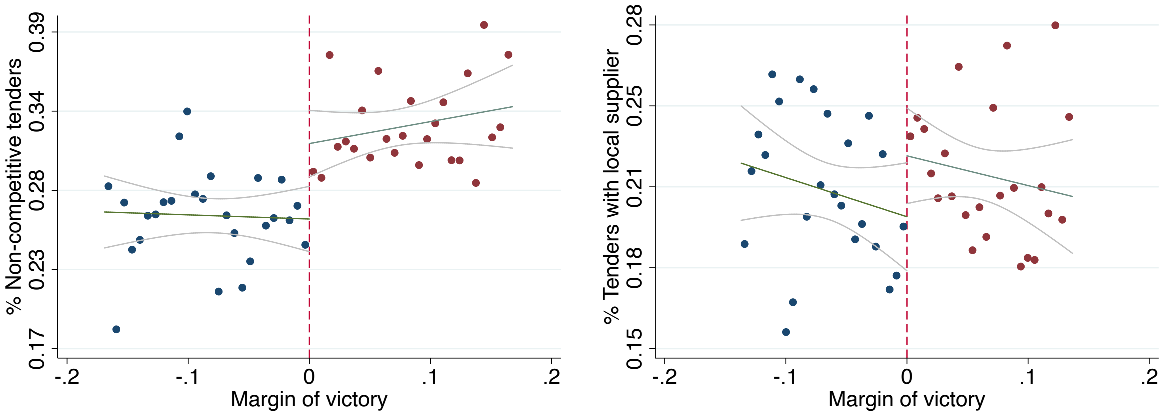
Figure 11: Average payment speed vs. GDP per capita



Notes: This figure showcases a binned scatter plot, plotting the logarithm of per capita GDP on the x-axis against average payment speed on the y-axis. Municipality average speed are weighted by the total amount paid/committed. This indicator is available for the states of RS, PR, SP, MG, PB, CE. We only consider commitments that are fully executed within a fiscal year, that is, the amount committed is equal to the amount verified and the amount paid. The scatter plot is constructed using the package developed in Cattaneo et al. (2022).

Figure 12: Reelection Incentives

(a) % Non-competitive Tenders (b) % Local Procurement



Notes: The figure shows the share of non-competitive tenders and the share of tenders awarded to local suppliers by the margin of victory of first-term mayors. The gray lines denote the confidence intervals plotted for fitted lines at the 90% level. The regression used the optimal bandwidth according to the minimum squared error (MSE) criteria (Calonico et al., 2014). We restrict the observations to races where there was an incumbent and a challenger ranked as the top two candidates.

Table 1: Descriptive statistics - municipalities

Variable	In-sample	Outside-sample
Population (2015)	36,804.56	36,591.19
GDP per capita (2015)	21,616.17	17,346.67
Child mortality 5- (2010)	19.18	24.25
Piped water (%) (2010)	87.80	83.05
Trash collection (%) (2010)	96.67	91.01
Electricity access (%) (2010)	99.21	94.86
Total revenues p.c. (2015)	3,300.55	2,942.78
Current revenues p.c. (2015)	3,108.13	2,807.96
Local tax revenues p.c. (2015)	223.98	185.34
Capital revenues p.c. (2015)	143.12	119.15

Notes: This table presents descriptive statistics about municipalities inside and outside our sample of seven states (CE, MG, PB, PE, PR, RS, SP). Each number is the average of that variable in each subset of data. Data sources are IBGE's population estimates, the 2010 Census, and SICONFI, all available at Data Basis (Dahis et al., 2022). We report descriptive statistics for each state in-sample in Table A.6.

Table 2: Procurement and budget execution coverage

State	#	Procurement				Budget Execution			
	Munic.	Tender	Tender Item	Tender Participants	Temporal Coverage	Commitment	Verification	Payments	Temporal Coverage
CE	184	✓	✓	✓	2009-2021	✓	✓	✓	2009-2021
MG	853	✓	✓	✓	2014-2021	✓	✓	✓	2014-2021
PB	223	✓		✓	2014-2020	✓	✓	✓	2003-2021
PE	185	✓		✓	2012-2021	✓	✓	✓	2012-2020
PR	399	✓	✓	✓	2013-2021	✓	✓	✓	2013-2021
RS	497	✓	✓	✓	2016-2021	✓	✓	✓	2010-2021
SP	644					✓	✓	✓	2008-2021
Total	3,076				2009-2021				2008 - 2021

Notes: This table reports temporal and geographical coverage of our dataset. For procurement data, the number of municipalities for PR is 392 due to problems with the conversion of xml files. In the budget execution data, the original data does not include the municipalities of *Quixabá* and *Santa Teresinha* in the state of PB. We could not obtain the data for the São Paulo municipality (state capital), which is supervised by a separate audit court.

Table 3: Descriptive statistics - public procurement

	CE	MG	PB	PE	PR	RS	Total
Number of distinct tenders	271,345	643,442	133,201	220,025	735,632	417,348	2,420,993
Deserted tenders (%)	-	-	-	3.1	2.6	0.5	1.2
Unsuccessful tenders (%)	-	-	0.0	6.3	3.0	0.6	1.6
Non-competitive tenders (%)	27.6	31.8	38.3	38.0	45.0	45.5	38.6
Non-competitive tenders value (%)	10.0	18.0	12.0	15.0	19.0	12.0	14.9
Has item information (%)	93.3	100	-	-	92.0	100	82.2
Avg. number of items per tender	25.1	25.4	-	-	32.2	12.4	23.8
Has participant information (%)	94.4	96.5	100	100	92.7	92.2	94.9
Number of distinct participants	189,738	330,745	50,236	94,864	175,024	119,322	959,929
Number of distinct suppliers	137,997	301,447	43,548	66,466	154,301	91,609	795,368
Firms among suppliers (%)	55.4	83.2	47.8	66.4	71.6	79.0	72.3
Competitive tenders							
Avg. number of participants per tender	2.8	2.3	2.6	3.9	3.2	3.6	3.1
Avg. number of suppliers per tender	1.5	2.1	2.0	1.4	2.2	2.2	1.9
Number of distinct municipalities	184	853	223	184	392	497	2333

Notes: This table presents the descriptive statistics from the public procurement dataset. Deserted tenders refers to a situation where no proposals were submitted by potential bidders in response to a tender notice, while unsuccessful tenders occur when proposals were submitted but did not meet the requirements or the tender process was canceled or revoked. The variables "Has item information" and "Has participant information" refer to the percentage of tender identifiers with any information related to items or participants, respectively. The definition of non-competitive tender encompasses both *dispensa* and *inexigibilidade*. To calculate the percentage of "Non-competitive tenders value " we use the variable `valor_corrigido` winsorized at percentiles 0.01 and 99.9. Additionally, the percentage of firms among suppliers is calculated as the number of distinct firms divided by the number of distinct suppliers, where firms are those whose identifier has 14 digits.

Table 4: Descriptive statistics - budget execution

	CE	MG	PB	PE	PR	RS	SP	Total
Commitments								
Observations	7,634,745	39,015,657	20,323,928	8,338,666	35,792,154	52,368,944	90,882,992	254,357,086
Distinct commitments	7,634,743	39,015,657	20,319,861	-	35,792,154	52,332,427	89,886,641	244,981,483
Related to procurement of goods (%)	26.7	30.3	19.1	19.9	29.3	26.6	31.7	28.5
Greater than zero (%)	97.8	96.5	98.7	95.9	96.9	96.4	96.6	96.8
Has verification information (%)	96.0	95.0	63.0	-	98.0	97.0	97.0	94.0
Has payment information (%)	82.0	89.0	95.0	-	97.0	96.0	92.0	93.0
Verifications								
Observations	15,189,831	63,757,882	13,787,845	15,229,631	40,457,210	65,789,353	87,894,462	302,106,214
Distinct verifications	-	63,753,322	-	-	40,457,210	34,941,675	81,410,584	220,562,791
Payments								
Observations payment	13,930,424	64,127,137	22,113,067	21,449,922	52,545,469	74,023,098	83,436,799	331,625,916
Distinct payments	13,243,955	64,127,137	22,109,079	-	52,545,469	72,428,292	69,293,735	293,747,667
Total amount of payments (billion BRL)	132.2	514.9	155.4	196.5	407.4	501.7	1691.6	3,599.7
Number of distinct sellers	548,503	1,710,005	1,326,612	-	758,735	1,541,115	3,141,460	9,026,430
Number of distinct municipalities	182	853	223	184	399	497	644	2,798

Notes: This table presents the descriptive statistics from the budget execution dataset. The variables "Distinct commitments", "Distinct verifications" and "Distinct payments" are simply the count of the identifiers that uniquely identify each table - *empenho*, *liquidacao*, *pagamento*. In the states of CE, PB and PE we cannot count the number of distinct verifications because we were unable to build a unique identifier for this table. Likewise for distinct commitments and distinct payments in the case of PE. The variables "Has verification information" and "Has payment information" refer to the percentage of commitment identifiers with any verification or payment information, respectively, in the current year or later. This means that they can be followed throughout the execution process. The state of PB has a low percentage of commitments with verification information due to different temporal coverage of those two tables - while the first starts on 2003, the later starts on 2008. The commitments related to procurement of goods and materials restricts the data to three categories: consumption material (code 30), material for free distribution (code 32) and, equipment and permanent material (code 52). Also, the number of distinct sellers is missing for PE because we don't have information about suppliers in the payment table. The variable "Total amount of payments" is in 2021 prices.

Table 5: Correlates of deviations

Dependent Variables:	Commitment (p.p)				Verification (p.p)				Payment (p.p)			
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Variables												
ln(GDP)	0.353***	0.536***	-0.136	-0.245**	0.948***	1.28***	0.007	0.091	0.800***	0.569***	-0.464*	0.091
	(0.025)	(0.055)	(0.074)	(0.108)	(0.038)	(0.143)	(0.062)	(0.158)	(0.049)	(0.178)	(0.221)	(0.176)
ln(Population)	-0.445***	-0.650***	0.200*	0.463	-1.00***	-1.37***	0.126	-4.54***	-1.02***	-0.737***	0.728*	-1.10
	(0.031)	(0.075)	(0.089)	(0.581)	(0.046)	(0.136)	(0.093)	(0.843)	(0.061)	(0.183)	(0.338)	(0.932)
Year Fixed Effects	✗	✓	✓	✓	✗	✓	✓	✓	✗	✓	✓	✓
State Fixed Effects	✗	✗	✓	✗	✗	✗	✓	✗	✗	✗	✓	✗
Municipality Fixed Effects	✗	✗	✗	✓	✗	✗	✗	✓	✗	✗	✗	✓
Fit statistics												
Observations	26,792	26,792	26,792	26,792	26,168	26,168	26,168	26,168	26,129	26,129	26,129	26,129
Dependent variable mean	1.0	1.0	1.0	1.0	2.5	2.5	2.5	2.5	4.2	4.2	4.2	4.2
RMSE	2.7	2.7	2.6	1.9	4.1	4.0	3.6	2.8	5.3	5.2	4.3	3.2
R^2	0.008	0.04	0.12	0.50	0.03	0.07	0.24	0.54	0.01	0.05	0.36	0.63
Adjusted R^2	0.008	0.04	0.12	0.44	0.03	0.07	0.23	0.48	0.01	0.04	0.36	0.59

Notes: This table presents results from OLS regressions where the deviation outcomes are defined as $D_{mt} = (T^{BE}_{mt} - T^{SICONFI}_{mt})/T^{SICONFI}_{mt}$ for each stage (commitment, verification, payment), as described in Section 3. All regressions include "% Procurement of goods and materials" as a control, which measures the percentage of all expenditures directed to procurement of goods and materials, as defined in Section 2.2. Each observation is a municipality-year. The data cover 6 states (CE, MG, PB, PR, RS, SP) and their corresponding years described in Table 2. Robust standard errors in parentheses. Significance levels: ***: 0.01, **: 0.05, *: 0.1.

Table 6: Correlates of purchases from local suppliers

Dependent Variable:	Local Supplier		
Model:	(1)	(2)	(3)
Variables			
ln(GDP)	0.003	0.012**	-0.003
	(0.005)	(0.006)	(0.008)
ln(Population)	0.037***	0.027***	0.047***
	(0.006)	(0.007)	(0.009)
Non-Competitive Tender	0.070***	0.072***	0.074***
	(0.008)	(0.008)	(0.008)
Fixed-effects			
Year	✗	✓	✓
State	✗	✗	✓
Fit statistics			
Observations	2,623,817	2,623,817	2,623,817
Dependent variable mean	0.27	0.27	0.27
RMSE	0.44	0.44	0.44
R^2	0.03	0.03	0.03
Adjusted R^2	0.03	0.03	0.03

Notes: This table presents results from OLS regressions, at the tender-item level, of the probability that the supplier is local. The data cover 6 states (CE, MG, PB, PE, PR, RS) and their corresponding years described in Table 2. Standard errors clustered at the municipality level in parentheses. Significance levels: ***: 0.01, **: 0.05, *: 0.1.

Table 7: Regression Table: Municipal vs. Federal local purchases

Dependent Variable:	Local Supplier	
Model:	(1)	(2)
Variables		
Constant	0.193***	
	(0.015)	
Municipal buyer	0.023	0.131***
	(0.016)	(0.009)
Fixed-effects		
Modality		Yes
Municipality		Yes
Fit statistics		
Observations	769,589	769,589
Dependent variable mean	0.21	0.21
RMSE	0.41	0.38
R^2	0.0006	0.11
Adjusted R^2	0.0006	0.10

Notes: This table presents regressions, at the participant level, on the probability that the winner of a contract is a local firm i.e. a firm located in the same municipality is the buyer. Column (1) includes no controls while column (2) includes modality of purchase (waivers, auctions, direct contracting and others) and municipality fixed-effects. The indicator for municipal buyer is equal to 1 for municipal entities and zero for federal entities. The sample includes approximately 130 municipalities for which we observe both municipal spending in MiDES and purchases from a federal agency located in the same municipality in 2021. Standard-errors clustered at the municipality-by-sphere of buyer level in parentheses. Significance levels: ***: 0.01, **: 0.05, *: 0.1.

Table 8: Correlates of payment speed

Dependent Variables:	Average Payment Speed	% Over 30 Days	% Over 45 Days	% Over 60 Days
Model:	(1)	(2)	(3)	(4)
Variables				
ln(GDP)	-1.74***	-3.86***	-2.83***	-2.02***
	(0.391)	(0.502)	(0.357)	(0.291)
Year Fixed Effects	✓	✓	✓	✓
State Fixed Effects	✓	✓	✓	✓
Fit statistics				
Observations	19,314	19,314	19,314	19,314
Dependent variable mean	20.5	19.4	10.5	6.7
RMSE	11.1	16.1	11.3	8.4
R^2	0.11	0.15	0.12	0.10
Adjusted R^2	0.11	0.15	0.12	0.10

Notes: This table presents regressions using different measures of payment speed as dependent variable and ln(GDP) as main independent variable. All regressions control for the log of population and include state and year fixed effects. Observations are at the municipality-year level and encompass the period 2014-2020. Standard errors clustered at the state-level in parentheses. Significance levels: ***: 0.01, **: 0.05, *: 0.1.

Table 9: Reelection Incentives and Procurement

	% Non-competitive tenders			% Tenders with local supplier		
	(1)	(2)	(3)	(4)	(5)	(6)
First-term mayor	0.060***	0.048*	0.063***	0.035**	0.047*	0.017
	(0.018)	(0.026)	(0.014)	(0.018)	(0.026)	(0.013)
Robust 90% CI	[.004 ; .11]	[-.02 ; .125]	[.021 ; .098]	[-.002 ; .103]	[-.03 ; .123]	[-.001 ; .073]
Kernel Type	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular
BW Type	CCT	.5CCT	2CCT	CCT	.5CCT	2CCT
BW	0.170	0.085	0.340	0.137	0.068	0.274
Observations	2149	2149	2149	2141	2141	2141

Notes: This table reports coefficients from the regression discontinuity (RD) specification described in Equation (1), estimating the effect of reelection incentives on (i) the share of non-competitive tenders and (ii) the share of tenders awarded to local suppliers. The outcomes are averaged at the term level. The sample includes mayoral terms starting in 2009, 2013, and 2017. Data for 2009 are available only for the states of Ceará (CE) and Pernambuco (PE), while subsequent terms include all states. The design compares municipalities where incumbent mayors narrowly lost and were replaced by new mayors with those where incumbents were reelected to a second term. All specifications control for mayoral characteristics (age, gender, and education), party affiliation, and state fixed effects. The BW Type refers to the bandwidth selection method, with CCT indicating the MSE-optimal bandwidth. The BW parameter reports the corresponding bandwidth used in each regression. P-values: * 0.10 ** 0.05 *** 0.01.

