Erasmus University Rotterdam

Erasmus School of Economics

Fostering Equality on the Ground

New Evidence on the Effectiveness and Needs-Responsiveness of Decentralized Public Spending on Social Infrastructure for the Poor in Mexico

Master Thesis MSc Economics and Business: Policy Economics

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Abstract

Fiscal decentralization has been on the reform agenda of many countries globally, for example, Mexico. Decentralizing expenditure responsibilities to subnational government levels holds the promise of increasing the effectiveness of public spending by, amongst others, improving the responsiveness of public expenditure to societal wants and needs. However, in practical examples such as the case of the "Fondo de Aportaciones para la Infraestructura Social" (FAIS), one of the large decentralization funds set up in Mexico, past evaluations have pointed to, if at all, modest effects on target measures such as extreme poverty rates. Still, none of these studies has examined the effectiveness of FAIS spending for the period after 2014, when a major reform of the FAIS was enacted. This thesis fills this research gap. It does so, firstly, by analysing the effectiveness of FAIS spending for the period 2005-2020, drawing on a rich fixed-effects model. Results indicate positive, but moderate effects of FAIS spending on social infrastructure access, but no or even negative effects on poverty and inequality measures. Secondly, this thesis is the first to present indicative evidence of a potential change in FAIS effectiveness following the 2014-reform. It emerges that the reform has positively affected the effectiveness of FAIS spending in the case of infrastructure access measures and might have positive long-run effects when looking at poverty or inequality measures. In the search for an explanation for these findings and related policy recommendations, this thesis, thirdly, reveals that the limited responsiveness of FAIS spending to local infrastructure needs plays an important role.

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List of Abbreviations

AGEB	Basic Geostatistical Area
CONEVAL	Mexican National Council for the Evaluation of Social Development Policy
FAIS	Fondo de Aportaciones para la Infraestructura Social
FISM	Fondo para la Infraestructura Social Municipal
IGP	Global Poverty Index
INEGI	Mexican National Institute of Statistics and Geography
IV	Instrumental Variable
OLS	Ordinary Least Squares
RC	Rodríguez-Castelán et al. 2020
VIF	Variance Inflation Factor
WS	Wellenstein et al. 2006

1. Introduction

"Too often, services fail poor people - in access, in quantity, in quality. But the fact that there are strong examples where services do work means governments and citizens can do better. How? By putting poor people at the centre of service provision: by enabling them to monitor and discipline service providers, by amplifying their voice in policy- making, and by strengthening the incentives for providers to serve the poor".
(World Development Report 2004)

Fiscal decentralization, that is, transferring revenue assignments and expenditure responsibilities to lower government levels (World Bank 2008) has been on the reform agenda of many countries globally since the 1990s (Smoke 2001). As a result, many countries around the world have transferred fiscal authority to sub-national governments over the past years (Martinez-Vazquez et al. 2016). For instance, 80% of all developing and transitioning countries underwent some form of decentralization process over the past two decades (Kimengsi and Gwan 2017).

This global prominence of fiscal decentralization over the past years can most likely be traced back to the promise that decentralizing public expenditures will lead to an increase in the effectiveness of public spending (Arends 2020). In the literature, a wide range of arguments supporting this claim can be found. Most importantly, authors point to the increased responsiveness of public investments to societal wants and needs that a decentralization of expenditure responsibilities is argued to foster (Borge et al. 2014). This increased needs-responsiveness and related efficiency benefits are argued to stem from, for instance, information and flexibility advantages at the local level.

However, when looking at empirical examples of countries that have undergone a fiscal decentralization reform process, it remains an open question whether these theoretically predicted benefits have materialized. An interesting example in this regard is Mexico, where fiscal decentralization reforms have been especially prevalent (Diaz-Cayeros 2016). In Mexico, fiscal decentralization efforts have mainly focused on the expenditure side. That is, while the national government collects more than 90% of all taxes (Salazar 2007), subnational governments have been given more and more authority when it comes to spending these tax revenues. As a result of this expenditure-focused decentralization, subnational governments spend more than half of the revenues collected through the national government nowadays, which is passing on the resources to lower government levels through transfers (Salazar 2007).

Among the manifold transfers that the Mexican government is allocating to subnational governments, one transfer program has gained particular attention in the academic literature (see e.g. Wellenstein et al. 2006, Moreno-Jaimes 2011, Diaz-Cayeros et al. 2016 or Rodríguez-

Castelán et al. 2020). This transfer program, called the "Fondo de Aportaciones para la Infraestructura Social" (FAIS), is earmarked for spending on social infrastructure to the benefit of the poorest and most disadvantaged (Ibarra-Salazar 2018). In 2014, the FAIS underwent a major reform aimed at further improving the incentives for subnational governments to spend FAIS resources in line with these aims of the fund (Ibarra-Salazar 2018).

Despite the manifold theoretical rationales backing up the Mexican decentralization of expenditure responsibilities through transfers such as the FAIS, empirical research paints a mixed picture regarding the effectiveness of FAIS spending. That is, when looking at the relation between FAIS spending and improvements in access to social infrastructure services and poverty alleviation, authors find positive (Diaz-Cayeros et al. 2016) but also mostly quite modest or even no effects (Diaz-Cayeros and Silva Castenada 2004, Ramones and Prudencio 2014, Rodríguez-Castelán et al. 2020).

This thesis, firstly, contributes to strengthening this existing evidence on the effectiveness of decentralized public spending targeted at the poor focusing on the example of the FAIS. To this end, the *first contribution* of this thesis consists in analysing the effect of municipal FAIS spending on social infrastructure access measures as well as poverty and inequality measures for the period of 2005–2020. Thereby, this thesis is the first to present evidence on the effectiveness of FAIS spending for the period after the 2014-FAIS-reform. For generating this evidence, the present analysis employs a panel dataset including FAIS expenditure data as well as data on municipal infrastructure access gaps, extreme poverty, and inequality and a fixed-effects approach.

By including data from the post-reform period, the analysis presented in this thesis provides the opportunity to, secondly, generate first indicative evidence on whether the 2014-FAIS-reform has, as intended, increased the effectiveness of FAIS spending. To this end, the *second contribution* of this thesis consists in analysing whether the effect of FAIS spending on infrastructure access, poverty, and inequality measures is significantly stronger for the post-reform period compared to the pre-2014 period.

Finally, this thesis also sheds light on the mechanism which drives these results regarding the effectiveness of FAIS spending as well as potential changes during the post-reform period. More specifically, the *third contribution* of this thesis consists in examining the needs-responsiveness of FAIS allocation decisions as a potential explanation for the findings on FAIS effectiveness and for building a basis for policy recommendations. To this end, the thesis makes use of a detailed dataset on municipal FAIS expenditure decisions and a rich ordinary least squares (OLS) model.

Overall, this thesis shows that earlier results indicating positive, but very modest effects of FAIS spending on access to social infrastructure services persist when also including data from the post-reform period 2015-2020. However, the analysis also reveals indicative evidence that FAIS spending has not significantly contributed to reducing extreme poverty and inequality during the period 2005-2020. And while the 2014-FAIS reform shows signs of promise when it comes to improving this situation, it has not yet led to a significant increase in the effectiveness of FAIS spending in this regard. A potential explanation for these findings emerges when analysing the needs-responsiveness of FAIS expenditure decisions between 2014 and 2021. This analysis reveals that there is no evidence for the claim that FAIS expenditure between 2014 and 2021 has been responsive to local infrastructure needs.

To arrive at these results, this thesis is structured as follows: The *second section* provides a detailed overview of fiscal decentralization reforms in Mexico, the FAIS as well as the 2014 FAIS reform. Against this backdrop, the *third section* presents a detailed review of existing research on the effectiveness of FAIS spending. Drawing upon this existing research, *sections four and five* present the empirical set-up of the analysis on FAIS effectiveness and the 2014-reform.

Section six presents both the first and the second contribution of this thesis. It does so by analysing the effect of FAIS spending across all municipalities in Mexico for the period 2005-2020 and by presenting indicative evidence regarding a potential change in effectiveness after the FAIS reform in 2014.

The *seventh section* presents the third contribution of this thesis. This contribution consists in illuminating the role of the needs-responsiveness of FAIS spending during the post-reform period as a potential mechanism driving the prior results on both FAIS effectiveness and the 2014-FAIS reform. To this end, the theoretical debate around decentralized public spending and needs-responsiveness is presented, followed by a discussion of existing empirical contributions in the context of the FAIS. The latter is then used for building the model employed to generate evidence on the needs-responsiveness of FAIS spending for the post-reform period.

The results emerging from the analyses in sections six and seven are shown to be robust to various sensitivity checks in the respective sections. However, a set of limitations that must be borne in mind when interpreting these results remain, which are outlined in the *eighth section*.

The *ninth section* formulates a set of policy recommendations emerging from the analyses presented before. *Section ten* concludes.

2. Fiscal Decentralization in Mexico, the FAIS, and the 2014 Reform

This section provides a brief overview of the fiscal decentralization process in Mexico over the past years, the FAIS as well as the 2014-FAIS-reform to provide the necessary background for deriving the three contributions of this thesis.

2.1. Fiscal Decentralization in Mexico

Mexico is one of the countries in which the global decentralization trend has been especially pronounced. This move towards fiscal decentralization was, however, preceded by highly centralizing tendencies characterizing the fiscal system in Mexico during the 19th and especially the 20th century. During this time, both the taxing and the spending powers of the national government were strongly increased (Diaz-Cayeros 2016).

In line with the rising popularity of decentralization worldwide (Rocha Menocal 2005), decentralization has become a declared goal of the Mexican government from the late 1980s onwards (Salazar 2007). However, the main push for decentralization can be traced back to the late 1990s, when the Zedillo administration set up a program for a “New Federalism” to overcome the “oppressive and backward, socially insensitive and inefficient” nature of centralization in Mexico (Diaz Cayeros et al. 2016, p. 116). One of the main promises of this program was to decentralize resources in areas such as health, education, and physical infrastructure, thus focusing on decentralization on the expenditure side (Courchene and Diaz-Cayeros 2000).

Following more than two decades of institutional and political reform, many important resources and powers are decentralized to subnational governments today. Since Mexico’s decentralization program has mainly been expenditure-focused, however, it is still the national government that collects the lion’s share of taxes, including most notably corporate and income taxes as well as the value-added tax (Hernandez-Trillo and Jarillo-Rabling 2008). Over 90% of overall tax revenues are collected by the national government in this way (Salazar 2007).

Still, the reform process towards fiscal decentralization has made subnational governments, that is, the 32 Mexican states and the 2469 Mexican municipalities, the dominating actors when looking at the expenditure side. Nowadays, more than half of the revenues collected by the national government are spent by the states and municipalities. The resources needed to undertake these expenditures are passed on by the national government to the subnational governments through transfers (Salazar 2007).

The most important mechanism that has led to this shift in expenditure powers from the national to the subnational governments in Mexico was the creation of expenditure item (“Ramo”) 33 in 1997, which contains a set of transfers allocated to Mexican states and municipalities (Courchene and Diaz-Cayeros 2000). Most of the transfers paid out through Ramo 33 relate to expenditures that were originally carried out by the federal government and are thus made conditional on the provision of these public services by subnational governments (Hernandez-Trillo and Jarillo-Rabling 2008).

With more than 830 billion Pesos paid out to Mexican states and municipalities in 2022, Ramo 33 constitutes one of the most important sources of finance for subnational governments in Mexico today. The expenditure item now comprises a total of eight funds covering a large variety of public services including education, health, and public safety, as can be seen in Figure 1 below.

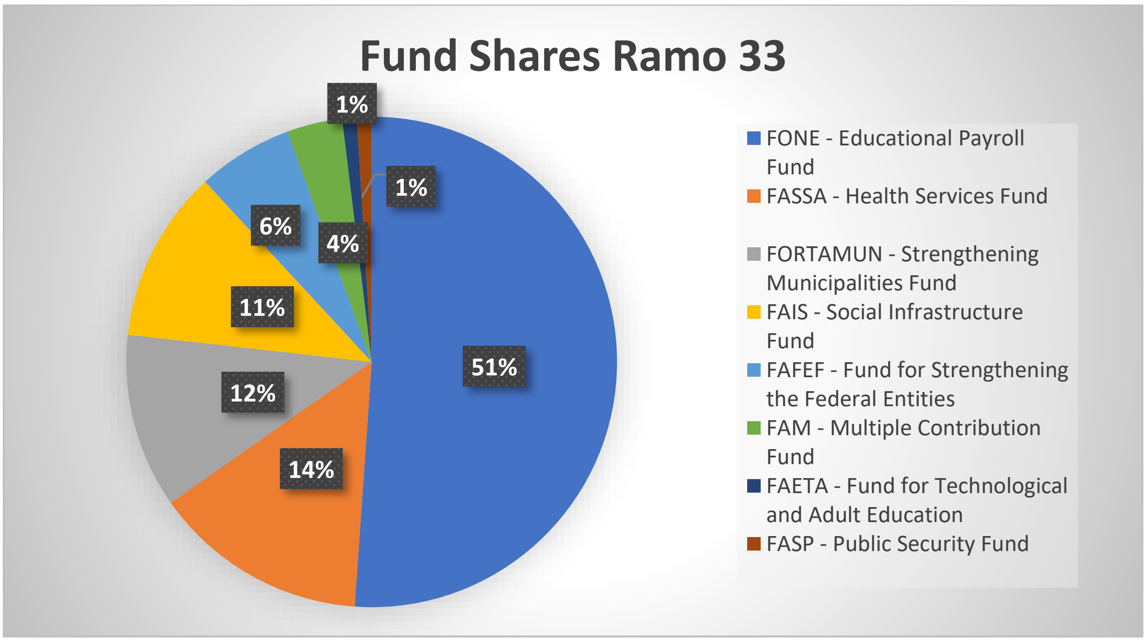

Figure 1: Overview and Shares Funds Ramo 33 (Data Source: Diario Oficial de la Federación 2022).

2.2. The Fondo de Aportaciones para la Infraestructura Social (FAIS)

The FAIS is one of the larger funds subsumed under Ramo 33. In 2022, it accounted for around 11% of the transfer resources paid out to Mexican subnational governments through Ramo 33 in 2022 and for around 2.5% of the total shared federal collection (Ibarra-Salazar 2018).

This 2.5% of the federal collection allocated to subnational governments through the FAIS has two components: The largest share of the 2.5% is allocated to the municipalities, the lowest level of governance in Mexico, through what is called the “Fondo para la Infraestructura Social Municipal” (FISM). The FISM is one of only two funds under Ramo 33 that is allocated directly to municipalities (Rocha Menocal 2005). The remaining 0.31% is allocated to the states as the intermediate level of governance in Mexico through the “Fondo de Infraestructura Social para las Entidades” (Ibarra-Salazar 2018).

The resources states and municipalities receive through the FAIS are earmarked for the investment in social infrastructure and the provision of social public works (Rocha Menocal 2005). More specifically, the infrastructure investments financed through the FAIS are intended to benefit the poor and marginalized in Mexico (Rodríguez-Castelán et al. 2020). This explicit focus on the distributional effects of the spending allocated through the FAIS makes this transfer unique among the funds subsumed under Ramo 33 (Wellenstein et al. 2006 and Rocha Menocal 2005).

Especially for municipalities, which receive the lion’s share of the FAIS resources from the national government, the transfer money covers a large share of local spending on infrastructure and public works. As calculations by Wellenstein et al. (2006) show, FISM resources account for up to 70% of the total municipal spending on public works in some municipalities.

These rich resources can be used by municipalities to finance infrastructure and public works projects that fall into the following categories: Water supply, drainage, sanitation, sewage, electricity, health, and education infrastructure, housing improvements as well as urbanization, an overarching category subsuming investments in roads and street lightning (Ibarra-Salazar 2018). However, municipalities are flexible in allocating their FISM resources across these categories, with the mayors playing a decisive role in the spending decision of the municipality (Diaz Cayeros et al. 2016). This flexibility makes the FAIS the fund which, among the funds subsumed under Ramo 33, offers the most discretion to local actors (Rocha Menocal 2005).

As can be seen in Figure 2 below, in 2021, the largest share (around 60%) of FISM resources was allocated to the urbanization category, financing investments in roads and street lightning. In contrast, municipalities chose to allocate only a small share of their FISM resources to sewage (around 2%) and housing (around 1%).

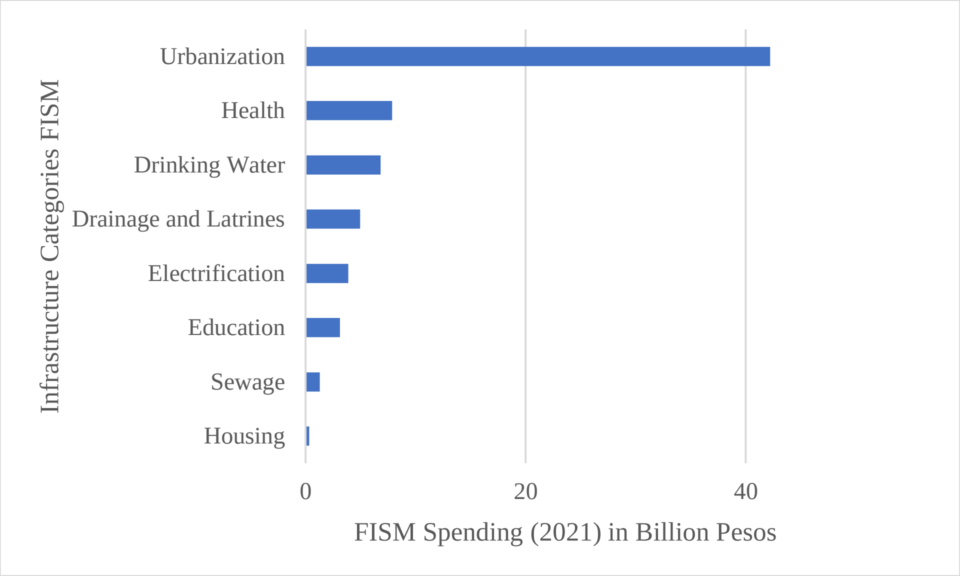

Figure 2: FISM Allocation Across Infrastructure Categories in 2021 (Data Source: Secretaría de Bienestar 2021).

2.3. The 2014 FAIS Reform

Municipalities make decisions on how to allocate their FISM resources across the eight infrastructure categories outlined above based on the amount of FAIS resources they receive from the national government. To determine the amount of the shared federal collection that each state and municipality will receive, specific allocation formulas for the FAIS have been put in place (Diaz-Cayeros et al. 2016).

Such a formula-based allocation system did not only promise to increase transparency and predictability of subnational funding but also to ensure that the poorest states and municipalities get the necessary funding for achieving the equity aims of the FAIS (Wellenstein et al. 2006). Again, the allocation formula of the FAIS makes this fund special under the funds subsumed under Ramo 33 as it is the only fund that allocates resources based on compensatory instead of equalization concerns (Trejo Nieto and Ibarra Armenta 2011).

Until 2014, the component of the FAIS allocation formula that gave it this special compensatory character was the Global Poverty Index (IGP), which was used to determine the share of households living in extreme poverty at the state level[1]. The amount that each state would then receive corresponded to the share of people living in extreme poverty in this state in comparison to the share of extremely poor in the country as a whole. Thus, states with relatively higher poverty shares would receive more of the available FAIS resources. States, in turn, are then

[1] The IGP subsumes indicators for income, education, housing, sanitation and electricity (Wellenstein et al. 2006).

asked to distribute the FISM share of the transfer money to the municipalities using the same criteria (Ibarra-Salazar 2018).

In 2014, the FAIS underwent a major reform targeted at improving the IGP-based allocation formula which had been in place until then. This reform did not only aim at aligning the FAIS allocation formula with a new multidimensional poverty index developed by the National Council for the Evaluation of Social Development Policy (CONEVAL) but also responded to mounting criticism of the IGP-based formula (see e.g. Diaz Cayeros and Silva Castaneda 2004; Wellenstein et al. 2006; Ramones and Prudencio 2014).

One of the most important criticisms regarding the IGP-based allocation formula points to the possibility that allocating more resources to states and municipalities where extreme poverty is relatively more prevalent might create an unintended incentive for subnational governments (Ramones and Prudencio 2014). States and municipalities, it was argued, might be encouraged by the allocation formula not to reduce extreme poverty to prevent a reduction in future FAIS resources (Ibarra-Salazar 2018). This incentive created by the IGP-based formula would run counter to the intentions behind the FAIS, making it a so-called “perverse incentive” (Ramones and Prudencio 2014).

To mitigate this perverse incentive, the new FAIS allocation formula introduced in 2014 is composed of three instead of only one element determining the amount of FAIS resources received by each state: Firstly, the intensity of poverty, measured by the average number of deprivations of the state population living in extreme poverty[2], is considered. This component is intended as a more precise version of the initial allocation formula. As such, it has the purpose of guaranteeing that more resources are allocated to states with a higher level of extreme poverty and social backwardness (Ibarra-Salazar 2018).

Secondly, the states’ effectiveness in reducing extreme poverty is also taken into consideration in the allocation of FAIS resources according to the updated formula. This effectiveness is measured by the decrease in the number of people living in extreme poverty and progress with overcoming social backwardness[3] in the state population. Thereby, this second component is intended to reward states which are effectively using their FAIS resources to reach the goal of

[2] Following the change in poverty measurement in 2010, people defined as living in extreme poverty have both an income below the cost of the basic food basket and three or more social deprivations (i.e. educational lag, lack of access to health services, lack of access to social security, housing with inadequate quality or insufficient space, lack of basic housing services, lack of access to food), see CONEVAL (2010).

[3] Social backwardness is measured by a weighted measure that summarizes four indicators of social deprivation (education, health, basic services, and quality and space in housing) in a single index that has the purpose to order the observation units according to their social deprivation, see also Benita (2015).

the fund, i.e. benefitting the poor and marginalized. By including this second component, the perverse incentive for subnational governments not to decrease extreme poverty to ensure high future FAIS inflows is counterbalanced. This, in turn, counters one of the main criticisms regarding the former formula (Ibarra-Salazar 2018).

To mitigate potentially adverse effects of fluctuations in FAIS resources due to the formula update, the new allocation formula, thirdly, contains a component that guarantees a fixed share allocated to each state based on their FAIS resources in 2013 (Ibarra-Salazar 2018).

In sum, the 2014-FAIS-reform thus counterbalances the perverse incentive to not reduce extreme poverty to uphold future FAIS payments while still taking into account local spending needs and guaranteeing stable payments despite the formula change. Thereby, the reform can be expected to lead to an increase in the effectiveness of FAIS spending. That is, in comparison to the pre-2014 period, one would expect that the updated formula would incentivize subnational governments to spend their FAIS resources in a way that is more aligned with the goal of the FAIS, i.e. to improve the situation of the extremely poor by increasing access to social infrastructure services.