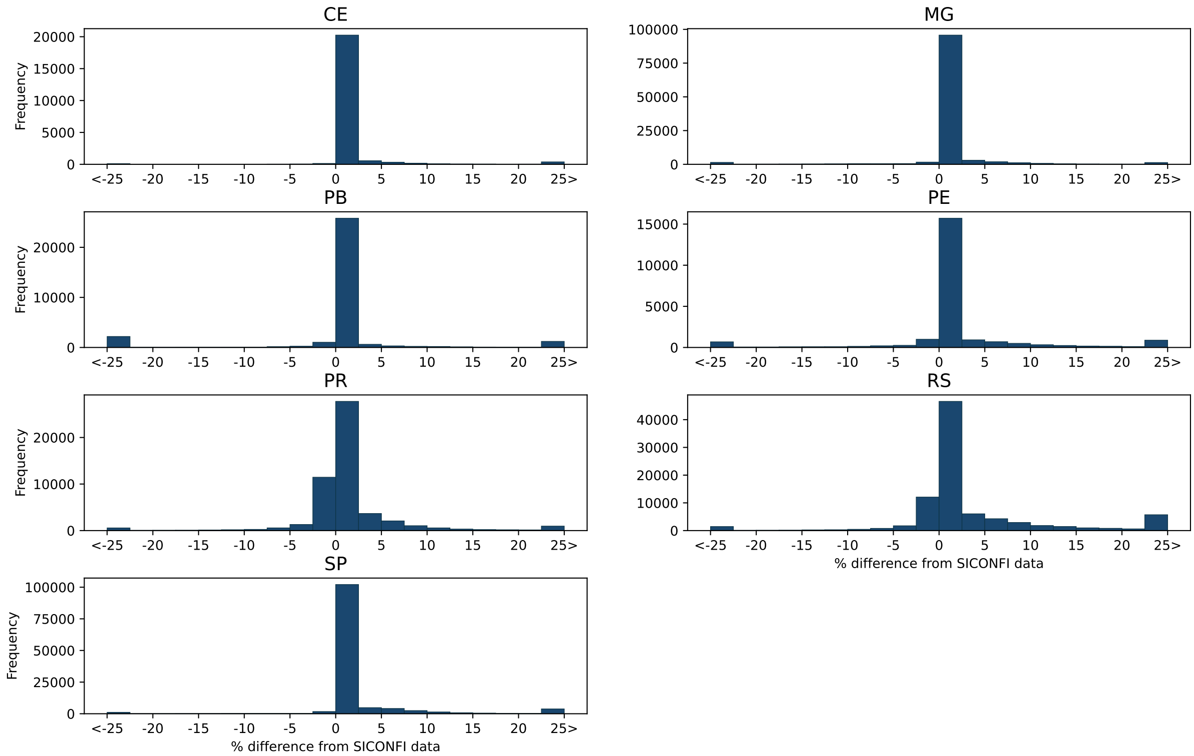
Online Appendix For

"Fiscal Capacity and Execution at the Local Level: New Evidence from Brazil"

Ricardo Dahis Bernardo Ricca Thiago Scot
Nathalia Sales Lucas Nascimento

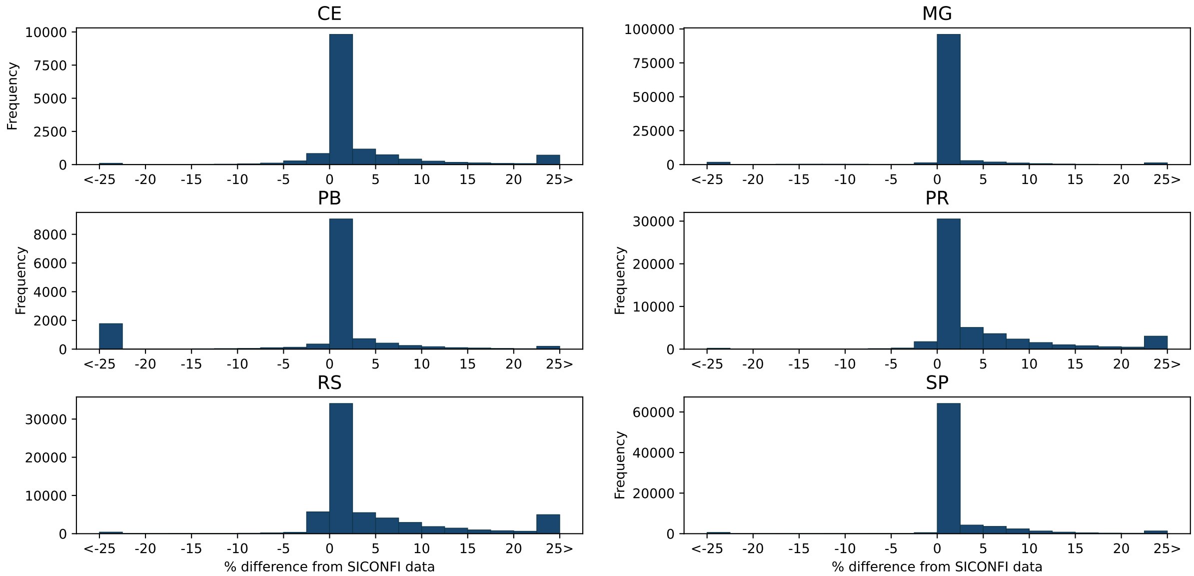
A Figures and Tables

Figure A.1: Validation with SICONFI data: commitment phase, by function



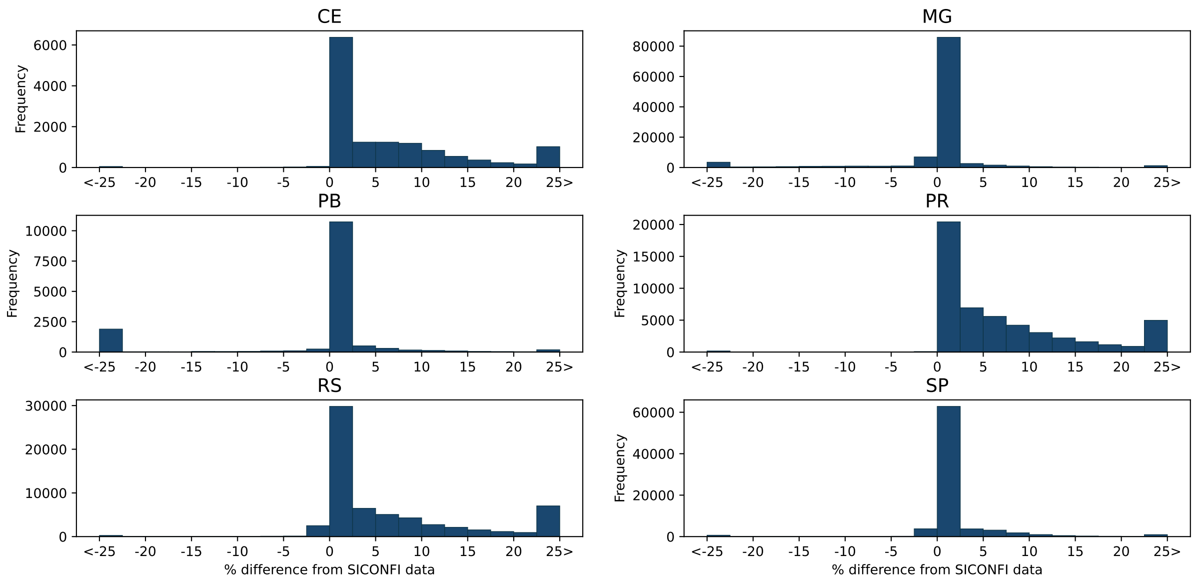
Notes: This figure presents the percentage difference of commitment data from the budget execution dataset in relation to data on committed expenses from SICONFI, as described in Section 3.

Figure A.2: Validation with SICONFI data: verification phase, by function



Notes: This figure presents the percentage difference of verification data from the budget execution dataset in relation to data on verified expenses from SICONFI, as described in Section 3.

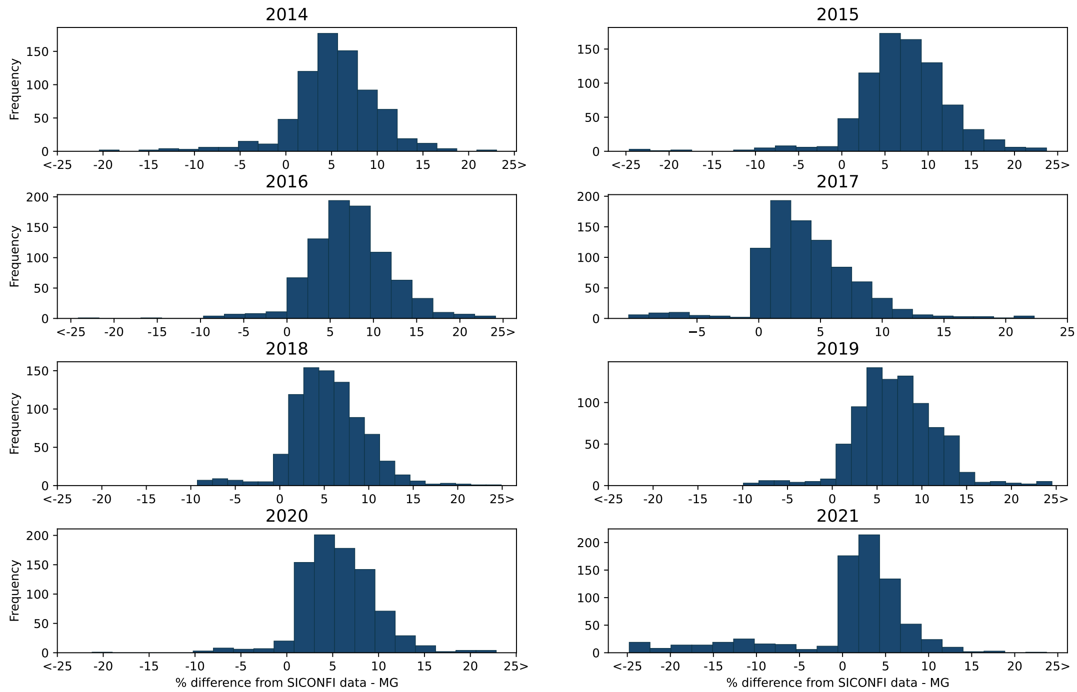
Figure A.3: Validation with SICONFI data: payment phase, by function



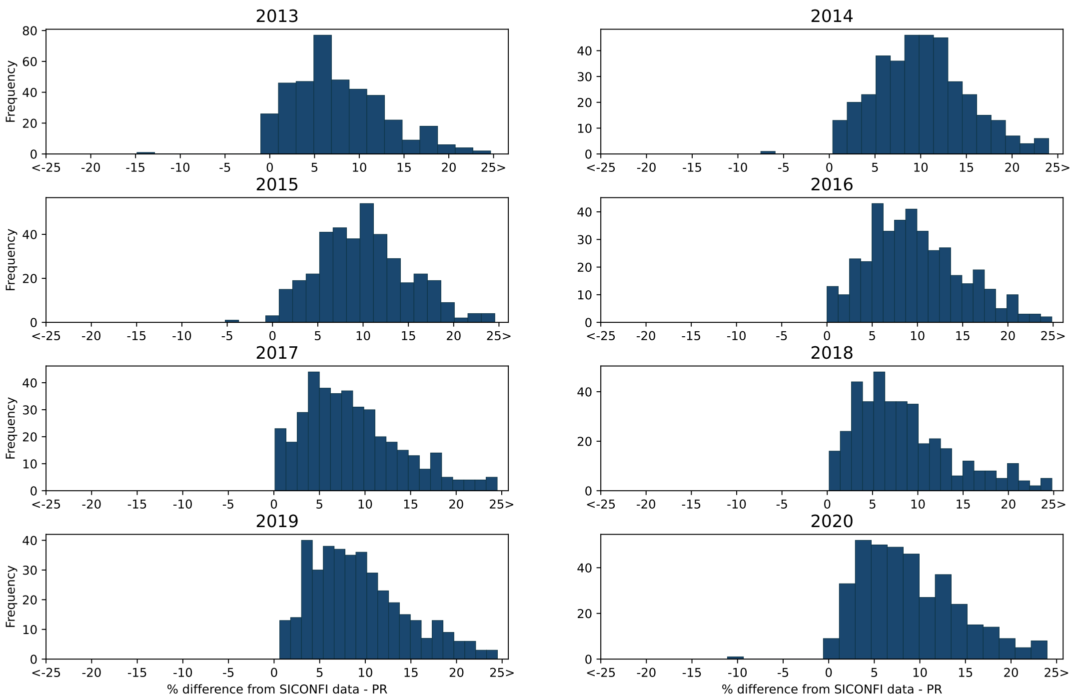
Notes: This figure presents the percentage difference of payment data from the budget execution dataset in relation to data on paid expenses from SICONFI, as described in Section 3.

Figure A.4: Validation with SICONFI data across years - payment

(a) Minas Gerais (MG)

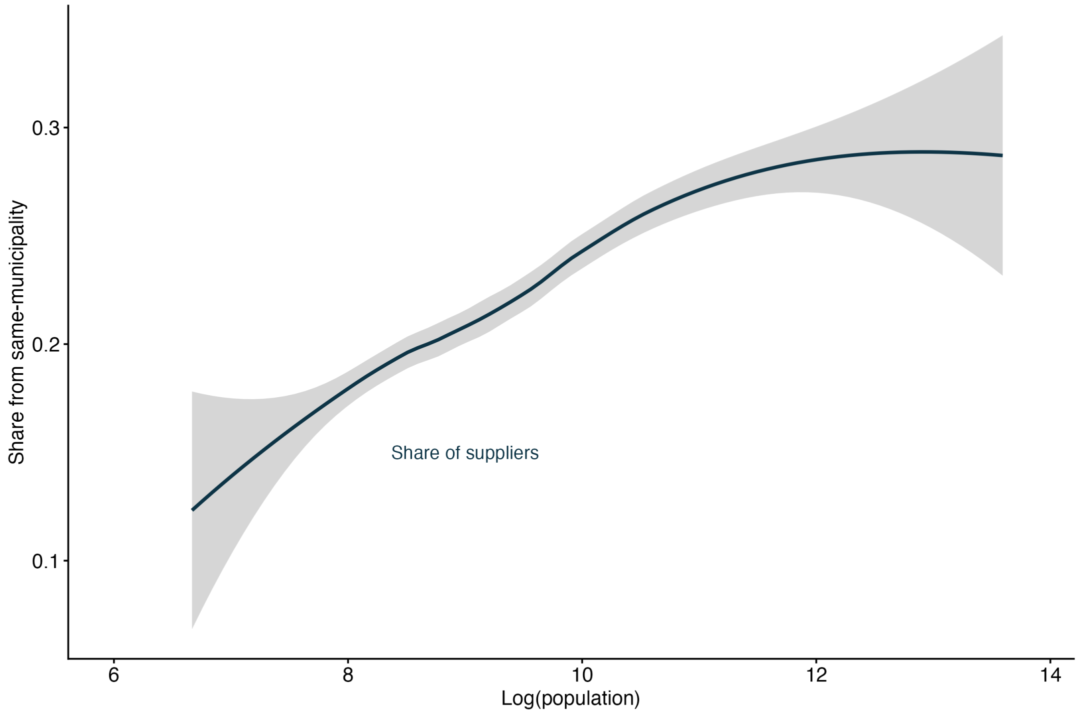


(b) Paraná (PR)



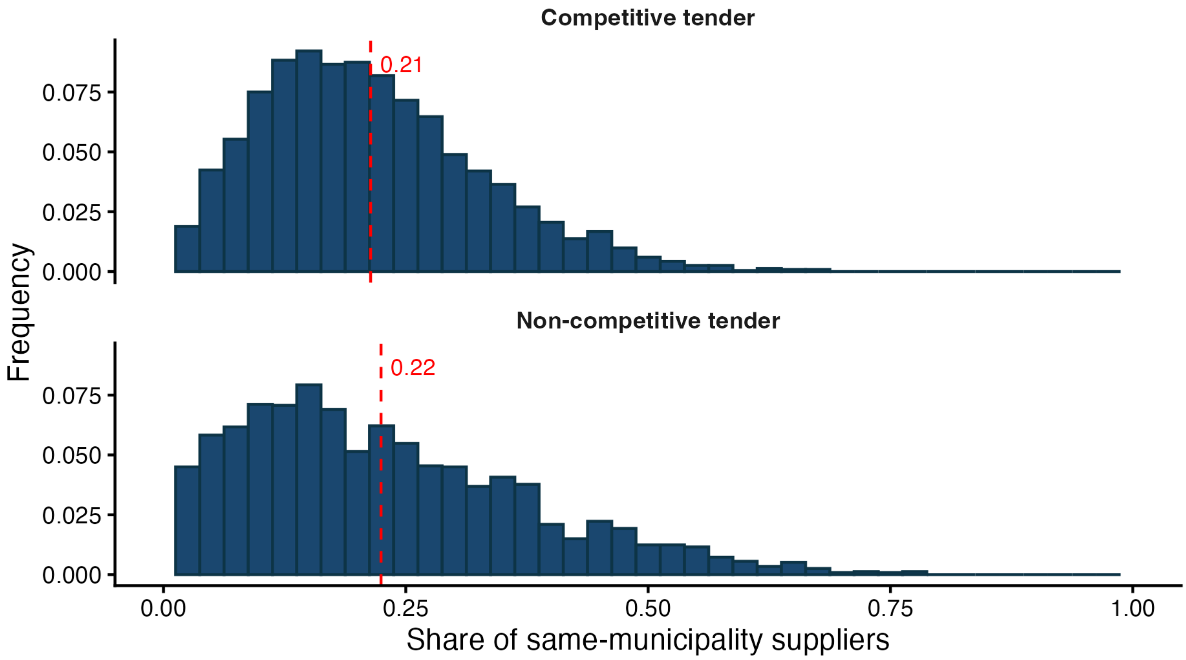
Notes: This figure presents the percentage deviation in total amount of budget payments, at the municipality-year level, between our dataset and SICONFI, the public finance dataset of the Brazilian Treasury. Values are positive whenever the total amount in our dataset, aggregated from individual payments, is larger than that of SICONFI. See Table 2 for more details on our data coverage. We truncate observations at -25% to the left and at 25% to the right.

Figure A.5: Share of local suppliers - by municipality size



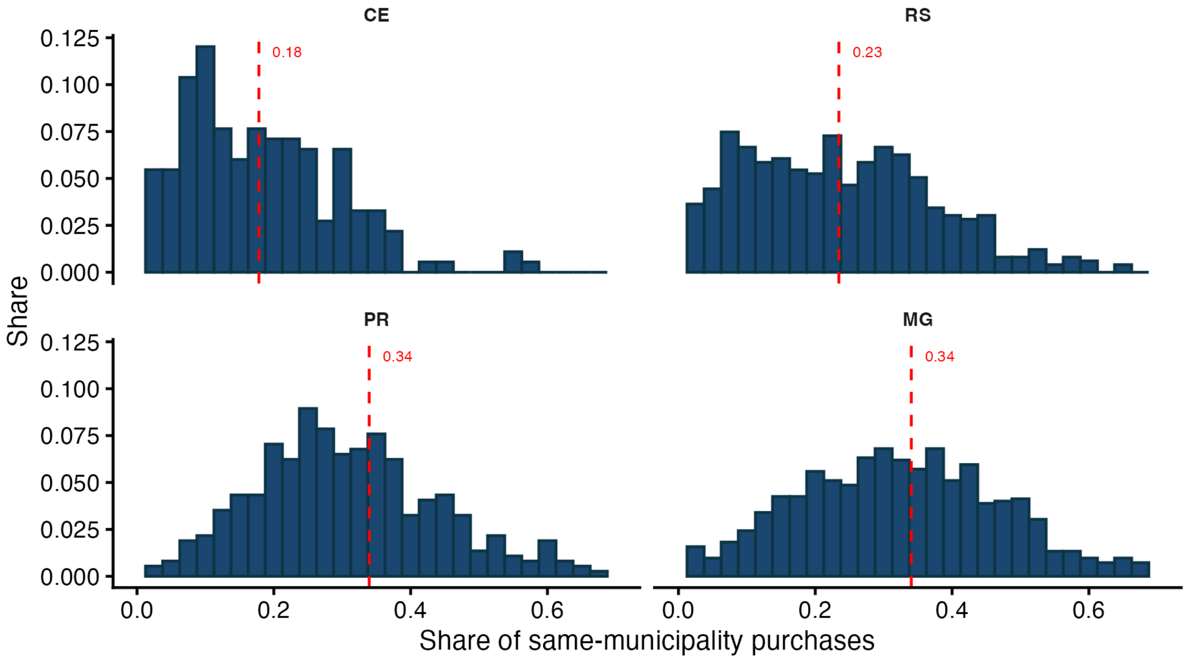
Notes: This figure presents the share of local suppliers across municipalities of different sizes. Estimates are from local non-parametric regressions (LOESS) and include 95% CI in shade. Data is drawn from the tender-participant table and includes only suppliers who won the tender process and whose identifier has 14 digits. We match this data with the *Cadastro Nacional de Pessoas Jurídicas* (CNPJ), a dataset provided by *Receita Federal* that contains information on every firm registered in Brazil. The temporal coverage of the data ranges from 2014 to 2021. See Table 2 for more details. We drop municipalities with over 1 million individuals for this figure for visualization purposes.

Figure A.6: Distribution of share of local suppliers, by type of purchase



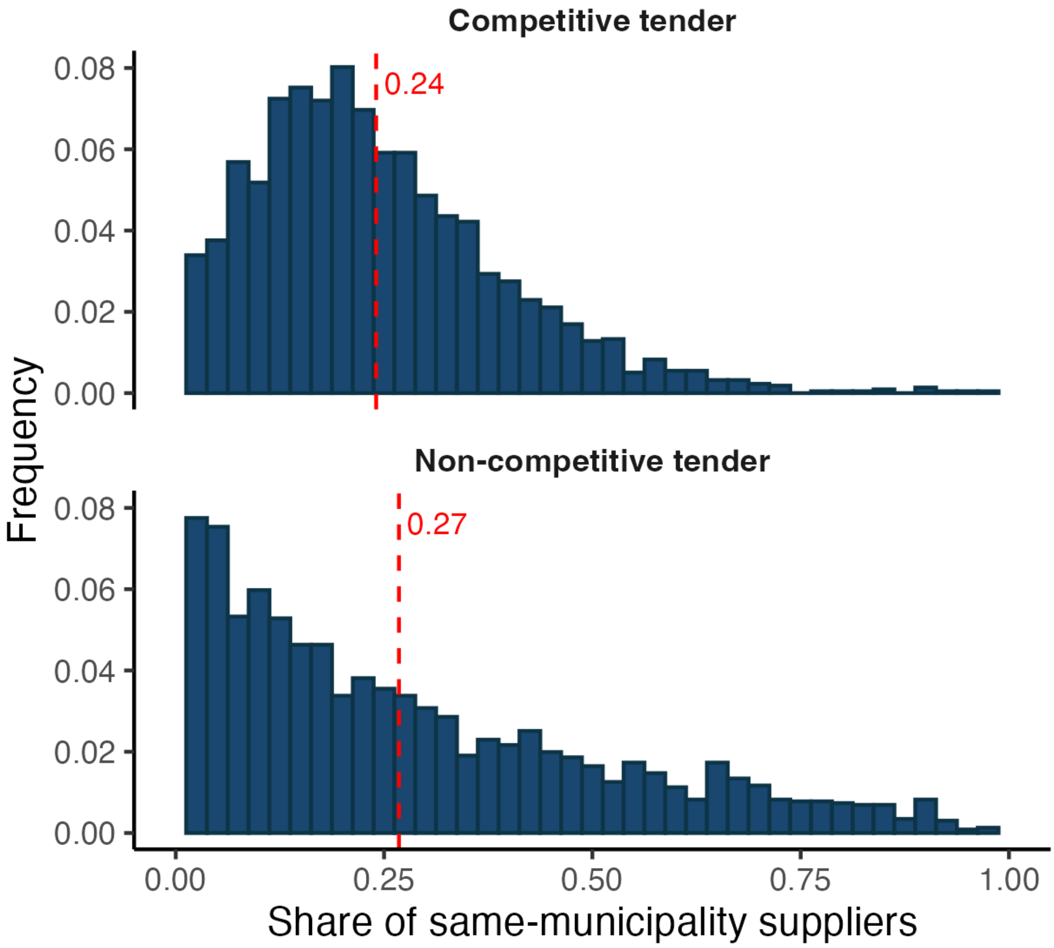
Notes: This figure presents the distribution of the percentage of firms located within the same municipality where the tender process occurs, regardless of whether it is a headquarters or a branch. The distribution is disaggregated by type of purchase - competitive and non-competitive. Data is drawn from the tender-participant table and includes only suppliers who won the tender process and whose identifier has 14 digits. We match this data with the *Cadastro Nacional de Pessoas Jurídicas* (CNPJ), a dataset provided by *Receita Federal* that contains information on every firm registered in Brazil. The temporal coverage of the data ranges from 2014 to 2021. See Table 2 for more details.

Figure A.7: Distribution of share of purchases from local suppliers across different states



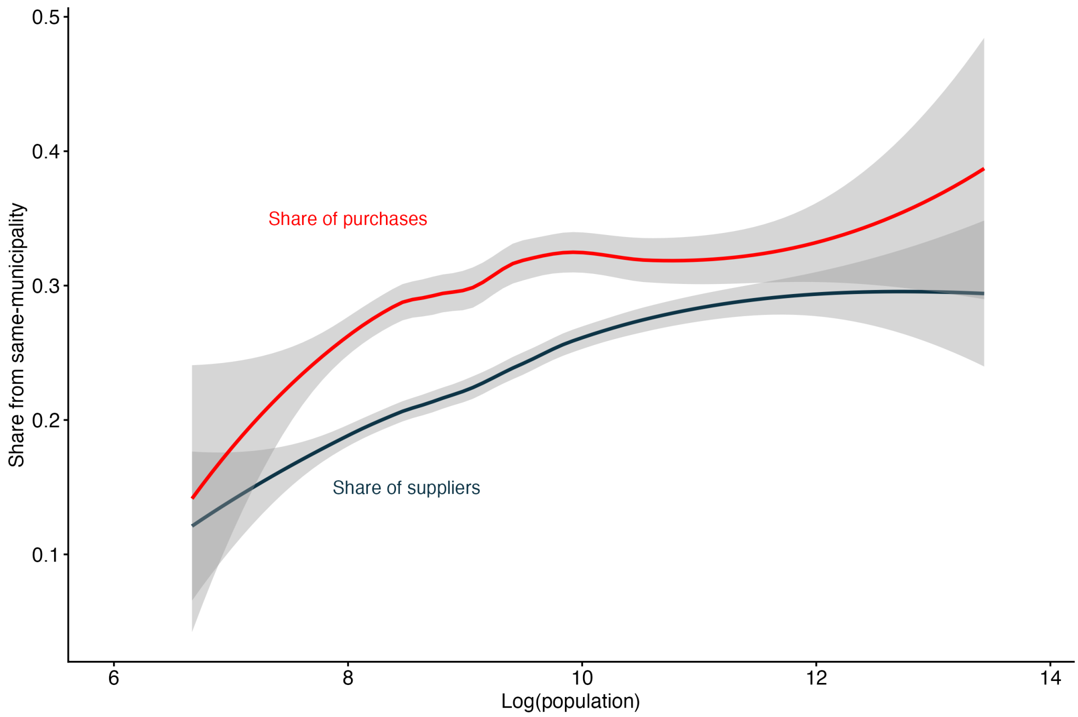
Notes: This figure presents the distribution of the percentage of purchases from suppliers located within the same municipality where the tender process occurs, regardless of whether it is a headquarters or a branch, for each state. Data are drawn from the tender-participant table, and encompass all types of purchases, including tender waivers, for both products and services. Here, we consider only the winners' (suppliers) information. We match this dataset with the *Cadastro Nacional de Pessoas Jurídicas* (CNPJ), a dataset provided by *Receita Federal* that contains information on every firm registered in Brazil (we use this information as of 2019, the earliest available year). Red dotted line marks the average value of the distribution. The temporal coverage of the data ranges from 2014 to 2021. See Table 2 for more details on our data coverage. Results in these figures are weighted by the contract value, and for this reason exclude all observations from the states of Paraíba (PB) and Pernambuco (PE), for which item-level information is not available.

Figure A.8: Distribution of share of purchases from local suppliers, by type of purchase



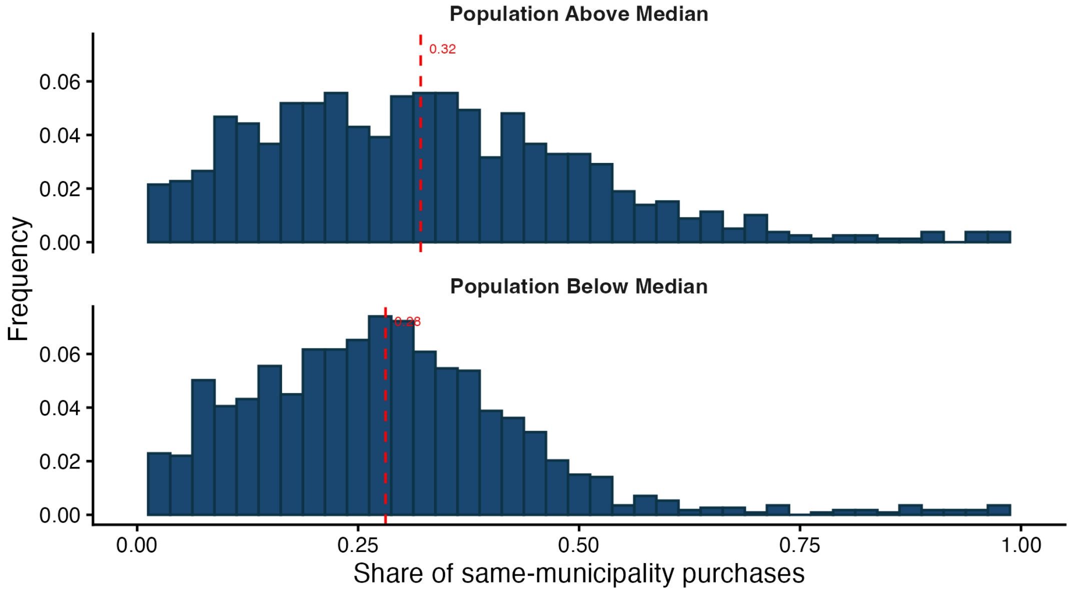
Notes: This figure presents the distribution of the percentage of purchases from firms located within the same municipality where the tender process occurs, regardless of whether it is a headquarters or a branch. The distribution is disaggregated by type of purchase - competitive and non-competitive. Data is drawn from the tender-participant table and includes only suppliers who won the tender process and whose identifier has 14 digits. We match this data with the *Cadastro Nacional de Pessoas Jurídicas* (CNPJ), a dataset provided by *Receita Federal* that contains information on every firm registered in Brazil. The temporal coverage of the data ranges from 2014 to 2021. See Table 2 for more details. Results in these figures are weighted by the contract value, and for this reason exclude all observations from the states of Paraíba (PB) and Pernambuco (PE), for which item-level information is not available.

Figure A.9: Share of local purchases and local suppliers across municipality size



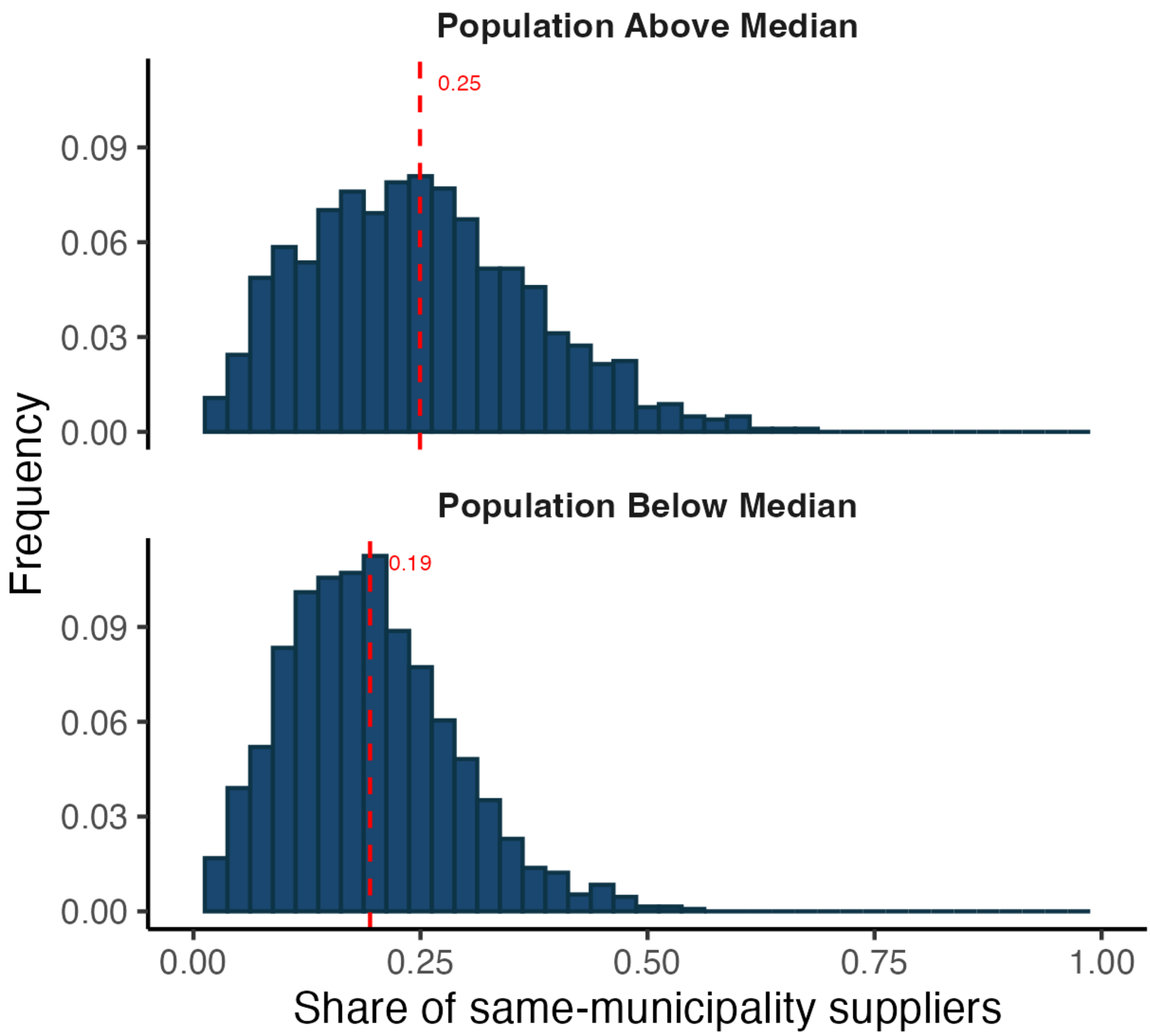
Notes: This figure presents the share of local suppliers and the share of purchases from local suppliers across municipalities of different sizes. Estimates are from local non-parametric regressions (LOESS) and include 95% CI in shade. Data is drawn from the tender-participant table and includes only suppliers who won the tender process and whose identifier has 14 digits. We match this data with the *Cadastro Nacional de Pessoas Jurídicas* (CNPJ), a dataset provided by *Receita Federal* that contains information on every firm registered in Brazil. The temporal coverage of the data ranges from 2014 to 2021. See Table 2 for more details. We drop municipalities with over 1 million individuals for this figure for visualization purposes. Results in these figures are weighted by the contract value, and for this reason exclude all observations from the states of Paraíba (PB) and Pernambuco (PE), for which item-level information is not available.