However, until yet, there is no empirical evidence available that could be used to verify this expectation. Before filling this research gap, the next section provides a brief overview of past studies on the effectiveness of FAIS spending. These studies all focus on the pre-reform period and thus offer a useful baseline against which the post-2014 results can be compared.

3. Empirical Evidence on the Effectiveness of FAIS Spending in the Pre-Reform Period

As Table 1 below shows, the share of the population lacking access to basic infrastructure services such as drinking water, drainage, sanitation, or electricity has steadily decreased since the introduction of the FAIS in 1998 and up to its reform in 2014. For instance, while 28% of the population lacked access to drinking water in 2000, only 9% did so in 2015. Available FAIS resources, as shown in Figure 3, have, on the other hand, steadily increased over time. However, it remains to be shown whether the increase in access to basic services observable following the introduction of the FAIS can be attributed to FAIS spending.

	2000	2005	2010	2015
Share of Population without Access to Drinking Water	0.28	0.21	0.2	0.09
Share of Population without Access to Drainage	0.5	0.31	0.25	0.2
Share of Population without Access to Sanitation	0.25	0.14	0.09	0.06
Share of Population without Access to Electricity	0.12	0.08	0.05	0.03

Table 1: Access to Basic Services in Mexico (share of the total population) from the FAIS Introduction Until the Reform (Source Data: INEGI 2000, 2005, 2010, and 2015).

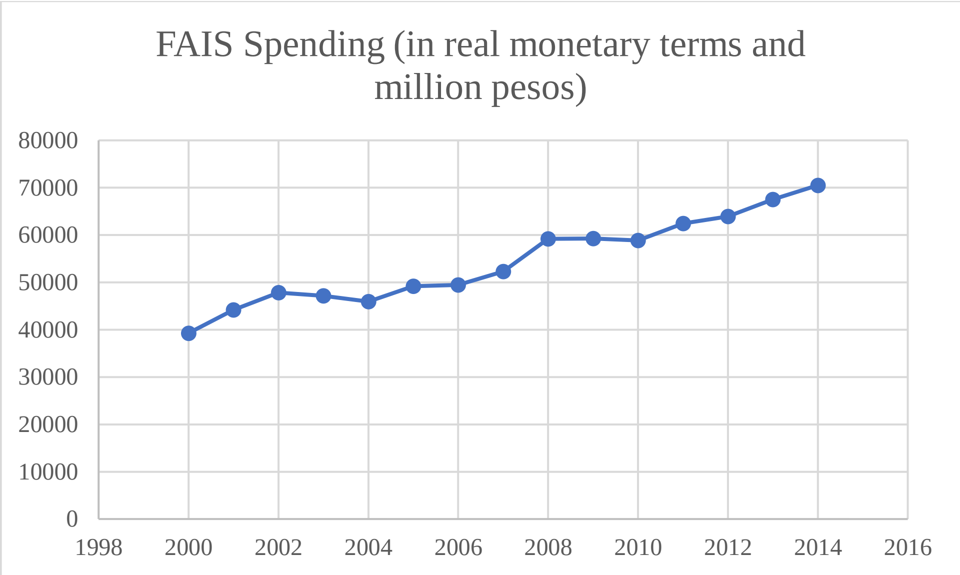

Figure 3: FAIS Spending from the FAIS Introduction Until the 2014-Reform (Source Data: ASF 2018).

Illuminating this relationship is certainly relevant given the large share of resources allocated through the FAIS and its status as one of the most important instruments in the fight against poverty in Mexico (Ramones and Prudencio 2014). Despite this relevance, only a few studies examining the effectiveness of FAIS spending have been carried out so far (Cejudo and Gerhard 2010; Ramones and Prudencio 2014). One obstacle hindering such studies has, for a long time, been the "fundamental lack of reliable and comparable data across municipalities" (Rocha Menocal 2005). That is, reliable data on municipal FAIS expenditure in the years following the introduction of the fund has not been available for a long time (cf. INEGI 2021).

Still, a few authors have attempted to shed light on the relationship between improvements in infrastructure access and related reductions in extreme poverty and FAIS spending. Just as the present analysis, all of them focus on the municipal part of the FAIS (“FISM”) which constitutes the largest share of the FAIS.

In a first study conducted in 2004, Diaz-Cayeros and Silva Castaneda estimated a Logit model to determine in how far FISM spending plays a role in explaining the probability of a household having access to drinking water and drainage. To this end, the authors make use of data on several household characteristics such as the household income or the number of household members per room as well as the share of FISM resources spent on drinking water and drainage, respectively. The authors obtain this data from the Municipal Presidents’ National Survey, which was carried out in 2002. As they find, FISM spending is of little importance when it comes to improving access to those services, while individual household variables such as changes in household income matter much more (Diaz-Cayeros and Silva Castaneda 2004).

In a second study from 2014, Ramones and Prudencio were interested in whether FAIS spending results in an improvement of various poverty measures. For their analysis, the authors focus on the period from 2000 to 2010 and make use of FISM data and data on the most commonly used poverty measures in Mexico. The authors obtain this data from the Municipal Public Finance Database, CONEVAL, and the Mexican National Population Council. Using an OLS model as well as an instrumental variable approach, the authors find that FAIS spending has had, depending on the poverty measure of interest, no or only very modest effects on poverty (Ramones and Prudencio 2014).

In 2016, Diaz-Cayeros et al. came forward with a detailed study on the relationship between FISM spending and improvements in access to basic services for the period between 1990 and 2000. To this end, the authors make use of data on infrastructure access measures available from the Census data collected by the Mexican National Institute of Statistics and Geography (INEGI), and FISM data. In addition, their specification makes use of a rich set of controls, including religious fractionalization, changes in literacy, or the share of the indigenous population, all of which are also available from the Census data. To further account for potential endogeneity, the authors also rely on an instrumental variable approach. Based on this set-up, the authors find a strong positive effect of FISM spending on access to basic services (Diaz-Cayeros et al. 2016).

A final study that makes use of the most current data so far was conducted by Rodríguez-Castelán et al. in 2020. In their study, which constitutes the basis for the present analysis, the authors use a fixed-effects model to determine the effectiveness of FISM spending for the period between 2005 and 2014. They find positive but modest effects of FISM spending on access to basic infrastructure services and average household income per capita. However, their analysis does not reveal an effect of FISM spending on poverty rates and even points to an increase in income inequality due to FISM spending (Rodríguez-Castelán et al. 2020).

In sum, the few available empirical studies examining the effectiveness of FAIS spending for the pre-reform period (until 2014) paint a mixed picture when it comes to the relationship between FISM spending and access to basic infrastructure services as well as poverty and inequality measures. However, we have seen above that there are strong reasons to believe that the 2014-FAIS-reform should have led to an improvement in the effectiveness of FISM spending. To see if that is the case, the following analysis presents evidence on the effectiveness of FISM spending including the post-2014 period, which constitutes the first contribution of this thesis.

4. Empirical Approach and Data

The empirical analysis presented in this section draws on the Rodríguez-Castelán et al. (2020) (in the following: RC) study presented above. The reason for this is that this is the only study that makes use of a fixed-effects approach for tackling potential endogeneity issues in the analysis of the effectiveness of FISM spending. Thereby, their approach allows for exploiting the benefits of the rich panel data on FISM expenditure, access to basic services as well as poverty and inequality measures that is available for Mexico.

4.1. Sample

The data for this panel data set is, firstly, obtained from the Mexican Census of Population and Housing, which is currently collected on a five-year basis[4] by INEGI. In the collection of the Mexican Census data, each of the housing units in Mexico is visited by an interviewer to collect information on their demographic, socio-economic, and cultural characteristics. The resulting dataset contains rich data on a range of topics such as demography, fertility, ethnicity, and education. Especially interesting for the present purpose is the Census data on infrastructure access measures, which spans information on population access to services such as drinking water and electricity, but also housing and health (see subsection 4.3.).

All this data is available at different aggregation levels, including the national, state, municipality, and down to the block level (INEGI 2020b). Given that most of the other data

[4] The Mexican Census was originally conducted every ten years but was supplemented with two Count Censuses in 1995 and 2005 as well as with an Intercensus in 2015. The latter is a survey with a sample size of more than 6 million which is used to update the Census information between the 2010 and the 2020 Census. To this end, typical Census topics are addressed to ensure comparability in addition to other topics of current interest (INEGI 2015).

sources used in the present panel are only available at the municipality level, the following analysis employs the Census data available for all of the 2469 Mexican municipalities.

The second key basis for the rich panel data set used in the present analysis comes from INEGI's State and Municipal Public Finance database. This database contains detailed income and expenditure information for all Mexican states and municipalities on an annual basis (since 1989), based on information reported by the local treasuries themselves. While this database provides valuable information on both municipal FISM expenditures (see subsection 4.4.) and municipal income as an important control variable (see subsection 4.5.), it is also plagued with small fluctuations in data availability at the municipal level due to factors such as changes in government (INEGI 2019).

As a third source for the present panel data set, this analysis relies on poverty and inequality data that is available from CONEVAL for being able to also assess the effectiveness of FISM spending when it comes to poverty and inequality. The poverty and inequality data employed to this end are based on poverty calculations relying on the updated Mexican multidimensional poverty measurement (see subsection 4.3.), which, in turn, are performed based on Census data.

The fourth and final set of data for the present panel comes from the Mexican Economic Census, which is collected on a five-year basis. The Economic Census contains information on all (non-agricultural) economic activity in the country, which is collected by interviewing all of the Economic Units. Doing so results in a rich dataset that is, just like the regular Census, available from the national down until the block level (INEGI 2022). Among the rich information available from this data the present analysis makes use of information that allows to control for the generation of private income (see subsection 4.5.).

4.2. Empirical Model

Based on this panel dataset, the present analysis builds on RC's fixed-effects model for assessing the effectiveness of FAIS spending. However, minor modifications to RC's model are undertaken to be able to evaluate the effectiveness of FAIS spending also for the period after 2014. The resulting fixed-effects model is presented below in more detail before employing it for generating evidence on the effectiveness of FAIS spending for 2005-2020:

$$\text{(I) Log } Y_{mt} = ß_0 + ß_1\text{Log}\mathit{FAIS}_{mt} + ß_2\text{Log}\mathit{FISC}_{mt} + ß_3\mathit{PROD}_{mt} + ß_4\text{ Log}\mathit{MUN}_{mt} + \delta_t + \gamma_m + \varepsilon_{mt}$$

In this model, Y_{mt} represents a set of logged outcome measures, with $m = 1,\dots, N$ representing indexes for the Mexican municipalities and $t = 2005,\dots, 2020$ representing the years for which data from the Mexican Census is available. The target regressor is logged FISM spending, measured as the monthly per capita FISM resources received by municipality *m* over the four years before Census year *t* (cf. Rodríguez-Castelán et al. 2020).

As will be discussed more closely in section 4.5., the specification also includes four sets of covariates: *FISC*, accounting for municipal fiscal resources, *PROD*, accounting for the municipal production factors and technology, *MUN*, accounting for municipal scale effects and a fourth set of controls (δ and γ) accounting for any potential unobserved heterogeneity across municipalities and over time (cf. Rodríguez-Castelán et al. 2020). Based on this initial sketch, the following subsections offer a closer discussion of the variables used in the present analysis.

4.3. Dependent Variables: Infrastructure Access Measures, Poverty and Inequality Measures

The set of outcome measures Y_{mt} from model (I) above include both monetary measures (i.e. poverty and inequality measures) as well as nonmonetary measures corresponding to the different FISM expenditure categories outlined above as follows:

Nonmonetary Outcome Measure	Corresponding FISM Expenditure Category
Share of Population with Access to Electricity	Electricity
Share of Population with Access to Drainage	Drainage and Latrines/Sewage
Share of Population with Access to Drinking Water	Drinking Water
Share of Population with adequate quality floors (i.e. no dirt floor)	Housing
Share of Population with Access to Health Services	Health
Share of population aged 15 or older who completed primary school	Education
Share of illiteracy among the population aged 15 or older	

Table 2: Nonmonetary Outcome Measures Model I

Given the close correspondence of these nonmonetary outcome measures with the infrastructure categories on which municipalities can spend their FISM resources[5], these measures allow for a natural way to measure the effectiveness of FISM spending: Effective FISM spending should

[5] The only FISM expenditure category not covered by these outcome measures is urbanization. This gap is also found in the study by RC and is due to the unavailability of data on road accessibility at the municipal level given the cross-jurisdictional nature of roads.

increase access to those infrastructure services that FISM resources can be spent on. Given this natural fit, the nonmonetary outcome measures listed in Table 2 form the largest share of the outcome measures employed in the present analysis. The data for these outcome measures is obtained from the Mexican Census at the municipality level. To be able to generate evidence on FISM effectiveness for the period of 2005-2020, data from the 2005 Count Census, the 2010 Census, the 2015 Intercensus and the 2020 Census[6] is employed to this end.

To be able to also shed light on the effect of FISM spending on poverty and inequality, the present analysis uses the share of the population living below the extreme poverty line and the Gini coefficient as additional outcome measures. The data on these two outcome measures for the post-reform period, calculated based on the new multidimensional poverty measurement introduced in 2010, is available from CONEVAL for 2010, 2015, and 2020. In addition to common factors figuring into poverty measures such as income and food access, the multidimensional measurement of poverty in Mexico also includes a range of indicators corresponding to FISM expenditure categories, i.e. access to basic services, health services, adequate housing, and education (CONEVAL 2010).

Due to the prominent role that infrastructure access measures play in the updated poverty measurement introduced in 2010, the resulting poverty and inequality measures nicely lend themselves to capturing the effectiveness of FISM-financed infrastructure projects on poverty and inequality. However, using these updated measures also implies, firstly, a shorter time horizon for the analysis of the effectiveness of FISM spending on poverty and inequality (i.e. 2010-2020 instead of 2005-2020). Secondly, this choice implies less comparability with RC's study, who use the poverty measures from before 2010 in their analysis.

When looking at the descriptive statistics for these outcome measures, the trends emerging from Table 1 above are, unsurprisingly, confirmed: As Figure 4 below displays, the share of the population with access to basic services (drinking water, drainage, and electricity) as well as adequate housing increases over time. Access to health services is also increasing until 2015 (86%) but then dropping slightly in 2020 (76%), potentially due to the Covid-19 pandemic.

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[6] The quality and accuracy of the 2020 Census data is disputed, mainly on grounds of Covid restrictions hindering data collection and new, computer-assisted methods being used for the first time (Vielma Orozco et al. 2020). This potential limitation of the present analysis is discussed in section 8.

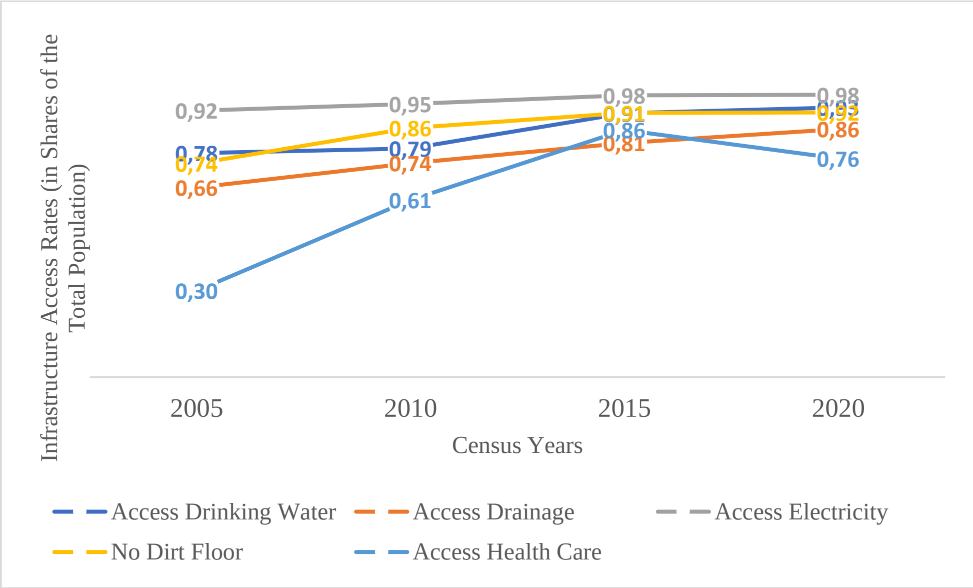

Figure 4: Descriptive Statistics Access to Basic Services, Housing, and Health (Data Sources: INEGI 2005, 2010, 2015, and 2020b)

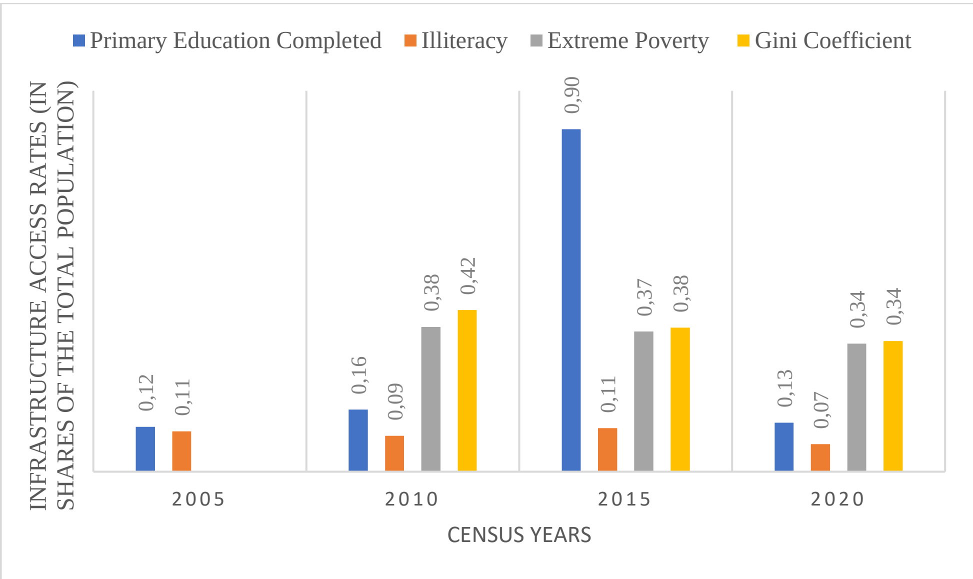

Figure 5: Descriptive Statistics Access to Education, Extreme Poverty, and Inequality

As can be judged from Figure 5, the illiteracy rate also displays a gradually declining trend over time, except for a slight increase in 2015[7], while no clear trend can be derived from the development of the completed primary education variable. Regarding the nonmonetary outcome measures, Figure 5 reveals a slight decrease in the share of people living in extreme poverty and a decrease in inequality measured by the Gini coefficient for the years 2010, 2015, and 2020. Detailed descriptive statistics are available in Tables A.1.i. – A.1.ix. in appendix 1.

[7] Outliers in the 2015 data might be explainable by pointing to the survey character of the 2015 Intercensus, which distinguishes the 2015 data from the "proper" Census data generated in e.g. 2010 and 2020.

4.4. FISM Spending as the Target Regressor

To assess the degree to which the largely positive development in the outcome variables just discussed can be attributed to municipal FISM spending, the present analysis focuses on municipal FISM spending as the key regressor. This variable is measured as the monthly average per capita FISM resources (in real terms in January 2020 Pesos) received by each municipality over the four years preceding Census year *t*. For instance, the 2020 FISM spending variable would correspond to the monthly average per capita FISM resources received by each municipality over the period 2016-2019[8]. This is done to smooth out potential measurement errors in the FISM data arising from reallocations between municipalities due to the discretion of states in the allocation of FISM resources[9] (Rodriguez-Castelan et al. 2020). As outlined above, the data on the FISM resources available for each municipality is obtainable from INEGI's State and Municipal Public Finance database on an annual basis from 2001 – 2019.

4.5. Covariates

While the FAIS is one of the larger funds within Ramo 33, it is by far not the only source of revenue for Mexican municipalities. In addition, municipalities also generate revenue from, for instance, other conditional transfers, unconditional transfers, and to a small extend also from fees and taxes. Thus, municipalities might also use these other sources of revenue for spending on social infrastructure (Diaz Cayeros et al. 2016), obscuring the effect of the FISM itself.

To account for this factor, the present analysis controls for all public financial resources *(FIN)* available to a given municipality in addition to its FISM resources. This control is measured analogously to the target regressor, i.e. by using the municipal monthly average per capita revenues, excluding FISM resources, over the four years preceding the Census year *t.* Again, this data is available from INEGI's State and Municipal Public Finance database and is expressed in real terms in January 2020 pesos (cf. Rodriguez-Castelan et al. 2020).

In addition, the present analysis accounts for municipal differences in production factors and technology to capture differences in the generation of private income. To this end, *PROD*

[8] Measuring the target regressor using lagged FISM revenues instead of present ones is important to avoid potential mechanical correlation between the target regressor and the dependent variables. This mechanical correlation might arise since the Census data, from which the data for most of the dependent variables comes from, is also used in the formula-based FAIS allocation, both pre- and post-2014 reform. By using lagged FISM data (before Census year *t*), this problem can be circumvented (Rodríguez-Castelán et al. 2020). In addition, the use of lagged FISM data can be seen as a way to account for potential lags between municipal FISM spending and the associated changes in infrastructure access as well as in poverty and inequality measures.

[9] The monthly per capita average over four years is used in the present analysis to make the most out of this smoothing effect, while RC only smooth out over a three-year period. In section 6.4.2., however, it is shown that the results of the present analysis are also robust to the usage of a three-year average.

summarizes three variables accounting for both the level and the rate of utilization of production factors: Firstly, the population share of blue and white-collar workers[10] is included as a proxy for unskilled and skilled labour. Secondly, *PROD* includes the total value of assets owned by the economic units (as a proxy for physical capital) and thirdly, the output per worker (as a proxy for productivity) (cf. Rodriguez-Castelan et al. 2020). This data is available from INEGI's Economic Census conducted in 2004, 2009, 2014, and 2019.

Finally, two population-size dummies are included as controls to account for scale effects. That is, it might, firstly, be the case that municipalities with a larger population can provide more of their inhabitants with infrastructure access using a given amount of FISM resources by exploiting economies of scale. Secondly, population size might be seen as a proxy for differences in initial infrastructure coverage rates across municipalities and thus account for potential non-linear effects in improving infrastructure access. The two dummies used to account for these factors are a dummy which equals one for municipalities with more than 15.000 inhabitants and a dummy which equals one for municipalities with more than 2.500 inhabitants (cf. Rodriguez-Castelan et al. 2020).