Figure A.10: Distribution of share of purchases from local suppliers, by population size



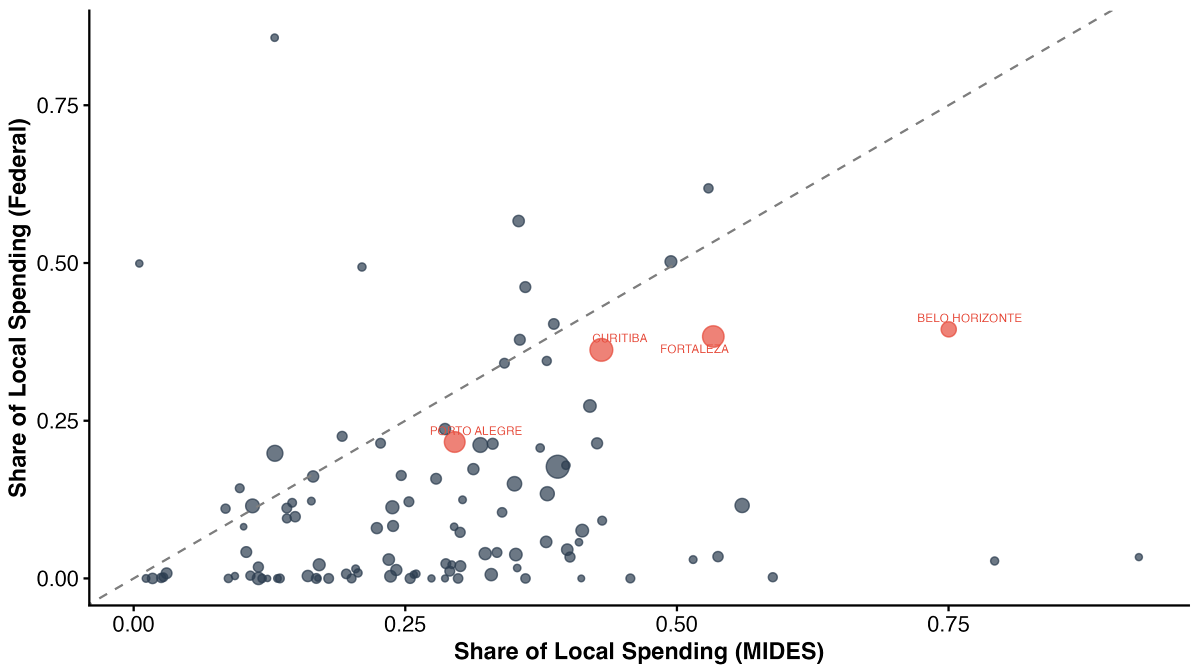
Notes: This figure presents the distribution of the percentage of purchases from firms located within the same municipality where the tender process occurs, regardless of whether it is a headquarters or a branch. The distribution is disaggregated by municipalities above and below the median population of 2018. Data is drawn from the tender-participant table and includes only suppliers who won the tender process and whose identifier has 14 digits. We match this data with the *Cadastro Nacional de Pessoas Jurídicas* (CNPJ), a dataset provided by *Receita Federal* that contains information on every firm registered in Brazil. Red dotted line marks the average value of the distribution. The temporal coverage of the data ranges from 2014 to 2021. See Table 2 for more details. Results in these figures are weighted by the contract value, and for this reason exclude all observations from the states of Paraíba (PB) and Pernambuco (PE), for which item-level information is not available.

Figure A.11: Distribution of share of local suppliers, by population size



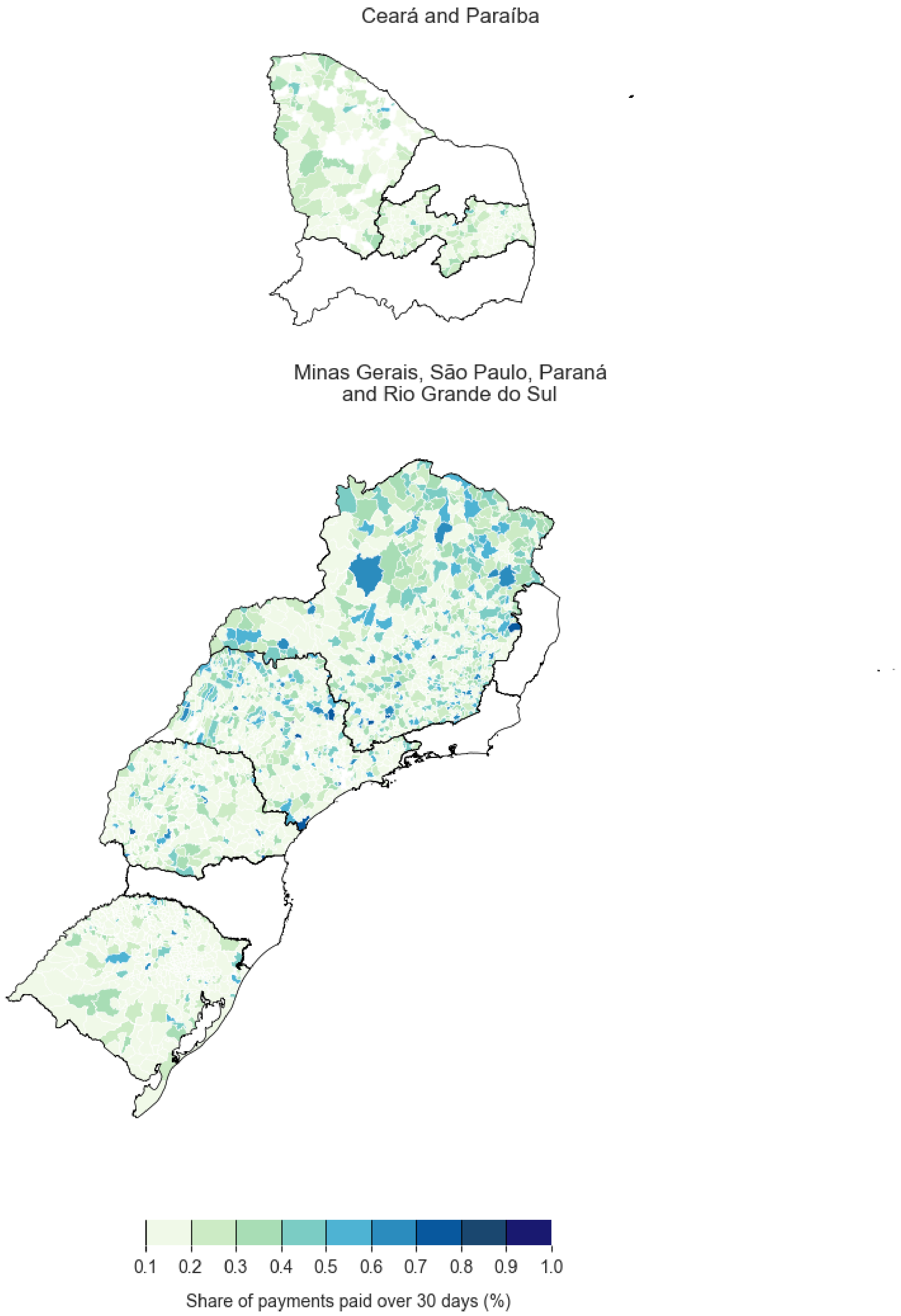
Notes: This figure presents the distribution of the percentage of firms located within the same municipality where the tender process occurs, regardless of whether it is a headquarters or a branch. The distribution is disaggregated by municipalities above and below the median population of 2018. Data is drawn from the tender-participant table and includes only suppliers who won the tender process and whose identifier has 14 digits. We match this data with the *Cadastro Nacional de Pessoas Jurídicas* (CNPJ), a dataset provided by *Receita Federal* that contains information on every firm registered in Brazil. Red dotted line marks the average value of the distribution. The temporal coverage of the data ranges from 2014 to 2021. See Table 2 for more details. Results in these figures are weighted by the contract value, and for this reason exclude all observations from the states of Paraíba (PB) and Pernambuco (PE), for which item-level information is not available.

Figure A.12: Share of local purchases - federal vs. municipal agencies



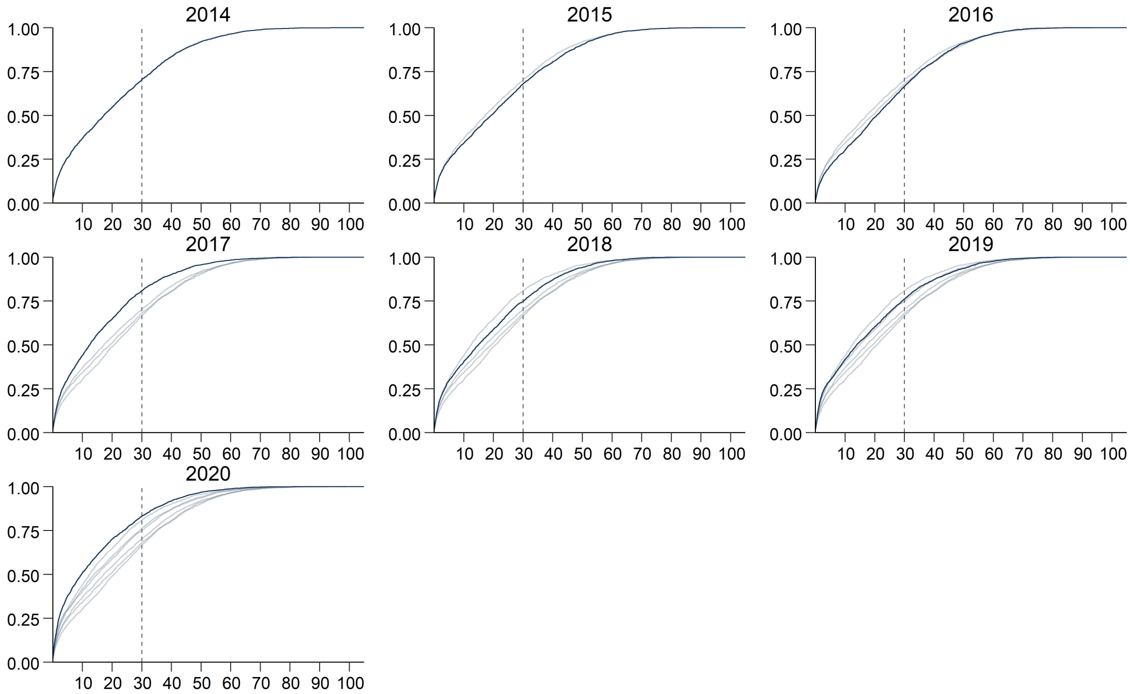
Notes: This figure presents, for each municipality, the share of local spending from federal agencies located in the municipality (in the y-axis) and the share of local spending by the municipal government (in the x-axis). The share of local spending is defined as the share of spending going to suppliers located in the same municipality, conditional on suppliers being incorporated entities (for which we can identify location). The sample includes approximately 130 municipalities for which we observe both municipal spending in MiDES and purchases from a federal agency located in the same municipality in 2021. We exclude from this figure municipalities with less than 10 purchases from local government or less than 10 purchases from a federal agency. Results in these figures are weighted by the contract value, and for this reason exclude all observations from the states of Paraíba (PB) and Pernambuco (PE), for which item-level information is not available.

Figure A.13: Share of payments paid over 30 days (%)



Notes: This figure presents a map of regions of Brazil where municipalities are colored according to the share of payments performed over 30 days. This indicator is available for the states of RS, PR, SP, MG, PB, CE. We only consider commitments that are fully executed within a fiscal year, that is, the amount committed is equal to the amount verified and the amount paid.

Figure A.14: Distribution of share of late payments (over 30 days)



Notes: This figure presents the cumulative distribution functions (CDFs) the share of payments that are made over 30 days, at the municipality level, across different years in the period 2014-2020. The underlying data cover six states (CE, MG, PB, PR, RS and SP). We are unable to calculate payment speed for PE due to our inability to match payments to their respective commitments.

Table A.1: Procurement and budget execution sources

State	Procurement	Budget Execution
CE	https://api.tce.ce.gov.br/	https://api.tce.ce.gov.br/
MG	https://dadosabertos.tce.mg.gov.br	https://dadosabertos.tce.mg.gov.br
PB	https://dados.tce.pb.gov.br	https://zeoserver.pb.gov.br/portaltcepb/tcepb/servicos/dados-abertos-do-sagres-tce-pb
PE	https://sistemas.tce.pe.gov.br/DadosAbertos	https://sistemas.tce.pe.gov.br/DadosAbertos
PR	https://servicos.tce.pr.gov.br/TCEPR/Tribunal/Relacon/Dados/DadosConsulta/Consolidado	https://servicos.tce.pr.gov.br/TCEPR/Tribunal/Relacon/Dados/DadosConsulta/Consolidado
RS	http://dados.tce.rs.gov.br	http://dados.tce.rs.gov.br
SP		https://transparencia.tce.sp.gov.br/conjunto-de-dados

Notes: This table presents urls with data sources for each state used in this paper.

Table A.2: Procurement methods

Purchasing method	Competitive	Characteristics	Contract size
Reverse auction (*Pregão*)	Yes	Reverse auction, open to any interested firm. Online or in-person. Off-the-shelf goods. Multiples bids per participant.	Any value
Waiver (direct contracting)	No	Small purchases.	Up to 17,600 BRL
Invitation to tender (*Convite*)	Yes	Participants are invited. Minimum of 3 bidders. Uninvited firms are allowed to participate. One bid per participant.	Up to 176,000 BRL
Competitive bidding (*Concorrência*)	Yes	Open to any interested bidder. One bid per participant.	Any value
Submission of prices (*Tomada de preços*)	Yes	Bidder must be previously registered. One bid per participant.	Up to 1,430,000 BRL
Direct contracting	No	There is only one supplier.	-
Contest	Yes	Artistic, scientific or technical work.	-

Notes: Contract size refers to the purchases of products and services other than construction (see Federal Decree 9,412, of June 18, 2018, for more details). Thresholds for construction are different (33,000 BRL). The maximum contract size for direct contracting changed in 2018 from 8,000 BRL to 17,600 BRL.

Table A.3: Share of tenders by level of government and year on ComprasNet portal

	2020	2021	2022	2023	2024
Federal	94.85	93.85	91.65	84.66	70.3
State	.54	.74	1.35	2.72	11.72
Municipal	.73	1.27	2.89	6.56	11.29
NA	3.88	4.14	4.11	6.06	6.68
Observations	167,063	141,941	156,289	165,152	120,579

Notes: This table presents the percentage distribution of government procurement records by administrative sphere—Federal, State, and Municipal—from 2020 to 2024, based on the federal ComprasNET portal. Percentages represent the share of purchases associated with each sphere. NA corresponds to tenders linked to UASGs (Unidades Administrativas de Serviços Gerais), Brazil's procurement management units, that could not be classified by sphere. "Observations" indicate the total number of purchase records, including both competitive and non-competitive procurements, in each year.

Table A.4: Regression Table: Correlates of purchases from local suppliers (value-weighted)

Dependent Variable:	Dummy Local Supplier		
Model:	(1)	(2)	(3)
Variables			
ln(GDP)	-0.0004	0.005	-0.012
	(0.013)	(0.015)	(0.019)
ln(Population)	0.018	0.013	0.034
	(0.015)	(0.018)	(0.021)
Non-Competitive Tenders	0.186***	0.187***	0.166***
	(0.029)	(0.029)	(0.029)
Fixed-effects			
Year		Yes	Yes
State			Yes
Fit statistics			
Observations	1,373,225	1,373,225	1,373,225
Dependent variable mean	0.27	0.27	0.27
RMSE	0.47	0.47	0.47
R^2	0.03	0.03	0.04
Adjusted R^2	0.03	0.03	0.04

Clustered (id_municipio) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: This table presents results from OLS regressions, at the tender-item level, of the probability that the supplier is local. The data cover 4 states (CE, MG, PR, RS) and their corresponding years described in Table 2. Regressions in this table are weighted by the contract value, and for this reason exclude all observations from the states of Paraíba (PB) and Pernambuco (PE), for which item-level information is not available. Standard errors clustered at the municipality level in parentheses. Significance levels: ***: 0.01, **: 0.05, *: 0.1.

Table A.5: Regression Table: Municipal vs. Federal local purchases (value-weighted)

Dependent Variable:	Share Local Purchase	
Model:	(1)	(2)
Variables		
Constant	0.2110***	
	(0.0269)	
Municipal buyer	0.0681**	0.1306***
	(0.0280)	(0.0162)
Fixed-effects		
Modality		Yes
Municipality		Yes
Fit statistics		
Observations	528,148	528,147
R^2	0.002	0.13
Dependent variable mean	0.20	0.20

Clustered (id_municipio,municipal)) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: This table presents regressions, at the participant level, on the probability that the winner of a contract is a local firm i.e. a firm located in the same municipality is the buyer. Column (1) includes no controls while column (2) includes modality of purchase (waivers, auctions, direct contracting and others) and municipality fixed-effects. The indicator for municipal buyer is equal to 1 for municipal entities and zero for federal entities. Regressions in this table are weighted by the contract value, and for this reason exclude all observations from the states of Paraíba (PB) and Pernambuco (PE), for which item-level information is not available. Standard-errors are clustered at the municipalioty-by-sphere of government level.