5. Econometric Strategy

5.1. Fixed Effects Strategy

The covariates just discussed capture a rich set of observable municipal-level differences that potentially obscure the effect of FISM spending on the outcome measures discussed in 4.1. However, unobservable differences between municipalities that are constant across time might still prevent an unbiased estimation of FISM effectiveness. This would be the case if these differences would be correlated with both FISM expenditures and outcome measures. For instance, one could imagine that municipal attitudes towards the poor affect both the access measures introduced in Table 2 and the FISM resources at the disposal of the municipality. This would be the case if municipalities with a more positive attitude towards the poor were more likely to ensure that they get their assigned resources from a pro-poor program from the state.

In addition to unobserved heterogeneity between municipalities that is constant over time, one could also imagine unobservable factors that are constant across municipalities but vary over time to bias estimates in a similar fashion. In this regard, examples would be macro-economic shocks or national policies (Rodriguez-Castelan et al. 2020).

[10] This variable refers to the share of blue- and white workers in the total population, which thus also includes categories such as unemployed or retirees.

The present analysis accounts for these two possibilities by making use of the panel structure of the dataset just described, which allows for the application of a fixed-effects method. By employing a fixed-effects approach, the potential omitted variable bias arising from both unobservable factors that are constant across time but vary across municipalities and unobservable factors that vary across time but are stable across municipalities is eliminated (Stock and Watson 2015).

5.2. Specification Tests

To confirm the suitability of a fixed-effects model for the dataset used in the present analysis and for grounding a final modification of (I) relating to the error terms, several specification tests were run.

Firstly, the importance of the inclusion of time-fixed effects in addition to municipality fixed-effects was confirmed. To this end, a joint test assessing whether all year dummies are equal to zero[11] was conducted, which would render the inclusion of time-fixed effects irrelevant. As the results shown in appendix A.2. (Figures A.2.i. – A.2.ix) reveal, this is not the case, thus confirming the importance of including time- in addition to municipality- fixed effects.

Secondly, it would also have been possible to use a random- instead of a fixed-effects model in the present context. This would be preferable in cases in which any variation across municipalities and time is random, that is, not correlated with the explanatory variables. To test whether this is the case and whether the random-effects model is thus preferable to the fixed-effects model, the Hausman Test is traditionally employed (Wooldridge 2013). As the results in appendix A.2. (Tables A.2.i. – A.2.ix.) reveal, the null-hypothesis, which postulates zero correlation between regressors and singular error terms, should be rejected in all cases, thus confirming that the fixed-effects model is the preferred one in this context.

Thirdly, the modified Wald test for groupwise heteroskedasticity in the residuals of a fixed effects model (appendix A.2., Figures A.2.x. – A.2.xviii.) and the Wooldridge test for autocorrelation in panel data models (appendix A.2, Figures A.2.xix – A.2.xxvii) confirm the potential presence of both heteroskedasticity and serial correlation of error terms (for most outcome variables in the latter case). To account for these two characteristics of the error terms, standard errors are clustered at the municipality level (Wooldridge 2013).

[11] In Stata, this test can be run using the "testparm" command.

In the following, we shall have a look at the results from applying the fixed-effects model sketched and adapted over the previous subsections to data from 2005 until 2020 before turning to using this data to generate first indicative evidence on the 2014 FAIS reform.

6. Results: Effectiveness of FAIS Spending and First Evidence on the 2014 Reform

6.1. Effectiveness of FAIS Spending from 2005 – 2020

Table 3 below shows the results from estimating equation (I) using the panel dataset described above for the period 2005 – 2020. The complete results (including year fixed-effects) can be found in appendix A.3 (Table A.3.i.).

	(1) Drinking Water	(2) Drainage	(3) Electricity	(4) No Dirt Floor	(5) Health Care	(6) Primary Education	(7) Illiteracy	(8) Extreme Poverty	(9) Gini
FISM	**.07983*** **	**.15171*** **	**.01975*** **	**.11629*** **	**.48349*** **	**.14484*** **	.0129916	.0218679	**.012164** **
	(.012778)	(.020894)	(.0046136)	(.0123878)	(.0385794)	(.0148586)	(.0087058)	(.0301933)	(.0056341)
Municipal Income	.0231492	.0293102	.0102205*	.0350664*	.0241915	.0017227	-.0113828	-.008049	.0008316
	(.023591)	(.0308259)	(.006055)	(.0179167)	(.0434249)	(.0151382)	(.0070453)	(.0226941)	(.0051373)
Blue Collar	-.21923**	-.396386*	-.0386567	-.168739*	-.60918**	-.1696235	.0247108	-.1578924	-.070995*
	(.086554)	(.2178324)	(.0339098)	(.0860653)	(.239631)	(.1657442)	(.1354557)	(.2154535)	(.0416756)
White Collar	-.3190384	-1.47888*	-.4307444	-.6483688	.1526918	-1.15445*	-2.125***	1.5218516	1.0262***
	(.3078161)	(.7739149)	(.3868696)	(.5477546)	(1.172505)	(.6959757)	(.497131)	(1.70417)	(.286743)
Assets	-5.000e-07	-1.500e-06***	0	-8.000e-07***	-4.900e-06***	-3.500e-06***	-5.000e-07	2.400e-06**	4.000e-07***
	(3.000e-1)	(5.000e-07)	(0)	(3.000e-07)	(1.400e-06)	(1.300e-06)	(4.000e-07)	(1.100e-06)	(1.000e-07)
Productivity	-.0032995	-.0038599	.0002304	-.006163	-.0306096	-.0173213*	.0029786	-.0089533*	.005***
	(.0026186)	(.0066468)	(.0005017)	(.0038828)	(.0221271)	(.0094027)	(.0023888)	(.0049739)	(.0011888)
Population >15000	-.0382317	-.0610715*	.0057128	.0047973	-.15801***	-.06757***	-.02925**	.0368553	-.0043326
	(.029098)	(.0325018)	(.011516)	(.0236455)	(.0462961)	(.0225183)	(.0126372)	(.0356205)	(.0085824)
Population > 2500	.1096647	.0171664	-.0106189	.1121777**	.2777832	.0813766*	-.07544***	.0590379	-.0181877
	(.07145)	(.1158849)	(.0194472)	(.055115)	(.1716327)	(.0470303)	(.0247918)	(.0731222)	(.0174796)
Constant	-.7492***	-1.2269***	-.1875***	-.9995***	-3.5723***	-2.718***	-2.366***	-1.8774***	-.89512***
	(.148304)	(.1856861)	(.0383141)	(.1034003)	(.2681769)	(.0857412)	(.0457404)	(.1554662)	(.0353864)
Observations	9279	9273	9283	9283	9274	9283	9283	6862	6866
R-squared	.1416449	.1420915	.051622	.1949281	.5397513	.9307213	.7292801	.3192653	.6939237

Table 3: Results Model I

Note: All dependent variables refer to logged per capita rates, except for the Gini coefficient, which is logged, but not a per capita measure. FISM and Municipal Income correspond to the logged average monthly per capita value of the three previous years and are expressed in real terms in January 2020 pesos. Blue and White Collar refer to the population share of blue- and white-collar workers. Assets refers to the total value of the assets owned by the economic units. Productivity is measured as output per worker. Population > 15000 and Population > 2500 are dummy variables which equal one for municipalities with more than 15000/2500 inhabitants and zero otherwise. Clustered standard errors in parentheses. ***: p-value < 0.01 **: p-value < 0.05 *: p-value < 0.1.

Based on the goal of the FAIS, i.e., alleviating poverty and inequality through fostering increased access to social infrastructure, one would expect the results to show positive and significant effects of FISM spending on infrastructure access measures and significantly negative effects on poverty and inequality measures. And indeed, the results in Table 3 above indicate that FISM spending has been effective in increasing average municipal access to drinking water, drainage, electricity, adequate housing, and health care during the period analysed. However, the effect sizes differ heavily across the different outcome measures: While an increase in FISM resources of 10% is, on average, associated with a 0.2% increase in electricity access rates, the associated average health care access improvement is 4.8%.

One explanation for these different effect sizes would be that they are driven by the different baseline coverage rates which emerged from the descriptive statistics available in appendix A.1. (Tables A.1.i. – A.1.ix.): While the share of the population with access to electricity has already been 92% in 2005 and increased to 98% in 2020, less than 76% of the population had access to health care in 2020. Connecting the remaining few households to the electricity network might pose a challenge since these are more likely to be located in remote, rural areas. This, in turn, implies higher marginal costs of providing electricity access compared to improving access to services that have not already reached such high coverage rates (cf. Rodriguez-Castelan et al. 2020).

When it comes to the two education outcome measures, the picture is less clear: While FISM spending is associated with an increase in the population with complete primary school education, the effect on the illiteracy rates is insignificant. This finding might reflect difficulties in targeting illiterate adults who have already left the school system with social infrastructure investments.

Finally, the two monetary outcome measures also paint a less encouraging picture: The coefficient of the extreme poverty variable indicates that FISM spending has, unlike intended, not contributed to reducing extreme poverty between 2010 and 2020. Furthermore, the coefficient of the Gini variable suggests that FISM spending has also not contributed to greater equality, on the contrary. We shall come back to this finding in section 7, where a potential mechanism behind this lacking effectiveness is illuminated in more depth.

Overall, the results from model (I) for the years 2005-2020 thus suggest positive and statistically significant, but modest effects of FISM spending on infrastructure access measures, no effect on the share of the population living in extreme poverty, and even points to an associated increase in inequality.

As will be discussed below, these results are robust to various sensitivity checks. However, before turning to the sensitivity analysis, let us first see whether these results, which are estimated based on data from 2005-2020 and thus include the post-reform period, confirm or contrast with prior findings which are not based on post-reform data. To this end, the following subsection compares the findings sketched above with those of RC.

6.2. Comparison Rodríguez-Castelán et al. 2020

	(1) Drinking Water	(2) Drainage	(3) Electricity	(4) No Dirt Floor	(5) Health Care	(6) Primary School Complete	(7) Illiteracy
FISM	**9.07*** **	**8.36*** **	**3.107*** **	.0.333	**18.36*** **	**-0.83*** **	**11.27** **
	(1.019)	(1.025)	(0.429)	(0.328)	(1.475)	(0.163)	(0.861)
Observations	6107	6107	6107	6107	6107	6107	6107

Figure 6: Results Rodríguez-Castelán et al. (2020)

Figure 6 above displays the findings of RC when running a fixed effects model in the spirit of (I) using their dataset spanning 2005-2015. Just as the present analysis which uses a very similar model for 2005-2020, the authors find positive effects on all nonmonetary outcome measures presented in Table 2, the only exception being the housing variable and the two education outcome measures.

Regarding the education variables, RC's findings point to the unintuitive result that a 1% increase in FISM spending is associated with a 0.8% decline in the share of the population who have completed primary school and with an 11% increase in the illiteracy rate among the population aged 15 or older. As discussed above, this unintuitive result vanishes when applying model (I) to a larger panel which also includes post-reform data.

Looking at the magnitude of the effects found by RC, stark differences with the effects found in the present analysis emerge. For instance, a 1% increase in FISM resources is associated with a 3% increase in access to electricity in the findings of RC but only with a 0.2% increase in the findings of the present analysis. However, both analyses find the largest effects when looking at the health care outcome measure.

Interestingly, the resemblance in magnitude and effect directions become much stronger when looking at the results RC obtain when conducting an additional analysis to tackle their unintuitive result regarding the two education variables. The authors trace back this unintuitive result to a potential endogeneity problem in their model when the nonmonetary outcome measures are concerned. That is, both the former IGP-based FAIS allocation formula and the post-2014 allocation formula take into account the municipal access rates to basic services, health, and education in their compensatory component. Therefore, municipalities with lower access rates are likely to receive higher FAIS resources, creating a potential endogeneity problem in models such as (I).

To address this potential endogeneity problem, RC run their fixed-effects model again, using an instrumental variable (IV) approach. As an instrument for the observed FISM spending, the authors use the amount of FISM resources that each municipality would have received if the FISM allocation would be completely based on the FAIS allocation formula, without any discretion for, for instance, the states. This instrumental variable, which has already been used similarly in prior studies by Ramones and Prudencio 2014 and Diaz-Cayeros et al. 2016, naturally displays a high correlation with the observed FISM spending. In addition, it is likely to fulfil the exogeneity condition for instrumental variables when a control variable for the effects of the individual formula components is included (Rodríguez-Castelán et al. 2020).[12]

Interestingly, the results obtained from running equation (I) based on data from 2005-2020 correspond much more closely to the results RC obtain using this instrumental variable model than they do to RC's results from the fixed-effects model. This is the case both in terms of effect sizes and effect directions.

Figure 7 displays the findings from RC's IV model for basic services, adequate housing, and health care. Just as the present analysis presented in Table 3, the authors find positive and significant effects for all basic services, housing, and health care. In addition, the largest effects are, again, found for access to health care while the smallest effects are obtained in the case of electricity. Finally, effect sizes closely resemble those from the present analysis. For instance, the 1.1% increase in access to adequate housing associated, on average, with a 10% increase in FISM spending displayed in Figure 7 almost matches the 1.2% increase found when using data from 2005-2020.

These numbers are probably more realistic compared to the large effect sizes found by RC when not employing an instrumental variable. For instance, a 3% increase in access to electricity associated with a 1% increase in the monthly FISM resources per capita seems very high when considering that the coverage rates for electricity were already above 90% during the period studied by RC.

[12] Unfortunately, replicating this analysis was not possible since RC neither report the data sources for their instrument nor the control variables they use for ensuring the exogeneity condition, even so this would have increased the reliability of the results of the present analysis presented in Table 3.

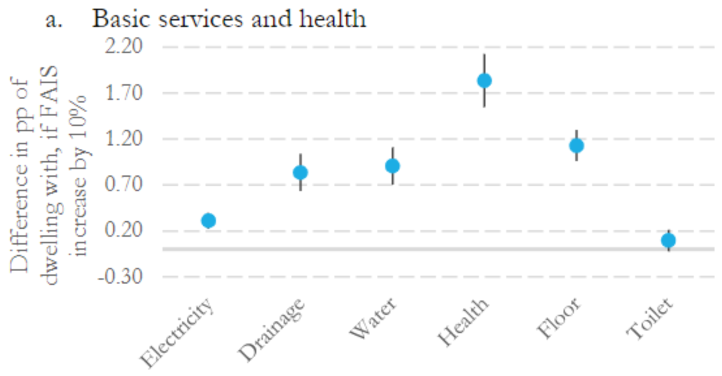

Figure 7: Results IV-Fixed Effects Model Rodríguez-Castelán et al. 2020

Turning to the two education outcome measures, the authors obtain a more intuitive result based on their IV approach than they did based on their fixed-effects model: Just like the findings from the present analysis, RC find a positive effect in case of one measure of education and no significant effect in case of the other. The only difference consists in the fact that RC find a significant effect in case of the illiteracy rates while the present analysis reveals a significant effect when looking at the share of people who completed primary school.

Finally, while the results regarding the poverty and inequality measures are not directly comparable due to the different measurements of poverty employed, it is interesting to point out that RC do not find an effect on poverty at the aggregate level. This result, which is found both in their fixed-effects and their IV model, is in line with the result in Table 3, which also reveals no significant effect of FISM spending on extreme poverty rates. In the case of the Gini coefficient, RC's findings also point to an increase in inequality as a consequence of FISM spending, even though the effect size is even more moderate compared to the one reported in Table 3.

In sum, the results from the present analysis, confirm the positive effects of FISM spending on access to basic services and health care found by RC. Looking at education and access to adequate housing, the present analysis finds a positive effect of FISM spending on the share of dwellings with an adequate floor and the share of the population who completed primary school which was not found by RC. Thus, overall, the present evaluation of FISM effectiveness in the case of social infrastructure access paints a more positive picture when it comes to effect directions and significance levels compared to the one by RC.

Turning to the magnitude of the effects, it is interesting that the results from the present analysis resemble the results from RC's fixed effects-instrumental variable model more closely than those from the fixed-effects model without an instrumental variable. This points to the conclusion that using a longer panel might eliminate potential endogeneity issues present when looking at a shorter time frame[13].

When it comes to the effect of FISM spending on extreme poverty and inequality, the present analysis also confirms RC's finding that FISM spending, in the aggregate, cannot be associated with effects on extreme poverty rates and has even led to an average increase in inequality. This points to a problem with the FAIS, given its goal to alleviate poverty and inequality through the construction of social infrastructure.

However, as discussed above, this problem might relate to the perverse incentives arising from the initial FAIS allocation formula. Given that the 2014-FAIS reform aimed at mitigating these perverse incentives, it is interesting to see in how far the problem of the lacking effectiveness of FISM spending when it comes to its core goals has been alleviated following the 2014-reform. To this end, let us turn to the second contribution of this thesis, which consists in generating indicative evidence regarding a potential change in FISM effectiveness following the 2014-reform.

6.3. First Evidence on the 2014 FAIS Reform

Since the data set used in the present analysis includes data from up to 2020, we have a six-year time frame across which the 2014 reform should plausibly have shown first effects on the effectiveness of FISM spending. This enables a first, tentative evaluation of potential changes in FISM effectiveness from 2015 through 2020.

To this end, one final modification of model (I) presented above needs to be undertaken: To gain insights into whether FISM spending has become more effective following the 2014 reform, an interaction term is included which interacts the target regressor with a dummy that equals 1 for the datapoints post-2014 and 0 otherwise, yielding the following specification:

$$\text{(II) Log } Y_{mt} = ß_0 + ß_1\text{Log}\mathit{FAIS}_{mt} + ß_2\text{Log}\mathit{FISC}_{mt} + ß_3\mathit{PROD}_{mt} + ß_4\text{Log}\mathit{MUN}_{mt} + ß_5\,\mathit{Post\text{-}2014} + ß_6\text{Log}\mathit{FAIS}_{mt} \text{ x } \mathit{Post\text{-}2014} + \gamma_m + \varepsilon_{mt}$$

As outlined above, the 2014 reform aimed at changing the incentives of the FAIS allocation formula to better align FAIS spending with the aim of the fund, i.e. the alleviation of extreme poverty through the construction of social infrastructure. This goal of the 2014-FAIS reform would give reasons to hypothesize that FISM effectiveness should have increased following the 2014-reform. In the present empirical set-up, this would be indicated by significantly positive

[13] However, an additional analysis in which RC's instrumental variable model is applied to the longer panel would be necessary to confirm this possibility.

coefficients of the interaction term in the cases of all infrastructure access measures except for the illiteracy rate and significantly negative coefficients in the case of the illiteracy rate.

In addition, the 2014-FAIS reform would especially be expected to yield significantly negative coefficients in the case of the extreme poverty and inequality outcome measures. Should this be the case, then this would provide evidence that the 2014-FAIS reform has been successful in reaching its main goal, thereby contributing to reversing the unexpected results on FISM effectiveness regarding these two outcome measures found in Table 3.

When running model (II) using the dataset covering the period 2005-2020, the following results emerge (with the full results, including those for the 2014 dummy, available in Table A.4.i. in Appendix 4):

	(1) Drinking Water	(2) Drainage	(3) Electricity	(4) No Dirt Floor	(5) Health Care	(6) Primary Education	(7) Illiteracy	(8) Extreme Poverty	(9) Gini
FISM	.0046	**.1821*** **	**.0104** **	**.1099*** **	**.4135*** **	**-.5797*** **	**-.1889*** **	**-.0935*** **	**-.0773*** **
1.Post2014xFISM	**.103*** **	**.0868*** **	**.0179*** **	**.0528*** **	**.2262*** **	-.0183	**-.064*** **	**.0384*** **	**.0103*** **
	(.0074)	(.0111)	(.0031)	(.006)	(.0159)	(.0129)	(.0061)	(.0132)	(.0025)
Municipal Income	.0358**	.1426***	.0209***	.1326***	.6328***	-.1247***	-.1685***	-.0597***	-.0512***
	(.0157)	(.0231)	(.0041)	(.0132)	(.0376)	(.0311)	(.0112)	(.0232)	(.0061)
Blue Collar	-.0878**	-.1251	-.0207	-.1889*	-1.3701**	-3.2129**	-.7999	-.2527	-.1951***
	(.044)	(.1122)	(.0296)	(.1023)	(.6347)	(1.5914)	(.5091)	(.2064)	(.0532)
White Collar	-.0414	-1.3025**	-.4212	-.9892*	-3.2384**	-6.4301*	-3.1673***	1.2336	.503*
	(.2377)	(.5973)	(.3815)	(.5087)	(1.374)	(3.8743)	(1.211)	(1.7077)	(.301)
Assets	0***	0	0**	0	0***	0***	0**	0**	0
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
Output	.0003	.0013	.001	-.0033	-.0186	-.0322	-.0045	-.0089	.0045*
	(.0011)	(.0021)	(.0006)	(.0023)	(.02)	(.0431)	(.0136)	(.0058)	(.0024)
Population > 15000	-.0073	.0271	.0151	.0625***	.1486***	-.3111***	-.1681***	.0012	-.0462***
	(.0282)	(.0324)	(.0117)	(.0232)	(.0453)	(.0738)	(.0253)	(.0352)	(.01)
Population > 2500	.0983	.0339	-.0093	.1443**	.5261***	.23**	-.0746**	.044	-.0301
	(.0711)	(.1157)	(.019)	(.0566)	(.1888)	(.0958)	(.0341)	(.0769)	(.0224)
Constant	-.5651***	-1.8797***	-.2069***	-1.4296***	-6.0975***	.584***	-.8815***	-1.157***	-.2652***
	(.0957)	(.1372)	(.022)	(.072)	(.2279)	(.1463)	(.0506)	(.1549)	(.0389)
Observations	9279	9273	9283	9283	9274	9283	9283	6862	6866
R-squared	.1632	.1272	.0553	.1794	.4241	.39	.2559	.3139	.5954

Note: All dependent variables refer to logged per capita rates, except for the Gini coefficient, which is logged, but not a per capita measure. FISM and Municipal Income correspond to the logged average monthly per capita value of the four previous years and are expressed in real terms in January 2020 pesos. Blue and White Collar refer to the population share of blue- and white-collar workers. Assets refers to the total value of the assets owned by the economic units. Productivity is measured as output per worker. Population > 15000 and Population > 2500 are dummy variables which equal one for municipalities with more than 15000/2500 inhabitants and zero otherwise. Post-2014 is a dummy equaling 1 for the post-reform period and 0 otherwise. Clustered standard errors in parentheses. ***: p-value < 0.01 **: p-value < 0.05 *: p-value < 0.1.