Table A.6: Descriptive statistics - municipalities

Variable	CE	MG	PB	PE	PR	RS	SP	Outside-sample
Population (2015)	48,393.80	24,465.53	17,812.57	50,514.45	27,977.49	22,631.73	68,831.76	36,591.19
GDP per capita (2015)	8,844.05	16,425.13	8,892.95	10,162.70	26,046.96	30,934.94	29,887.32	17,346.67
Child mortality 5- (2010)	26.54	19.05	28.72	28.31	16.37	14.49	16.70	24.25
Piped water (%) (2010)	76.11	88.38	66.66	69.94	92.91	91.82	96.56	83.05
Trash collection (%) (2010)	89.90	95.56	94.69	92.95	98.50	98.19	99.53	91.01
Electricity access (%) (2010)	98.64	98.74	99.11	99.06	99.26	99.55	99.76	94.86
Total revenues p.c. (2015)	2,271.10	2,859.31	2,715.13	2,139.26	3,547.15	4,277.53	3,796.92	2,942.78
Current revenues p.c. (2015)	2,170.23	2,735.92	2,586.18	2,019.02	3,320.44	3,940.09	3,578.81	2,807.96
Local tax revenues p.c. (2015)	102.73	158.00	67.63	104.63	247.46	271.32	380.04	185.34
Capital revenues p.c. (2015)	87.70	107.58	104.74	51.99	193.34	206.92	160.43	119.15

Notes: This table presents descriptive statistics about municipalities inside and outside our sample of seven states (CE, MG, PB, PE, PR, RS, SP). Each number is the average of that variable in each subset of data. Data sources are IBGE's population estimates, the 2010 Census, and SICONFI, all available at Data Basis (Dahis et al., 2022).

B Example of data extraction and analysis

In this section we exemplify how researchers can use our dataset for generating descriptive statistics about public procurement and budget execution across Brazilian municipalities. The full documentation on using datasets hosted on the Data Basis platform can be found at https://basedosdados.github.io/mais (in Portuguese), including video tutorials and details on how to create projects at Google BigQuery.

Here we provide a simple example using the 'basedosdados' R package. This package allows users to connect to their BigQuery projects (and billing ID) and directly make SQL queries on BigQuery datasets, which are then loaded in R.

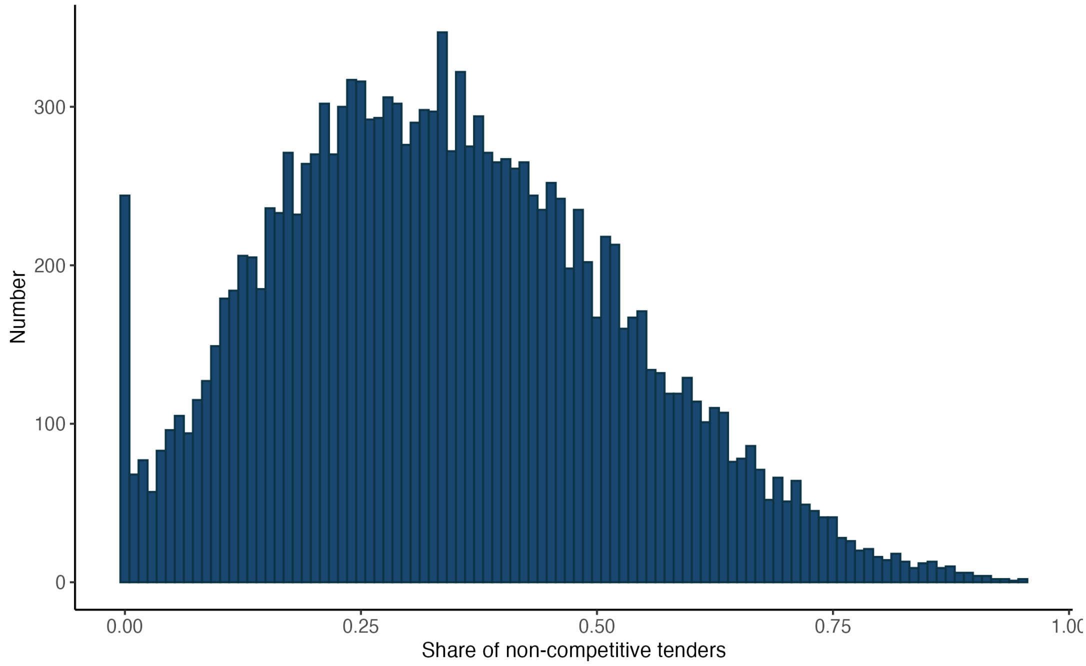
The SQL query presented below does the following: it connects to the *licitacao* (tender) table including tender-level information for all municipalities and years covered in our data (over 2.3 million unique tenders); it creates an indicator for when the modality is defined as categories 8 (waiver) or 10 (non-requirement); then it computes the average share of tenders that are non-competitive and the total number of tenders at the municipality-year level. The resulting table, loaded in the 'data' object, includes 19,033 municipality-year observations. When executed, this query took 3 seconds to process the 2.3 million observations and provide us these summarized statistics.

We then can simply plot a histogram of the share of non-competitive tenders across municipality - year (in this case, we filter the dataset for observations with at least 50 tenders). We present the results in Figure B.15. We can see that the average we describe in Table 3 of 30%-40% masks substantial heterogeneity: while a substantial amount of municipalities in a given year do not use non-competitive modalities, in some municipalities the share of these is above three-quarters.

Using this dataset and auxiliary tables also easily accessible in the 'basedosdados' package, we could also explore additional questions, such as whether the use of non-competitive tenders vary systematically over time and whether it correlates with other municipality traits, such as GDP per capita.

```r
#Install (if not yet installed) and load packages
require(ggplot2)
require(basedosdados)
require(dplyr)

#Set user's BigQuery billing ID
set_billing_id("<BILLING-ID>")

#Define SQL query to extract data
query <- "
    SELECT
        id_municipio,
        ano,
        AVG(
            CASE WHEN modalidade = '8' OR modalidade = '10'
            THEN 1 ELSE 0 END
        ) AS share_discretion,
        COUNT(id_licitacao_bd) AS count
    FROM `basedosdados.world_wb_mides.licitacao`
    GROUP BY id_municipio, ano"

#Execute query and create data frame from output
data <- read_sql(query)

#Create histogram of share of non-competitive tenders
data %>% filter(count > 50) %>%
  ggplot() +
  geom_histogram(aes(x = share_discretion), bins = 100,
                 color = "#0D3446",
                 fill = "#1A476F") +
  xlab("Share of non-competitive tenders") +
  ylab("Number") +
  theme_classic() +
  theme(
    strip.text = element_text(size = 7, face = "bold"),
    axis.title = element_text(size = 11),
    axis.text=element_text(size=10)
  )
```

Figure B.15: Histogram of share of non-competitive tenders



Notes: This figure presents a histogram of share of tenders that are non-competitive at the municipality-year level. Non-competitive tenders are defined as those tagged with modality categories 8 (waiver) and 10 (non-requirement).

C Data Quality

This section briefly describes some aspects of the quality of our newly created dataset on local procurement and budget execution. Despite the large effort in harmonizing a variety of original sources as described in Section 2, there are still some issues that researchers using our data should be aware of.

First, we plot the percentage of observations we cannot uniquely identify for each table in Figure C.1, Figure C.2, Figure C.3, and Figure C.4. After harmonizing and stacking each state's information we create unique identifiers for each observation. For example, for the *tender table*, to create the `id_licitacao_bd` variable, we concatenate the following original variables: tender number, agency identifier, and state identifier.[1] This identifier can be null in rows where (1) any of these components are missing or (2) this combination of variables still does not uniquely identify it. In Figure C.1 we report that CE was the only state in which we could not uniquely identify all observations - the percentage of null tenders identifiers exceeds 3% in 2010 but later remains stable around 1%.

Similarly, for the *commitment* table, to create the `id_empenho_bd` variable, we concatenate the following original variables: number, agency identifier, unit identifier, municipality identifier, year, and month. In Figure C.2 we document that the vast majority of observations are uniquely identified, i.e. the percentage of null commitment identifiers is never above 2%. When adding the total value committed from observations with null identifiers this percentage is at most about 5% in SP between 2008 and 2012.

The situation is worse for verifications and payments. In Figure C.3 we report that is was impossible to uniquely identify observations in the states of CE and PB, while the state of RS has a percentage of up to 60% in the early years. For payments in Figure C.4 we show that the states of CE, RS, and SP have values up to 10%. In other states such as MG or PR we are able to fully identify observations.

Second, in Figure C.5 and Figure C.6 we plot the percentage of missing municipalities for each table and state. The relevant pattern observed is that for most states the number of missing municipalities is stable and close to zero over time. The exceptions are the state of CE, ranging around 5%-10% missing, the state of PE in 2013 in the *payment* table, the state of PR in 2022 in the *payment* table, and the state of PE in 2012 in the *tender* and *tender-participant* tables.

Finally, we compare the number of municipalities present in each of our budget execution tables to the number in SICONFI in Figure C.7, Figure C.8, and Figure C.9. We document that for most states and most years both datasets have similar coverage or at most a 10% difference. Some exceptions are the state of MG in 2014 or the state of RS in 2021, for which our dataset has very little coverage.

[1] The combination of these variables might vary depending on the state. In CE, for example, there is no agency identifier, instead we use the municipality identifier. Also, in RS, we had to include the year and an additional identifier for the type of purchase.

Table C.1: Limitations in the budget execution data

	CE	MG	PB	PE	PR	RS	SP	Obs
Incomplete temporal coverage								
Commitment								
Verification			✓					From 2009
Payment								
Has some municipality missing								
Commitment	✓				✓	✓	✓	See Figure C.6
Verification	✓				✓	✓	✓	See Figure C.6
Payment	✓				✓	✓	✓	See Figure C.6
Does not have unique ID								
Commitment				✓				
Verification	✓		✓	✓				
Payment				✓				
Has missing IDs								
Commitment	✓		✓	✓		✓	✓	See Figure C.2
Verification	✓		✓	✓		✓	✓	See Figure C.3
Payment	✓		✓	✓		✓	✓	See Figure C.4

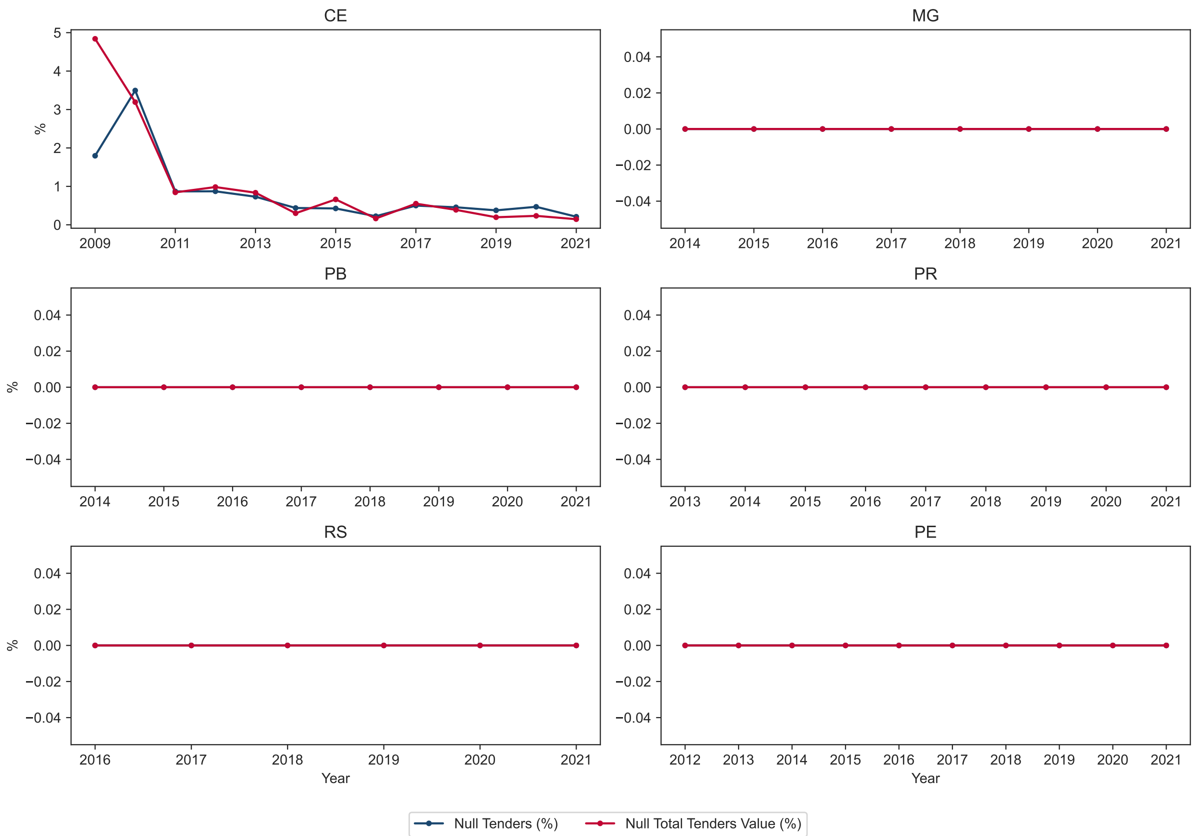
Notes: This table presents the limitations in the budget execution data. 'Does not have unique ID' refer to the cases where we were not able to build an identifier that uniquely identifies each row in the given table. Even if we manage to construct a unique identifier for most of the observations of a state-table pair, we may still have observations within that table for which this is not possible. In these cases, we mark it with a tick in 'Has missing ID'. The percentage of cases in which that happens can be found in Figure C.2, Figure C.3 and Figure C.4.

Table C.2: Limitations in the procurement data

	CE	MG	PB	PE	PR	RS	Obs
Incomplete temporal coverage							
Tender							
Item							
Participant							
Has some municipality missing							
Tender	✓	✓		✓	✓	✓	See Figure C.5
Item	✓	✓	✓	✓	✓	✓	See Figure C.5
Participant	✓	✓		✓	✓	✓	See Figure C.5
Does not have unique ID							
Tender							
Item							
Participant							
Has missing IDs							
Tender	✓						See Figure C.1
Item	✓	✓					
Participant							

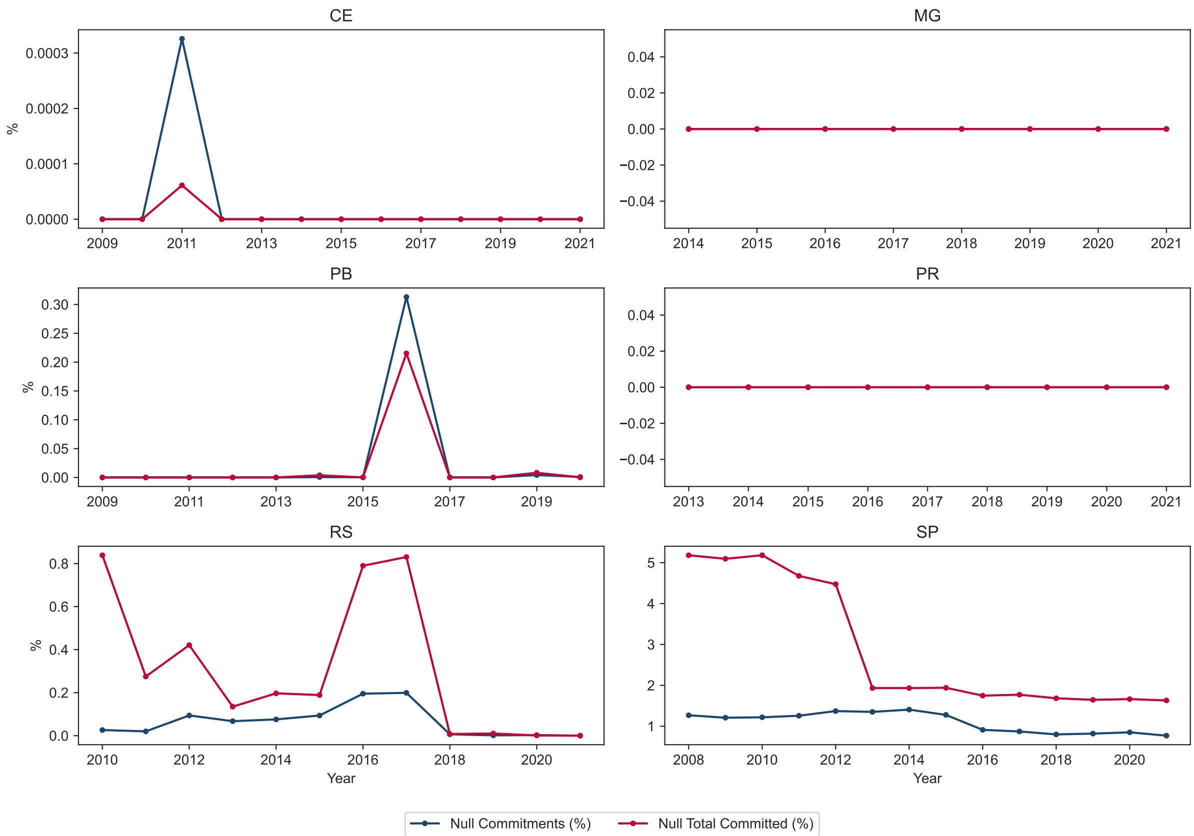
Notes: This table presents the limitations in procurement data. 'Does not have unique ID' refer to the cases where we were not able to build an identifier that uniquely identifies each row in the given table. Even if we manage to construct a unique identifier for most of the observations of a state-table pair, we may still have observations within that table for which this is not possible. In these cases, we mark it with a tick in 'Has missing ID'. The percentage of cases in which that happens can be found in Figure C.1.