Table 4: Results Model II

As shown in Table 4, the interaction term is indeed significant for all specifications except for (6), indicating that the effect of FISM spending for the years after the 2014 reform is significantly different from the effect for the years before the reform. This provides indicative evidence for a change in FISM effectiveness due to the 2014 reform, as would have been expected.

In addition, the sign of the coefficient of the interaction term is in line with the expectations formulated above when looking at the infrastructure access measures: That is, the positive coefficients in the case of basic services, housing, and health care, as well as the negative coefficient in the case of the illiteracy rate, indicate an increase in FISM effectiveness in light of the 2014-reform. For instance, a 1% increase in FISM resources is associated with an average additional increase in drinking water access of 0.1% following the 2014-reform.

However, when turning to the outcome measures that are of most interest in an evaluation of the 2014-FAIS reform, i.e. the extreme poverty and the inequality measure, the results in Table 4 appear far less promising. That is, the coefficients of the interaction term are positive and significant in the case of both (8) and (9). This indicates that the 2014-reform has not, unlike expected, increased the effectiveness of FISM spending when it comes to the main aims of the fund, i.e. poverty and thus inequality alleviation, but has rather had contrary effects.

Another interesting finding emerging from Table 4 in this regard is the following: Once accounting for a potential reform-driven change in FISM effectiveness by including an interaction term, the sign and significance levels of the FISM coefficients in the cases of (8) and (9) are in line with the expectations formulated above. That is, unlike indicated by the results shown in Table 3 and the results found by RC, the results in Table 4 point to a significant reduction in extreme poverty rates and inequality associated, on average, with FISM spending.

In conjunction with the results on FISM effectiveness found in Table 3 above, these two sets of findings seem to, at first glance, point to the following explanation: The unexpected results regarding the lacking effectiveness of FISM spending on poverty and inequality in Table 3 might mainly be driven by developments following the 2014-reform, and thus reverse once accounting for post-reform changes, as done in model (II).

This would also fit with the unexpected results regarding the lacking effectiveness of the 2014-reform when it comes to extreme poverty and inequality measures which point to adverse developments following the 2014-reform. In addition, the fact that the results for both poverty and inequality measures presented in Table 3 were mainly estimated based on post-reform data (i.e. from 2010, 2015, and 2020) lends additional plausibility to this hypothesis. Unfortunately, this potential explanation cannot be tested empirically[14] and can hence not be ruled out as a driver behind the results in Table 4. However, the fact that RC found similar results regarding the lacking effectiveness of FISM spending when it comes to reducing extreme poverty and inequality when using pre-reform data only seems to speak against it[15].

However, the findings regarding the lacking effectiveness of the 2014-reform when it comes to extreme poverty and inequality could also point to another explanation, which can, contrarily to the former explanation, be tested empirically. According to this alternative explanation, the results in Table 4 merely reflect difficulties in adjusting to the changes of the reform. That is, local governments might need some time to adjust their FISM spending in light of the formula change such that it responds to the new incentives set by the adjusted formula and effectively contributes to tackling poverty and inequality.

To test this hypothesis empirically, model (II) is slightly adapted to be able to gauge changes in FISM effectiveness over time since the 2014-reform. This can be achieved by interacting FISM spending with two year-dummies, one that equals 1 for the 2015 datapoints and 0 otherwise, and one that equals 1 for the 2020 datapoints and 0 otherwise (cf. Wooldridge 2013), resulting in the following model:

$$\text{(IIA) Log } Y_{mt} = ß_0 + ß_1\text{Log}\mathit{FAIS}_{mt} + ß_2\text{Log}\mathit{FISC}_{mt} + ß_3\mathit{PROD}_{mt} + ß_4\text{Log}\mathit{MUN}_{mt} + ß_5\,\mathit{Year2015} + ß_6\,\mathit{Year2020} + ß_7\text{Log}\mathit{FAIS}_{mt} \times \mathit{Year2015} + ß_8\text{Log}\mathit{FAIS}_{mt} \times \mathit{Year2020} + \gamma_m + \varepsilon_{mt}$$

When running model (IIA), the following results emerge (with the full results, including year dummies, available in Tables A.4.ii. in Appendix 4):

[14] Assessing the potential of this hypothesis by running model (I) only using pre-reform data is not possible because the poverty and inequality data based on the new multidimensional poverty measurement used in the present analysis is only available for 2010, 2015 and 2020, thus spanning only one point in time before the 2014-reform.

[15] In addition, model (I) performs better in terms of R2 in the cases of the Gini coefficient and the extreme poverty variable as well as in the cases of the two education outcome variables, for which the results on the FISM coefficient in Table 3 and 4 also differ slightly.

	(1) Drinking Water	(2) Drainage	(3) Electricity	(4) No Dirt Floor	(5) Health Care	(6) Primary Education Complete	(7) Illiteracy	(8) Extreme Poverty	(9) Gini
FISM	-.0154	**.1117*** **	**.0074***	**.1155*** **	**.5995*** **	**.0799*** **	**-.0289*** **	-.0035	**.011***
	(.0121)	(.023)	(.004)	(.0138)	(.0503)	(.0165)	(.0085)	(.0364)	(.0062)
1.Year2015xFISM	**.0749*** **	-.0265	**.0108** **	**.0316*** **	**.2437*** **	**.0353*** **	**-.1157*** **	**.1062*** **	**.0172*** **
	(.0104)	(.0166)	(.0053)	(.01)	(.0173)	(.0054)	(.0062)	(.0138)	(.0024)
1.Year2020xFISM	**.1281*** **	**.1923*** **	**.0251*** **	**.0804*** **	**.2847*** **	**.1985*** **	**.0661*** **	**-.0485*** **	**-.0121*** **
	(.0073)	(.0118)	(.0025)	(.005)	(.0181)	(.0065)	(.0046)	(.0149)	(.0026)
Municipal Income	.0361**	.1475***	.0217***	.141***	.7014***	.1211***	-.0901***	-.0476**	-.006
	(.016)	(.0231)	(.0041)	(.0135)	(.0386)	(.0127)	(.0064)	(.0217)	(.005)
Blue Collar	-.1057**	-.1442	-.0146	-.0952	-.4573*	.0507	.1899**	-.2852	-.0965***
	(.0454)	(.108)	(.0257)	(.0625)	(.2582)	(.1094)	(.0799)	(.1951)	(.029)
White Collar	.1584	-.3888	-.3492	-.6241	-1.5582	-.3501	-.7519	-.5642	.6138**
	(.2539)	(.5936)	(.3891)	(.488)	(1.3104)	(.4413)	(.5292)	(1.6853)	(.2738)
Assets	0***	0*	0**	0**	0	0**	0	0*	0
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
Output	.0002	.0011	.001	-.0028*	-.0128	-.0115**	.0017	-.0092	.0049***
	(.0009)	(.003)	(.0006)	(.0016)	(.0098)	(.0051)	(.0026)	(.006)	(.0013)
Population >15000	-.0151	.0004	.0142	.0666***	.2376***	.0052	-.0871***	.0424	-.0034
	(.0282)	(.0328)	(.0115)	(.0232)	(.0469)	(.0193)	(.014)	(.0361)	(.0085)
Population > 2500	.1008	.042	-.009	.1422**	.4909***	.1049**	-.1081***	.054	-.0187
	(.0705)	(.1154)	(.019)	(.0567)	(.1826)	(.0471)	(.0239)	(.074)	(.0174)
Constant	-.4958***	-1.6576***	-.201***	-1.4943***	-7.1239***	-3.0686***	-1.8685***	-1.5658***	-.8528***
	(.099)	(.1349)	(.022)	(.0757)	(.2407)	(.0745)	(.0333)	(.1739)	(.0368)
Observations	9279	9273	9283	9283	9274	9283	9283	6862	6866
R-squared	.1707	.1709	.0575	.1849	.4693	.9355	.7644	.3458	.7047

Table 5: Results Model IIA

Note: All dependent variables refer to logged per capita rates, except for the Gini coefficient, which is logged, but not a per capita measure. FISM and Municipal Income correspond to the logged average monthly per capita value of the four previous years and are expressed in real terms in January 2020 pesos. Blue and White Collar refer to the population share of blue- and white-collar workers. Assets refers to the total value of the assets owned by the economic units. Productivity as measured as output per worker. Population > 15000 and Population > 2500 are Dummy variables which equal one for municipalities with more than 15000/2500 inhabitants and zero otherwise. Year 2015 and Year 2020 are year dummies. ***: p-value < 0.01 **: p-value < 0.05 *: p-value < 0.1.

From the results depicted in Table 5, tentative evidence in favour of the adjustment hypothesis formulated above emerges: In line with what would be expected in case of an adjustment of municipalities to the reform over time, in the case of basic services, housing and health, the coefficients point to an increase in the effectiveness of FISM spending between 2015 and 2020. That is, while FISM spending has already had a positive and significant, though moderate, effect on the respective infrastructure access measures when looking at the year directly after the 2014-reform, effect sizes for all these infrastructure services increase when looking at the 2020 interaction coefficient. In the case of drainage, the coefficient even only turns positive and significant when looking at the 2020-interaction term.

Similar to the results from models I and II, a mixed picture emerges when looking at the two education variables: Here, the results point to a rather large increase in the effectiveness of FISM spending over time when it comes to the primary education outcome measure. More specifically, a 10% increase in FISM resources is associated with an average increase in the population with a completed primary education of 0.4% in 2015, but of almost 2% in 2020. However, in the case of literacy, it seems that the effectiveness of FISM spending on illiteracy reduction that can be observed directly after the reform reverses over time.

Let us now turn to the extreme poverty and inequality measures, which, as discussed above, are the most important outcome measures to look at when tentatively evaluating the success of the 2014 reform. Regarding these two measures, the negative picture painted by the results in Table 4 can be qualified: While the results in Table 4 seemed to indicate that the 2014-FAIS reform has not reached its intended goal, the results in Table 5 suggest that this finding is driven by the 2015-data only. That is, while FISM spending can be associated with an average increase in extreme poverty and inequality in the year directly following the reform, this effect has already reversed six years after the 2014-reform when municipalities have had sufficient time to adjust to the new incentives.

In addition, the results regarding the effectiveness of FISM spending when it comes to extreme poverty and inequality emerging from Table 5 are in line with the findings presented in Table 3 and with those of RC. This also seems to support the adjustment hypothesis over a post-reform driven result on FISM effectiveness in the cases of extreme poverty and inequality.

In sum, all findings except the one on the illiteracy coefficient point to a slowly emerging success of the 2014-reform, after an initially rough start. Therefore, the results in Table 5 provide evidence for the adjustment hypothesis formulated above. Thus, while a look at the whole period following the 2014-reform seemed to indicate a lacking success of the reform when looking at poverty and inequality measures, the more fine-grained analysis presented in Table 5 suggest that the reform, after some time for adjustment, will bear fruit in the near future.

6.4. Sensitivity Analysis

Before turning to the third contribution of this thesis by shedding light on the mechanism driving these results on FISM effectiveness and the 2014-FAIS reform, the following subsection presents two sensitivity checks that confirm the robustness of the findings emerging from models I, II, and IIA. More specifically, it is shown that the results presented above are robust to (a) population-weighting and (b) different measures of the target regressor.