Figure C.1: Missing tender identifiers



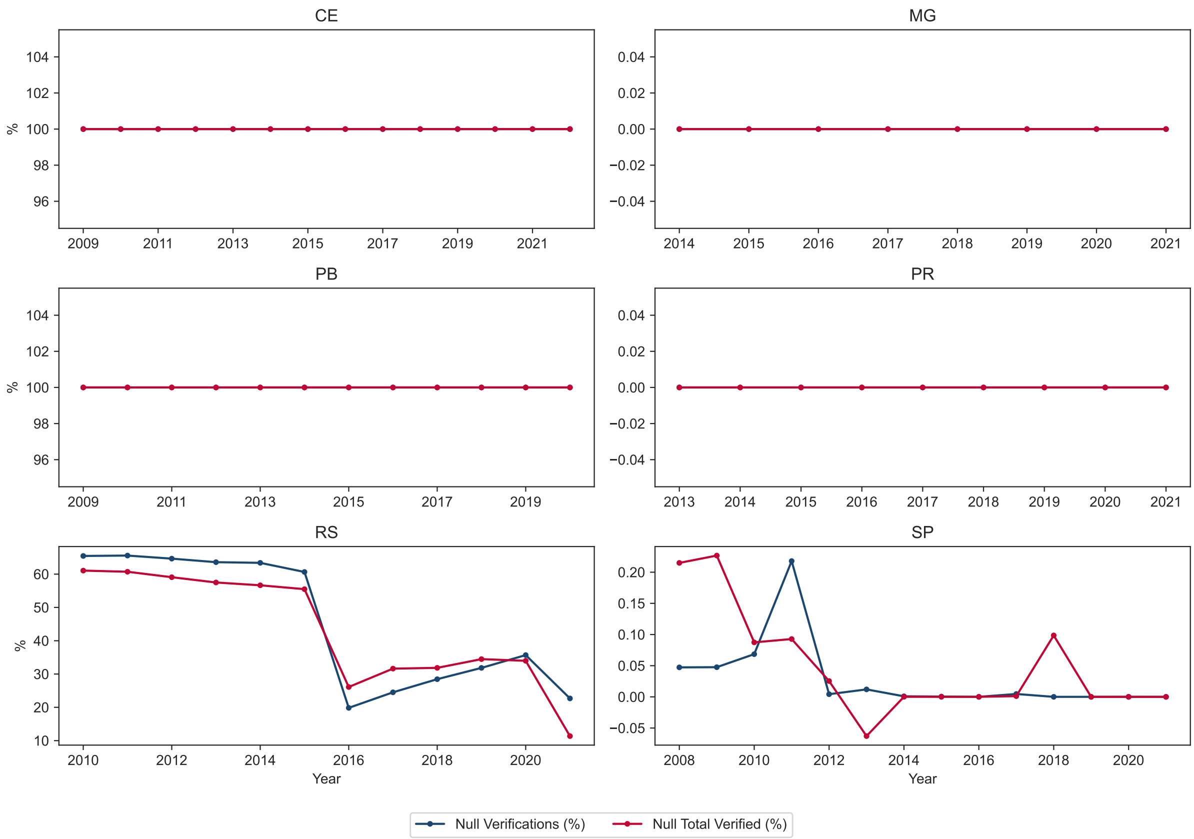
Notes: This figure presents the percentage of observations by year for which we were unable to build a unique identifier (`id_licitacao_bd`) in the *tender* table. To calculate the percentage of "Null Total Tenders Value " we use the variable `valor_corrigido` winsorized at percentiles 0.01 and 99.9.

Figure C.2: Missing commitment identifiers



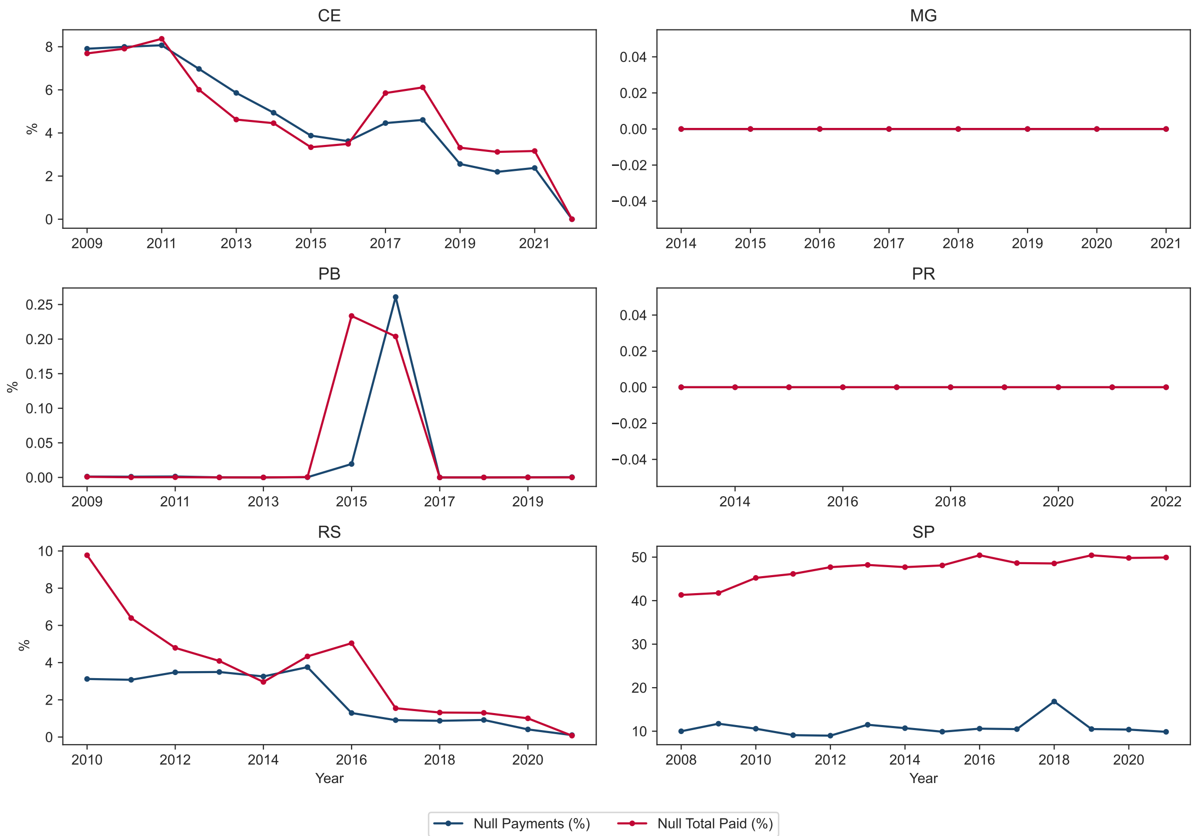
Notes: This figure presents the percentage of observations by year for which we were unable to build a unique identifier (`id_empenho_bd`) in the *commitment* table.

Figure C.3: Missing verification identifiers



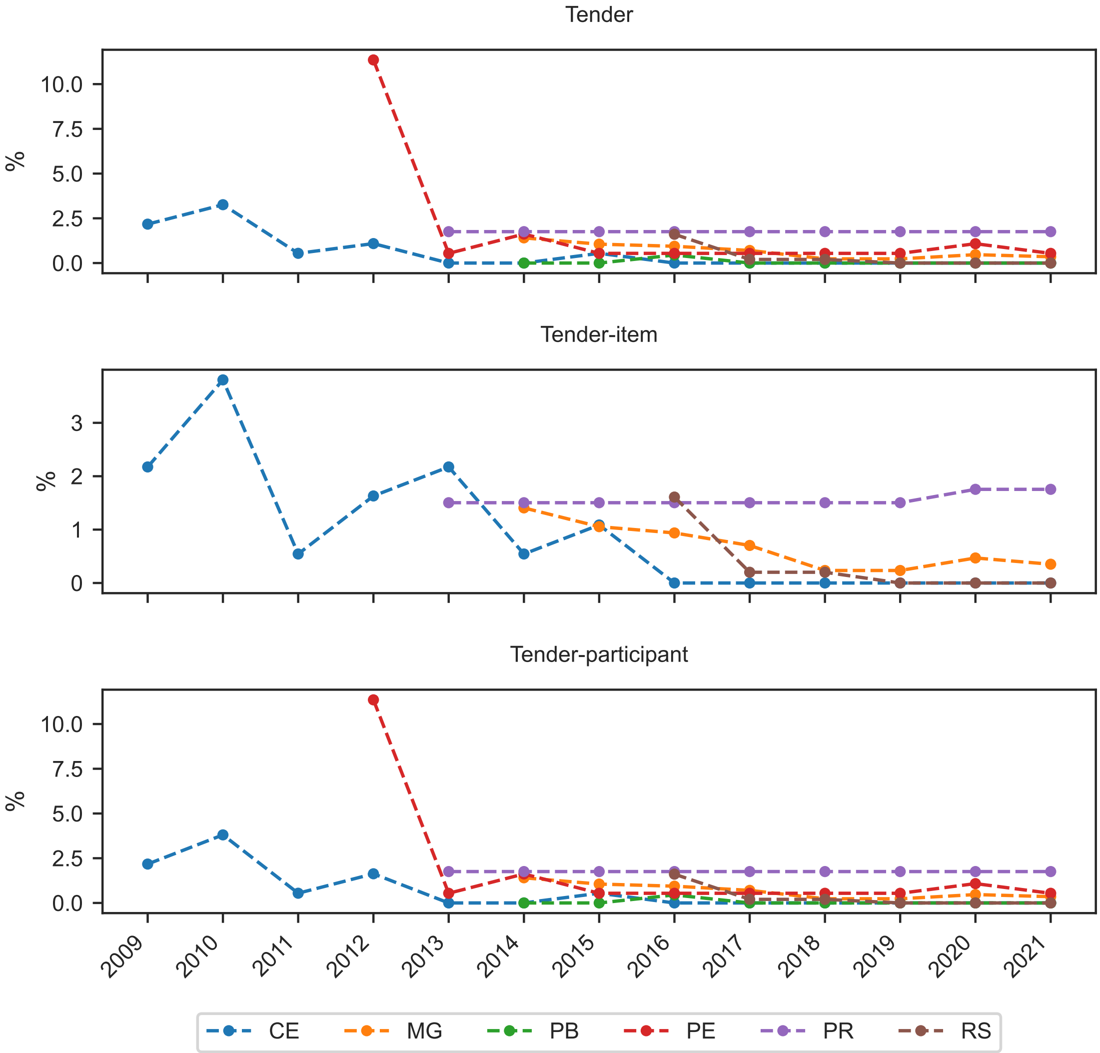
Notes: This figure presents the percentage of observations by year for which we were unable to build a unique identifier (`id_liquidacao_bd`) in the *verification* table.

Figure C.4: Missing payment identifiers



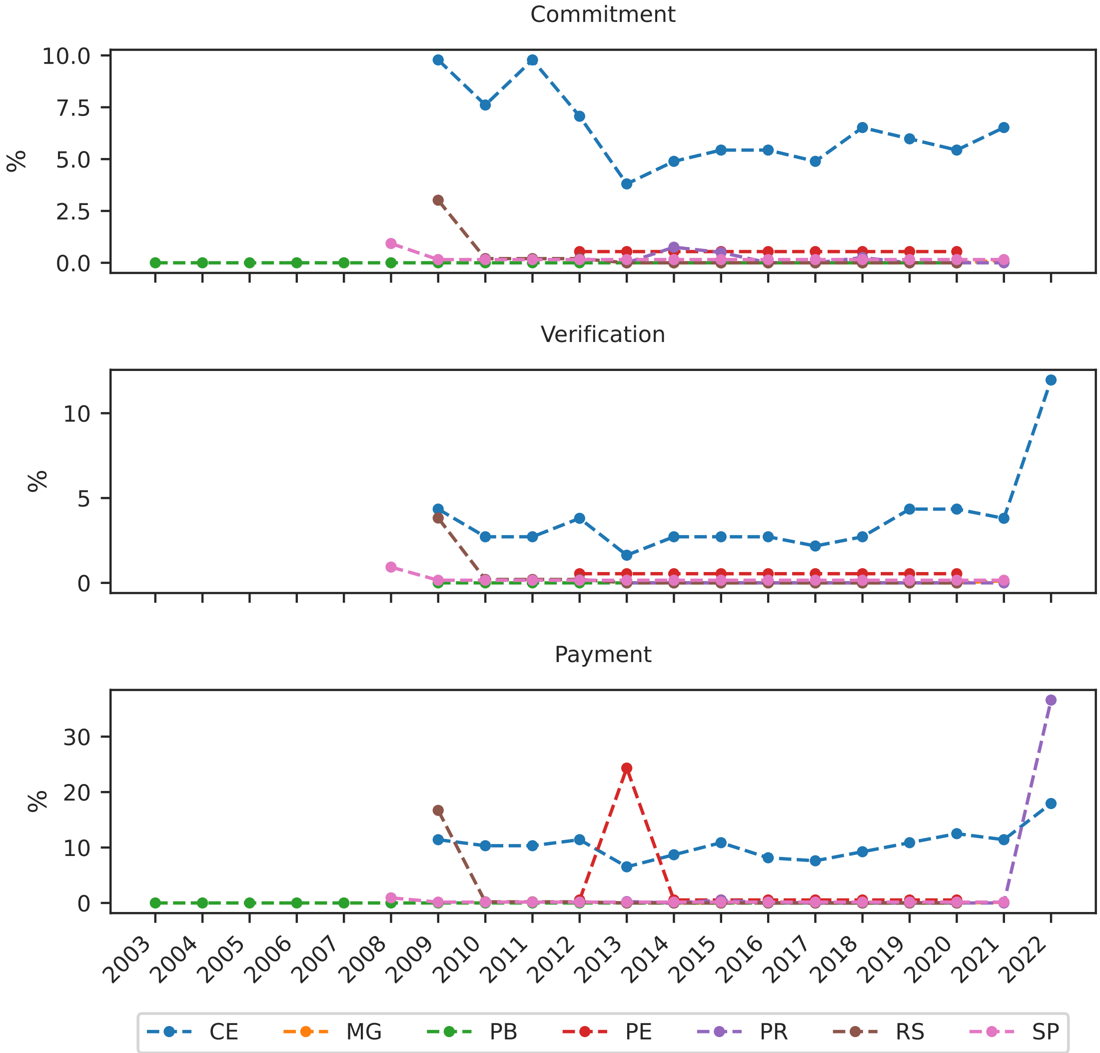
Notes: This figure presents the percentage of observations by year for which we were unable to build a unique identifier (`id_pagamento_bd`) in the *payment* table.

Figure C.5: Missing municipalities: procurement



Notes: This figure presents the percentage of municipalities by year for which we do not have data in the procurement dataset.

Figure C.6: Missing municipalities: budget execution

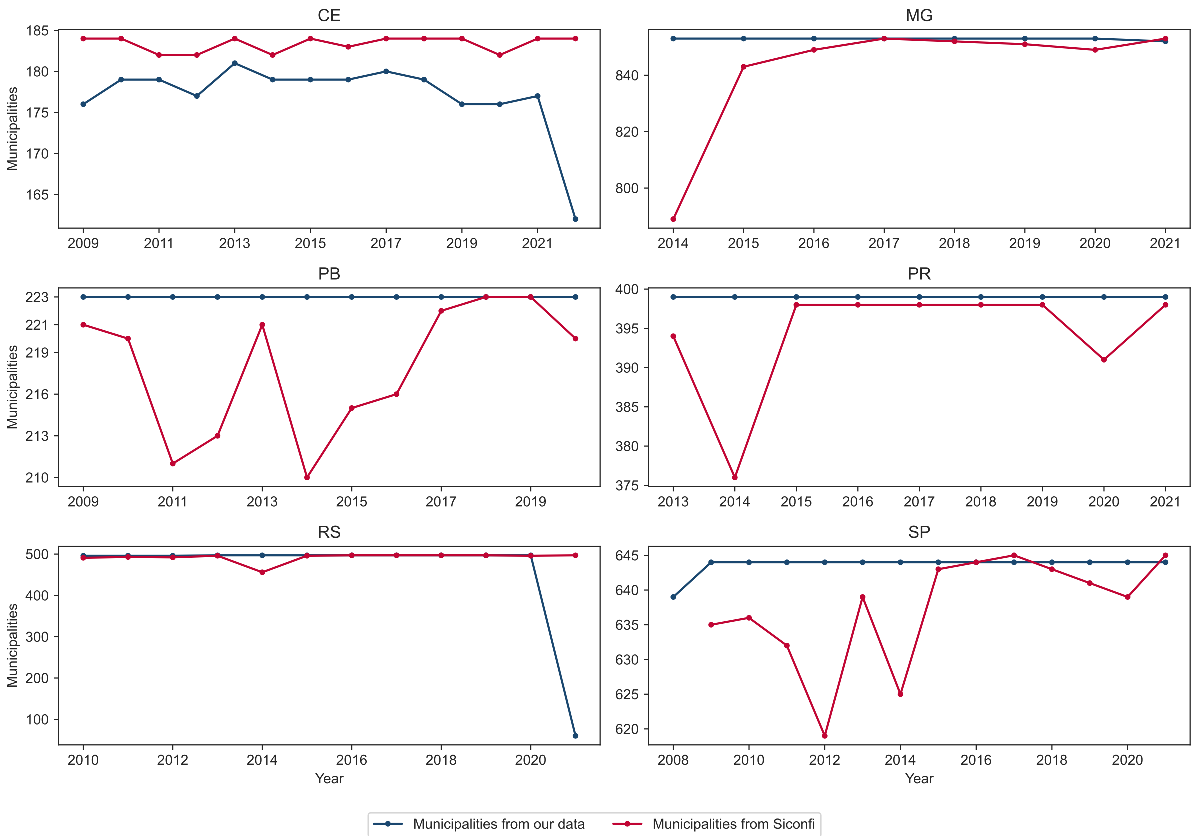


Notes: This figure presents the percentage of municipalities by year for which we do not have data in the budget execution dataset. Data from RS are restricted between 2009 and 2020 to avoid distorting the graph. In 2008, commitment data are unavailable for over one third of the municipalities from RS, whereas in 2021 we only have data for 12% of the municipalities.

Figure C.7: Number of municipalities: commitment

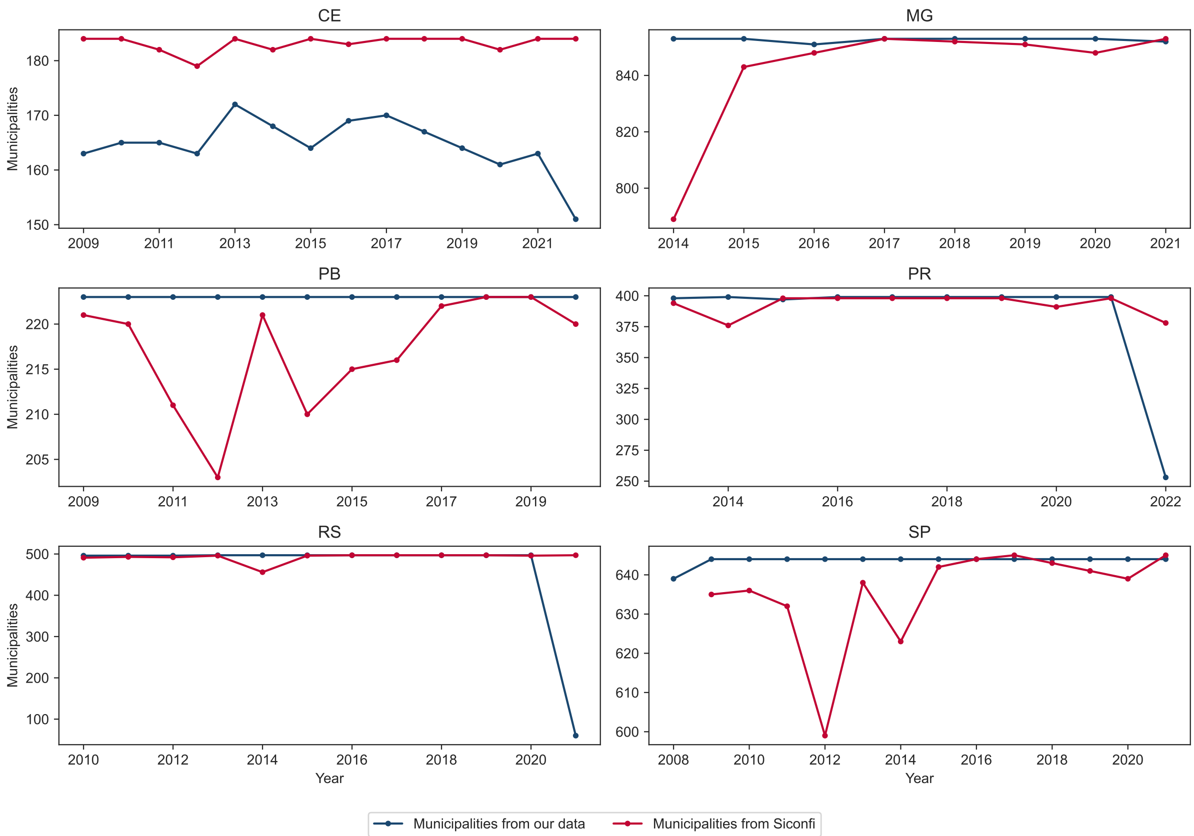
Notes: This figure compares the number of municipalities in our dataset and the number of municipalities in SICONFI in commitment data.

Figure C.8: Number of municipalities: verification



Notes: This figure compares the number of municipalities in our dataset and the number of municipalities in SICONFI in verification data.

Figure C.9: Number of municipalities: payment



Notes: This figure compares the number of municipalities in our dataset and the total of municipalities in SICONFI in payment data.

D Comparing amounts of tenders and procurement-related budget

In this section we perform a series of exercises that shed light on how data on the value of tenders compare with the execution of budget related to those tenders.

Building on the discussion from Section 3.2, one possible approach to validate the completeness and accuracy of our data on tenders, similar to what we do for budgets, would be to compare aggregates of tenders' values with budget commitments on procurement-related expenses, at the municipality-year level. Unfortunately, these aggregates are not directly comparable for a few reasons, which we illustrate by exploiting data from the state of Paraná (PR), for which we have identifiers that connect tenders with all budget execution actions that arise from them.

We first compute, at the tender level, the percentage deviation between the final value of a tender and all commitments related to that tender.[1] We present the histogram of those deviations in Figure D.1a. What we observe is that, for close to half of tenders, the information on value from our procurement dataset almost perfectly matches the sum of all budget commitments related to that tender. But there is quite a substantial dispersion for remaining tenders, including a long right tail - for 8% of purchases, the tender value is more than triple the commitments we observe linked to that tender. We provide more insights on the drivers of these differences in Figure D.1b, where we plot the distribution separately by purchase modality. For low-value purchases for which competitive bidding is waived ($\approx$ 23% or tenders), deviations are close to zero in almost 80% of purchases. Deviations are also much smaller in direct contracting processes, which are also lower-value on average. So for these cases we can see that procurement and budget data available at MiDES closely align. On the other hand, deviations are small in only one out of every three auctions – here we see much larger dispersion, particularly in those cases where tender value is much larger that committed amounts. While our data does not provide a definitive answer on what drives these differences, the description of auctions with large discrepancies suggest that many of them are *price registrations* or framework agreements, where the government registers suppliers through auctions for future purchases, without the commitment of purchasing the full value. This would explain why tender values are systematically larger than committed values.

These discrepancies that arise when we compare procurement value with budget expenses related to the same tender become even more relevant when we aggregate these quantities at the municipality-year level. One additional challenge is that budgets can be executed over multiple years, creating additional noise in yearly comparisons: in Paraná, where we can collect all expenses related to one tender, over half of auctions will be linked to expenses

[1]Our sample for this exercise is restricted to the period 2014-2020 (to exclude the first and last year of the sample, due to multi-year budget execution) and only include tenders which can be connected to at least one commitment.

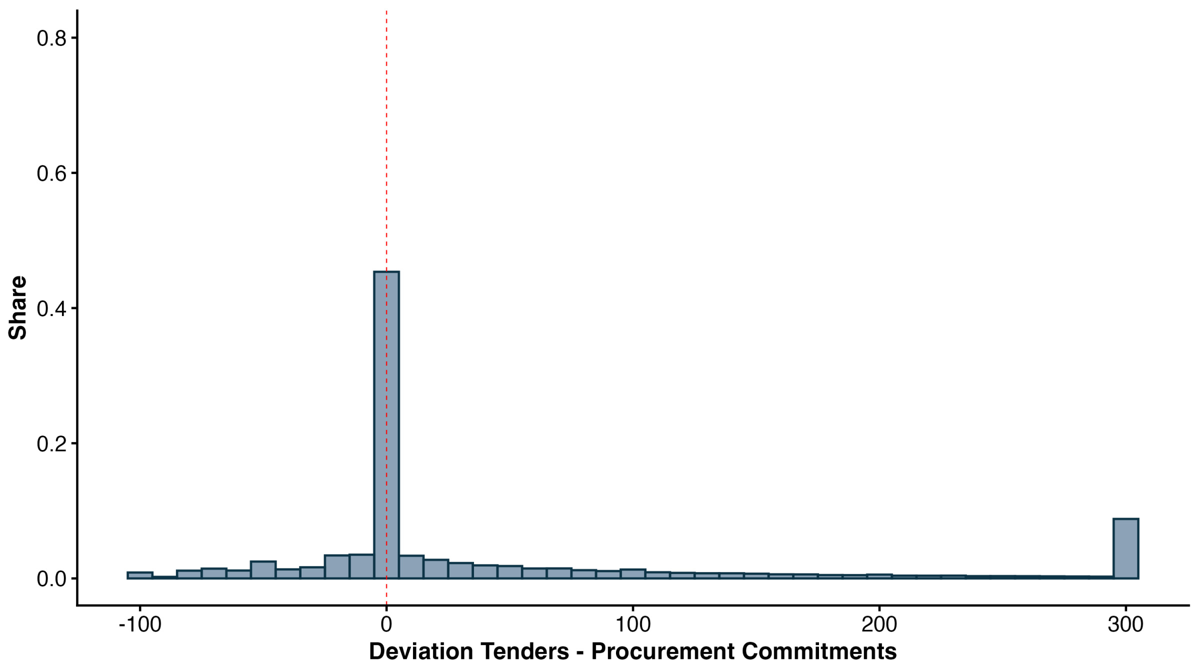
in different years. Again, this is partially driven by framework agreements but also to the fact that auctions are on average much larger contracts, which might entail more complex budgeting decisions — the median number of commitments in an auction is 8 vs. one single commitment for waivers. We document those discrepancies in Figure D.2. Using the same data as above, but plotting deviations in the aggregates of tender values and procurement-related expenses at the municipality-year level, we observe a distribution that is centered slightly above zero and exhibits a lot of dispersion, particularly at the right tail where tender values are much larger than expenses.

These facts from Paraná are informative to explain the results when we compare these aggregates for the remaining states, where we do not observe directly the connection of tenders and budget execution. We present in Figure D.3a the distribution of deviations between tender amounts and procurement-related commitments[2] at the municipality-year level. The distribution is centered around zero, with a median deviation of -5% (meaning that aggregate tender value is 5% smaller than commitment value), but there is a lot of dispersion: only 15% of the deviations are within +- 10% and one-third are within +-20%. Looking at these deviations by state in Figure D.3b, we see that median deviations are very close to zero in states like MG, PR and PB, but farther in the remaining states – our tender aggregates are systematically smaller in RS and PE, but larger in CE.

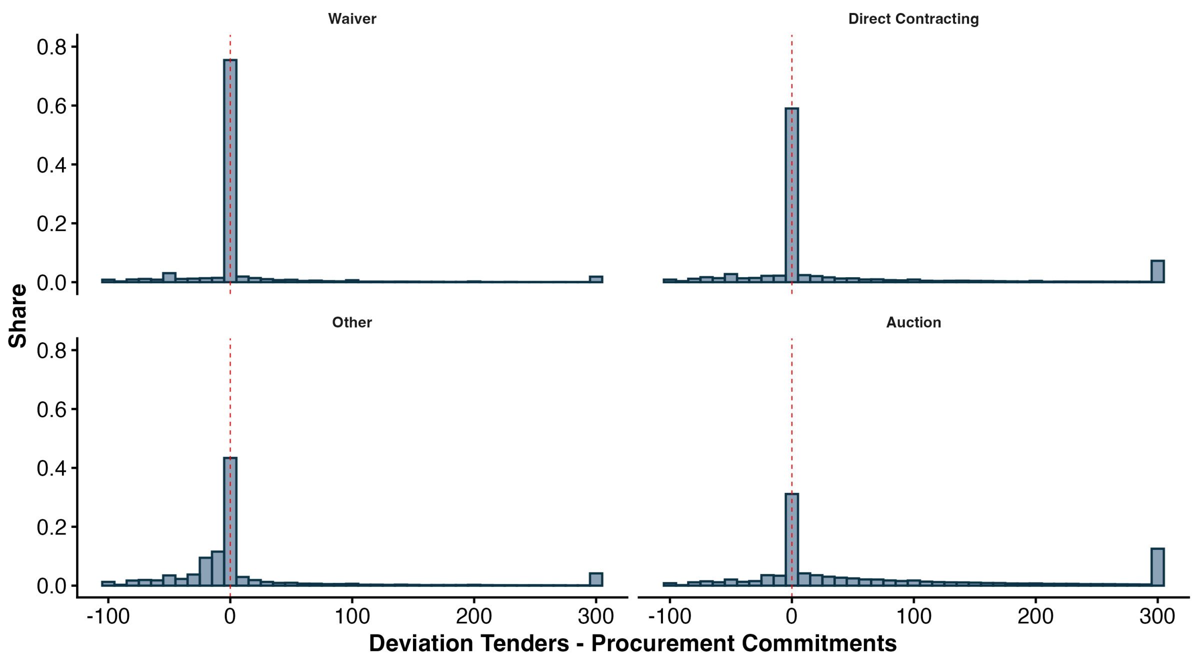
In summary, our results from the state of Paraná, where we can connect individual tenders with budget execution, illustrates the clear limitation of comparing aggregates of tender values and budget amounts at the municipality-year level.

[2]Specifically, we use the following codes for procurement related activities in budget execution data: 30 (goods and materials), 32 (goods and material for free distribution), 35 (consulting services), 36 (other services from individuals), 37 (labor hiring as service provision and not wage employment), 39 (other services from corporations), 51 (construction), and 52 (equipment and permanent assets).

Figure D.1: Validation of procurement data



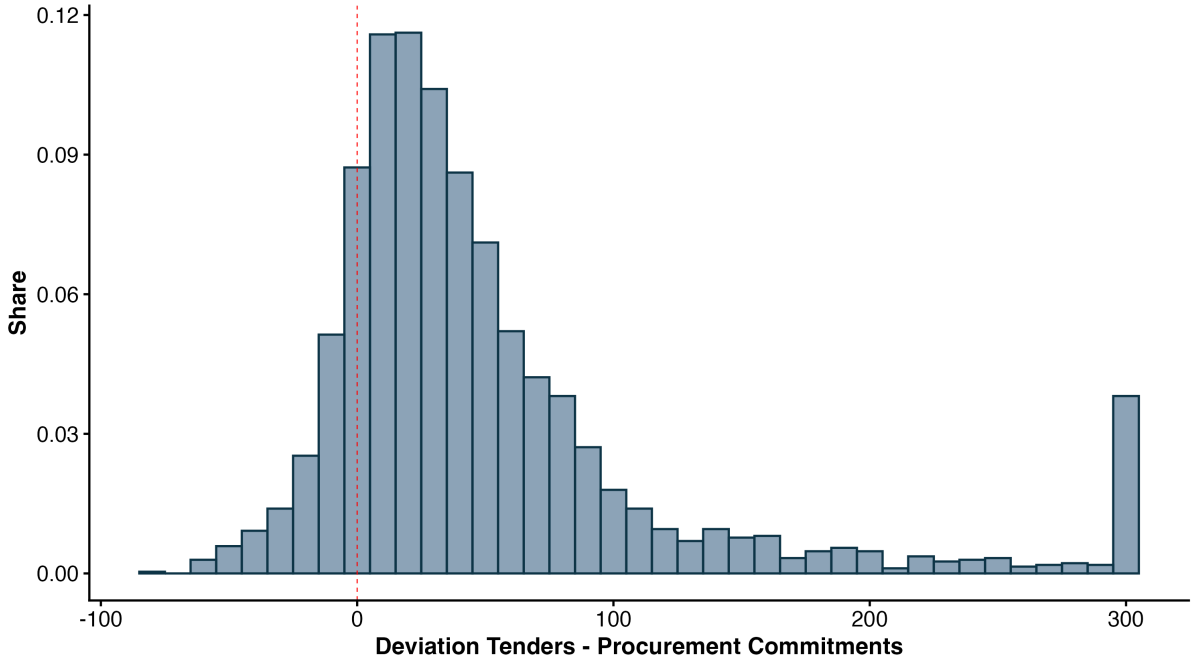
(a) All sample for Paraná state



(b) By purchase modality

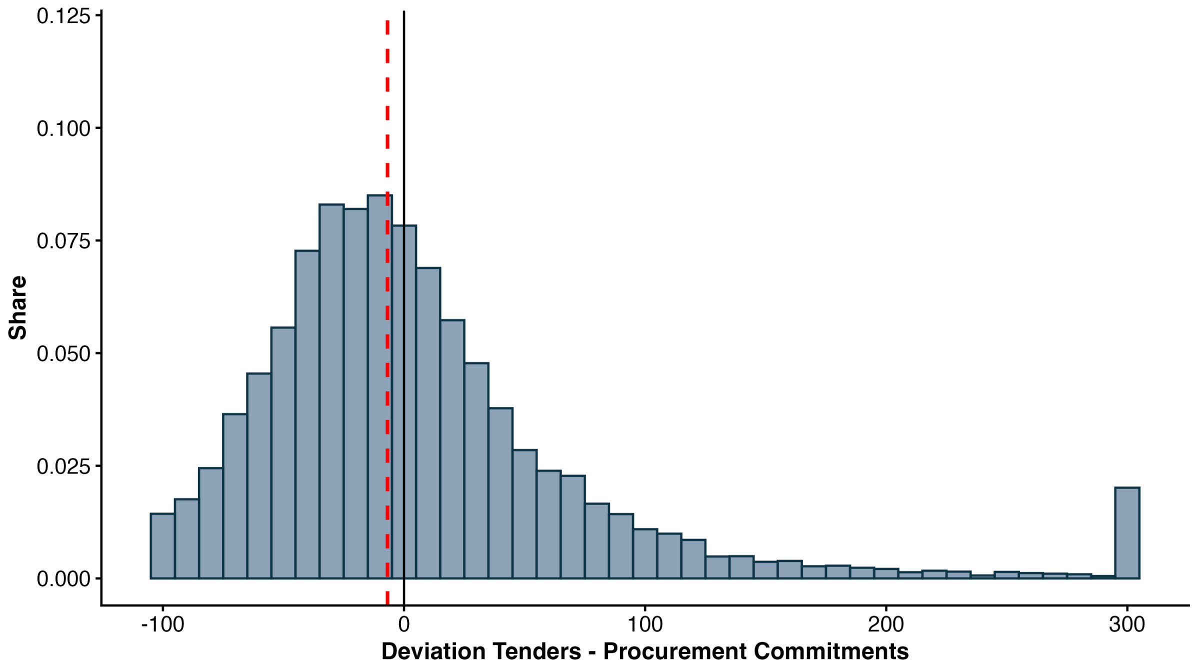
Notes: This figure presents the histogram of percentage deviations between tender values and the sum of all budget commitments related to those tenders, at the tender level in the state of Paraná. The underlying sample only includes tenders linked to at least one commitment and in the period 2014-2020. Deviations above 300% are pooled in the last bin. Panel (a) presents all tenders while panel (b) presents histograms separately by purchase modality (tender waivers, direct contracting, other modalities and auctions).

Figure D.2: Comparing Procurement and Budget Execution - Paraná

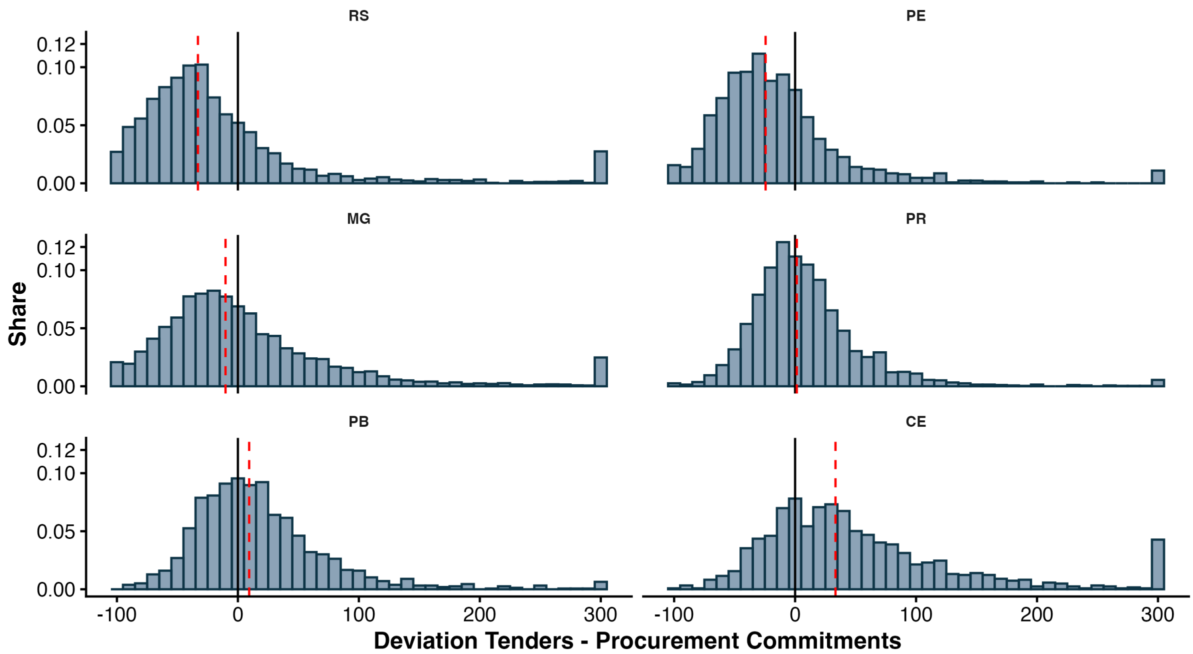


Notes: This figure presents the histogram of percentage deviations between total tender values and budget commitments, at the municipality-year level in the state of Paraná. The underlying sample only includes tenders linked to at least one commitment and in the period 2014-2020. Deviations above 300% are pooled in the last bin.

Figure D.3: Comparing Procurement and Budget Execution data



(a) Full sample



(b) By states

Notes: This figure presents the histogram of percentage deviations between total tender values and procurement-related budget commitments, at the municipality-year level. Panel (a) includes all municipalities and year for which both procurement and budget execution data are available at MiDES; while panel (b) presents the data separately by state. The dashed red line marks the median of the distribution. Deviations above 300% are pooled in the last bin.

E Details on procurement by municipalities in Brazil

In this section we provide additional details on the nature of public procurement by Brazilian municipalities in our sample, with a particular focus on benchmarking some of our findings using federal procurement microdata.

We start by recapping some of the main features of our procurement data documented in Table 3. Across all periods and states, our data includes 2.4 million unique tenders. With the exception of the states of Paraíba (PB) and Pernambuco (PE), we have information on the specific items being sold in each process for almost all tenders – overall, we see on average 24 distinct items being sold in one tender. We also observe almost 1 million distinct participants in these tenders, which include both those that did not win a contract and those that win (we observe close to 800,000 unique winners).

Providing a systematic comparison about the nature and complexity of purchases in municipalities vs. state or federal agencies is a challenging task. First, for states we have no systematic data on procurement activities, such as the one we built for municipalities, so comparison becomes unfeasible for our period of study.[1] Second, it is challenging to systematically categorize what is being bought in the MiDES municipal data, since it does not include a classification of items (unlike federal data from the *ComprasNet* portal, for example, where items are classified using catalogs of goods and services).

We instead provide comparisons in different dimensions which can offer some insights on how the nature of municipal procurement compares to that of other spheres of government.

First, we exploit the fact that budget execution data, SICONFI (which we know closely matches our own budget microdata), includes information on the nature of expenditures, such as pensions, wages, interest payment and purchase of goods and services. What we do then is to provide comparisons of the composition of procurement-related expenditures between Municipalities, States and the Federal Government.[2]

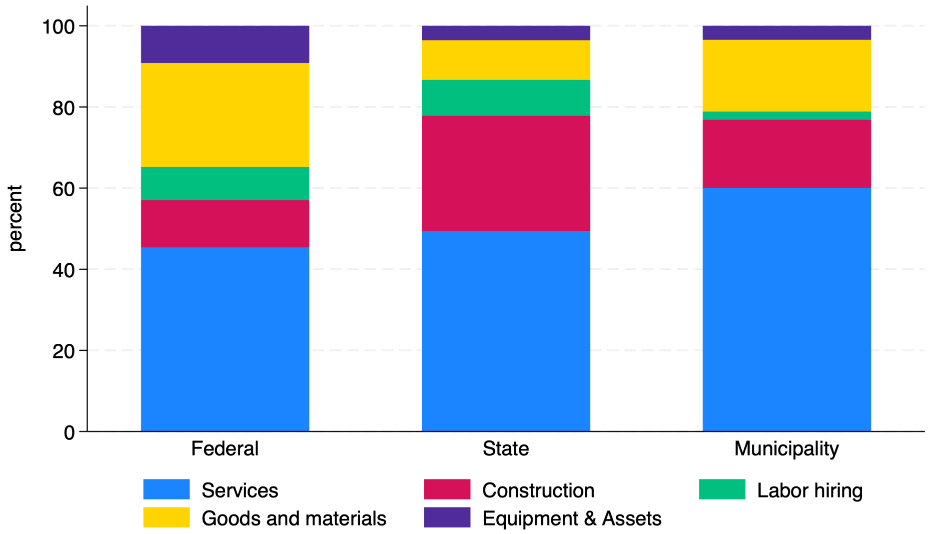
In Figure E.1, we present the composition of procurement-related expenditures in 2018, across Federal, State and Municipal expenditures, aggregated in five main categories: general services; construction; labor hiring (non-wage work); goods and materials; and equipment and assets. Our main takeaway is that, according to expenditure data, there are systematic differences in what municipalities buy when compared to states and the federal government, but they are not completely dissimilar. For example, general services (excluding construction) are the most common category, representing 45% of purchases of the federal government, 50% of states and 60% of municipalities. Construction services represent a higher share of expenditures in states (close to 30%) than in municipalities (17%) or the federal government (12%). Relative to the other spheres, federal purchases are relatively larger for goods and

[1]Since 2024, states were mandated to file all procurement data on the National Portal of Public Procurement, but this is a recent development.

[2]The definition of procurement-related expenditures is the same as that used in Appendix D when validating our procurement data with budget information.

materials, and equipment and permanent assets.

Figure E.1: Composition of procurement-related expenses - by levels of government



Notes: This figure presents the composition of public-procurement related expenses for Municipalities, States and the Federal government in Brazil in 2018. "Services" are defined as expenses with code 35, 39 and 40; "Goods and materials" as codes 30 and 32; "Construction" as code 31; Equipment and Assets as code 52; and labor hiring as code 37. Data for Municipalities and States are from SICONFI, while data for the Federal Government is from the federal Transparency Portal.

While the exercise above provides insights on the broad categories of goods and services being bought in all municipalities in Brazil when compared to the federal government and states, it clearly cannot provide a granular comparison on the nature of these purchases. Even if we could compare narrower categories (say materials for education), it could still be true that purchases at the municipal level are very different from those of the federal government, for example.

We provide more qualitative evidence on the specific items being commonly purchased in municipalities in our dataset vs. federal purchases in Figure E.2, where we show the most common words used in the description of these items. We separate items in services vs. goods and materials. In the top panels, we show the most common words for goods, separately for our dataset and federal purchases. Some items like "paper", "paint", [car fuel] "filter", "gloves" and [medical] "sutures" are among the top items in both spheres of government - these are mostly low-cost items that are purchased often. At the federal level, some words indicate the more complex medical needs of federal hospitals and clinics - "laboratory", "diagnostic", "clinic" and "hospital". But among top words we also see food items ("fruit", "legume", "natural") – these are often bought by federal universities and the armed forces, which provide meals to students and staff. On the bottom panels, we present the top words for services. Again, we observe a lot of overlap in key words, particularly related to hiring of transportation services – "vehicle", "transport" and "car". "Security", "cleaning" and "construction" services are also among top words in both spheres.

Figure E.2: Word Clouds for procured items

(a) Municipalities in MiDES: Goods and materials

(b) Federal: Goods and materials

(c) Municipalities in MiDES: Services

(d) Federal: Services

Notes: These figures present the 30 most common words in the description of the items being purchased in each sample. Panel (a) and (b) present words from items classified as goods and materials, from our MiDES dataset and federal purchases from the Transparency Portal, respectively. Panels (c) and (d) present items classified as services from MiDES and federal purchases, respectively. The classification of items into services vs. goods and materials was done using a list of keywords that identify services (e.g. "rent", "consulting", "maintenance", "training", etc.) and classifying as services any item whose description including any of those words; the remaining items were classified as goods and materials. We use a random sample of approximately 100,000 items from municipal and federal items bought in 2021. The top words exclude common stop words and others recurrent words we deem not informative ("unit", "product", "service", "hiring", etc.).

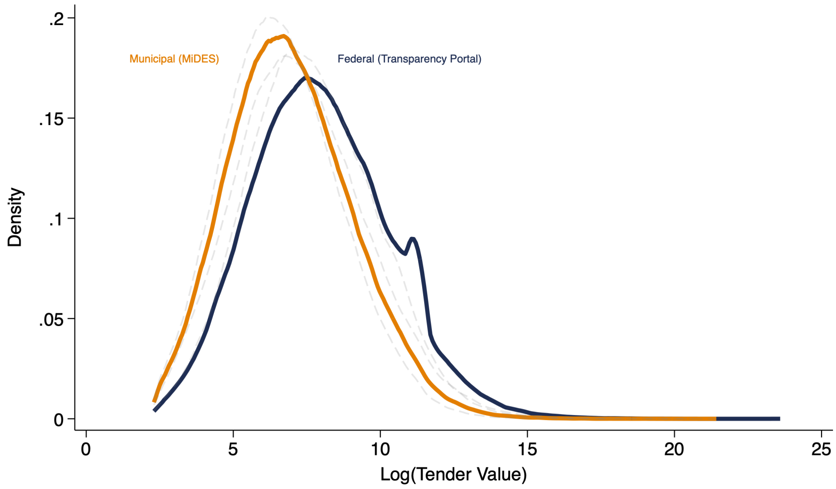
One additional comparison we can provide is between the total value of tenders and of items being purchased by municipalities in MiDES and the federal government.

We start by looking at the distribution of items' values across all federal purchases and municipal purchases in the MiDES dataset for 2021, in Figure E.3a. What we document is that the distribution of municipal purchases is slightly shifted to the left, with smaller prices – the median item price for municipal purchases is R$800 vs. R$2,500 for federal items. But there is substantial overlap between the two distributions. One important caveat is these these are not unit prices, but the total value being purchased for each specific item within tenders (e.g. one item can be one truck or 100,000 pens).[3]

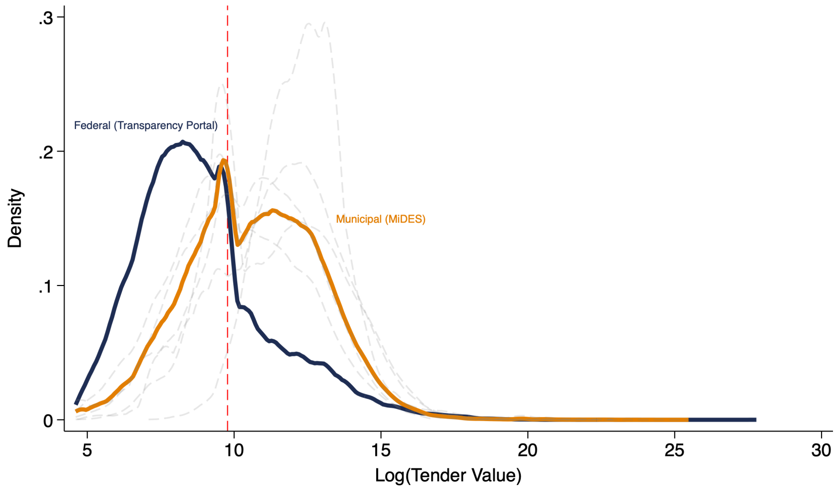
We then perform the same exercise but now comparing the distribution of total estimated value of tenders - this is the estimate initially provided that inform whether tenders qualify for waivers, for example. We show the distribution of estimated values for federal data and our pooled data for 2021 in Figure E.3b. Although there is a lot of overlap, tender values are much higher in the municipal dataset than in the federal one - the median value of federal tenders is R$4,700 vs. almost R$40,000 for municipal tenders. The distributions we plot are consistent with the composition of purchase modalities: while 61% of all tenders use waivers in the federal government, that shares ranges from 20% in the state of Pernambuco (PE) to 42% in Ceará (CE).

[3]We only include municipalities in the states of MG, RS and CE in this analysis, since item-level data is not available in PE and PB, and for the state of PR the data includes unit-values instead of total values.

Figure E.3: Comparing items' and tenders' value - Municipal vs. Federal purchases



(a) Distribution of item value



(b) Distribution of tender value

Notes: These figures present the distribution of items' values (panel a) and tenders' estimated values (panel b) for municipalities in the MiDES dataset and federal purchases (obtained from the Brazilian Transparency Portal). Grey dotted lines present state-specific distributions. Panel (a) only includes municipalities from the states of MG, RS and CE, for which total item value is available; wheres panel (b) includes all six states for which procurement data is available. In panel (a) we plot the distribution for a 20% random sample of all items, for computational purposes. The red dotted line in panel (b) marks R$ 17,600, the threshold for use of tender waivers in 2021.

One important context for these findings is that federal purchases are highly decentralized: in 2021, we see 2,200 different federal buyers located in 470 municipalities. The median aggregate value of items across these purchasing units was R$ 2.9 million in 2021, and typical units with this size include the Regional Office of the National Foundation of Indigenous People (FUNAI) in Chapecó (SC); the Fine Arts National Museum; and Embrapa Algodão, one of the 43 units of the Brazilian Agricultural Research Enterprise, located in Campina Grande, Paraíba. In contrast, the median total item purchase across municipalities in MiDES dataset was R$12 million, in municipalities like Bom Repouso, MG (population ~ 12,000); Sede Nova, RS (~ 3,000) and Barro, CE (~ 19,000). For these reasons, we assess it is reasonable that the evidence suggests that typical purchases are not too different among federal and municipal buyers; while it is also true that the federal government will make some purchases that are much more complex that any municipality could buy (e.g. in 2021 we observe the federal government buying over 100 million doses of COVID-19 vaccine from Pfizer for an estimated value of R$ 7 billion).