6.4.1. Robustness to Population Weighting

The present analysis relies on per capita measures for the dependent variables, the target regressor, and most of the controls. However, municipalities in Mexico are extremely heterogenous when it comes to the number of residents: As Table 6 below demonstrates based on population data from 2020, resident numbers in Mexico's 2469 municipalities range from 81 (Santa Magdalena Jicotlán in the State of Oaxaca in Southwestern Mexico) to almost two million (Tijuana in the State of Baja California in Northwestern Mexico).

Variable	Obs	Mean	Std. Dev.	Min	Max
Population (2020)	2469	51038.487	146990.73	81	1922523

Table 6: Heterogeneity in Resident Numbers Across Municipalities in Mexico (Data Source: INEGI 2020b)

Given this extreme heterogeneity in resident numbers across Mexico, there is also a large variability in the reliability of the per capita measures used in the present analysis, such as the infrastructure access rates. That is, the per capita measures for municipalities with larger population sizes have less variance and thus provide more reliable information (Moreno-Jaimes 2011).

To tackle this potential issue, authors such as RC use population weighting for obtaining results on FISM effectiveness. Population-weighting means that the regression gives a higher weight to municipalities with larger resident numbers, thereby reducing the variance in the per capita measures.

As Table 7 below shows, the results of the present analysis are largely robust to the application of population weights, the only exception being the effectiveness of FISM spending on access to electricity. This might have to do with a phenomenon already discussed above, i.e. that electricity access is already very widespread in Mexico, and the only households yet unconnected are most likely located in remote, rural areas. Since this is also where the sparsely populated municipalities which are now given less weight in the analysis are located, this might explain why the coefficient of FISM spending loses its significance in the case of (3).

	(1) Drinking Water	(2) Drainage	(3) Electricity	(4) No Dirt Floor	(5) Health Care	(6) Primary Education Complete	(7) Illiteracy	(8) Extreme Poverty	(9) Gini
FISM	**.0707*****	**.0694*****	.0063	**.0757*****	**.3055*****	**.1482*****	-.0045	.0754	**.0375*****
	(.0108)	(.0141)	(.0088)	(.0096)	(.0272)	(.0203)	(.0205)	(.0475)	(.0089)
Observations	9279	9273	9283	9283	9274	9283	9283	6862	6866
R-squared	.1467	.1189	.099	.1616	.4833	.9588	.8137	.3126	.7545

Table 7: Weighted Model I

Note: Importance given to observations increases in municipal population size, using population data from 2020. All dependent variables refer to logged per capita rates, except for the Gini coefficient, which is logged, but not a per capita measure. FISM corresponds to the logged average monthly per capita value of the four previous years and is expressed in real terms in January 2020 pesos. Other variables included in the regression but not shown are (1) municipal income other than FISM, (2) blue-collar and white-collar workers per capita, (3) output per worker, (4) business assets (5) semi-urban municipalities (more than 2.500 but less than 15.000 inhabitants) and (6) cities (more than 15.000 inhabitants). Clustered standard errors in parentheses. ***: p-value < 0.01 **: p-value < 0.05 *: p-value < 0.1.

Turning to the population-weighted version of (II), which includes an interaction term to assess the success of the 2014-FAIS reform, similar results emerge. Again, as demonstrated in appendix A.5 (Table A.5.ii.), the results on the success of the 2014-FAIS reform are confirmed in the cases of access to basic services, adequate housing, health care and education, with electricity again being a notable outlier.

However, the case is different for the remaining outcome variables: In the case of extreme poverty, the results now point to improvements in FISM effectiveness following the 2014-reform. In the case of the Gini coefficient, no change post-2014 is found in the weighted model. Thereby, this robustness-check already seems to foreshadow the qualified results found when disentangling the post-2014 dummy. As can be seen in appendix A.5. (Table A.5.iii.), these results of the disentangled analysis using model (IIA) are robust to population weighting, with a minor exception in the case of health care.

6.4.2. Robustness to Different Measures of the Target Regressor

As discussed in section 4, the present analysis uses the monthly average per capita FISM resources received by each municipality over the four years preceding Census year *t* as a measure for the target regressor. This contrasts slightly with RC, who make use of a three-year average. As discussed in footnote 9, this slight adaptation is intended to make the most out of the smoothing effect to counter potential measurement errors in the FISM data.

However, RC argue that a three-year average, even if it does not make the most out of the smoothing effect, is most suitable given that it allows controlling for the local political cycle. And indeed, mayors, who play the largest role in the allocation of FISM resources, are elected every three years in Mexico. This reasoning would support the usage of a three-year over a four-year average, even though it must be pointed out that electoral cycles vary from state to state and are rarely congruent with the three years before the Census years *t* (cf. Instituto Nacional Electoral 2018).

To see if the results presented above are robust to this alternative measure of the target regressor, models (I), (II), and (IIA) were re-run using a three- instead of a four-year FISM average. The results of this sensitivity check are presented in appendix A.5. (Tables A.5.iv. – A.5.vi.). These results demonstrate the overall robustness of the findings regarding FISM effectiveness and the effect of the 2014-reform to this different measure of the target regressor when it comes to effect sizes, directions, and significance levels.

7. Needs-Responsiveness of FISM Spending Post-2014

As we have seen, the results of the analysis presented above reveal that FISM spending has had positive, but moderate effects on access to basic services, adequate housing, health care, and to some degree also education. In addition, we have seen that this effectiveness has increased following the 2014-reform, especially after a few years that allowed for adjustments to the new allocation formula.

These positive results on decentralized public spending through the FAIS in Mexico appear to be in line with the promise of fiscal decentralization sketched in the introduction: Decentralizing public spending as it was done in Mexico through the FAIS should increase the effectiveness of such spending. As discussed above, these efficiency benefits of fiscal decentralization are argued to materialize, among others, through increased responsiveness of decentralized investment decisions to local wants and needs.

However, we have also seen that the promise of fiscal decentralization has not been fulfilled when it comes to the overall aim of the fund: Reducing extreme poverty and thus inequality. As discussed above, FISM spending has not been found to be effective in reducing extreme poverty and has even led to an increase in inequality. In addition, the 2014-FAIS reform has, initially, not been found to be successful in reversing this trend, even though it shows promise in the mid- to long term.

These sets of findings invite the question of why decentralizing public spending on poverty alleviation in Mexico does not seem to have generated the desired outcomes when it comes to fighting extreme poverty and inequality. In the same vein, what would it take to reverse this trend and generate reducing effects of FISM spending on poverty and inequality measures, additional to the positive effects FISM spending has been found to have on infrastructure access measures? Answering these questions is not only crucial for understanding the dynamics behind the results found above but also for being able to derive policy recommendations for future improvements of the effectiveness of FAIS spending.

To answer these crucial questions, this section comes forward with the third contribution of this thesis. More specifically, it analyses to which degree the main mechanism argued to foster the increased effectiveness of decentralized public expenditure, i.e. by fostering increased responsiveness of public spending to local wants and needs, is at play in the case of FISM spending.

That is, a potential explanation for the lacking effectiveness of FISM spending regarding poverty and inequality measures, even following the 2014-reform, would be that FISM spending, unlike argued by decentralization proponents, is not responsive to local needs. Thus, on the one hand, FISM spending has effectively increased access to social infrastructure because FISM resources have to be spent on social infrastructure. On the other hand, FISM spending has not effectively decreased poverty and inequality because FISM resources have not been allocated to those infrastructure services where local needs are the starkest.

This potential explanation is also hinted at by RC, who suggest that "[r]ewards to municipalities that demonstrate effective reductions in local social infrastructure gaps could help establish appropriate incentives for the use of FAIS resources" (Rodríguez-Castelán et al. 2020, p. 21). Thereby, the authors also seem to suggest that a weak targeting of FISM resources towards closing infrastructure gaps could drive their, and hence the present, results.

To test this potential explanation for the findings on FISM effectiveness discussed above and for deriving policy recommendations, this section will develop an empirical model for assessing the needs-responsiveness of FISM spending. To this end, this section draws and improves upon past research on the needs-responsiveness of FISM spending conducted by Wellenstein et al. (2006) and Moreno-Jaimes (2011). To have the background for developing this model, the following subsection presents the key theoretical arguments on the relationship between decentralized public spending and needs-responsiveness.

7.1. Fiscal Decentralization and Needs-Responsiveness: Literature Review

The increased responsiveness of public investments to societal wants and needs that fiscal decentralization is argued to foster has been one of the main points brought forward to support the surge towards fiscal decentralization outlined in the introduction (Borge et al. 2014). Responsiveness of public investments can be defined as the government making investment decisions that are signalled to be preferred by citizens (adapted from Manin et al. 1999).

7.1.1. Arguments in Favour: Fiscal Decentralization Increases Needs-Responsiveness

The mechanisms by which fiscal decentralization is argued to foster increased responsiveness of public expenditures to societal preferences and needs are manifold. The *first set of arguments* often brought up relates to local governments' information advantages regarding local preferences and needs and increased flexibility to tailor expenditure decisions to this information (Martinez-Vazquez et al. 2016). That is, while national governments often lack the time and local knowledge to ensure that expenditure decisions respond to societal wants and needs, local governments are argued to have better access to local information on preferences and needs. In addition, they are also argued to be better able to come up with tailored solutions for serving these wants and needs (Abbott et al. 2017 and Arends 2020).

The *second set of arguments* concerns the increased participatory possibilities at the local level compared to the national level. Arguments in this set refer to the greater possibilities of local interest groups to gain access to local decision-makers and the greater possibilities to involve citizens in public expenditure projects at the local level (Faguet 2004). Using the example of decentralized infrastructure investments financed through the FAIS, these greater possibilities might, for example, come in the shape of participative planning techniques (Faguet 2004) or of involving citizens in the evaluation of the projects carried out (Taguenca Belmonte and Lugo Neria 2020).

The *third set of arguments* that supports the increased responsiveness of public investments due to fiscal decentralization relates to accountability. In this regard, it has been argued that moving the level of decision-making regarding expenditures such as investments in social infrastructure closer to the citizens increases government accountability to citizens (Andres et al. 2014). For instance, the potential threat of being punished by the voters for not spending funds responsively might be greater at the local level, where local infrastructure projects play a larger role in voting decisions and the public discourse. This is argued to create stronger incentives for local policymakers to make expenditure decisions based on local wants and needs (cf. Martinez-Vazquez et al. 2016).

7.1.2. Arguments Against: Fiscal Decentralization Does Not Increase Needs-Responsiveness

Despite these manifold arguments in favour of fiscal decentralization fostering increased needs-responsiveness and thereby leading to important efficiency benefits, many authors have also pointed to factors that might prevent these positive consequences from materializing.

Relating to the *first set of arguments* discussed above, one worry concerns the lack of human, financial, and technical resources available at the local level in comparison to those available at the national level (Faguet 2004). For instance, if fiscal decentralization implies that subnational governments are being made responsible for providing complex services that had been provided by the national government before, they will likely lack the technical expertise on how to best deliver these services (Arends 2020). Therefore, it is argued, local governments will not be able to invest public resources in a manner that responds to citizens' needs, even given factors such as the information and flexibility advantages outlined above.

Relating to the *second set of arguments*, another worry concerns the possibility of interest capture, that is, a diversion of public resources based on the interest of elites instead of society in general (Hernandez-Trillo and Jarillo-Rabling 2008). And while this is arguably a concern at any level of government, it has been argued that local elites might find it, just as citizens in general, easier to influence expenditure decisions compared to the national level (cf. Andres et al. 2014). If true, this concern would be especially worrisome in the case of programs like the FAIS which target marginalized groups, who do not have the resources to engage in interest capture (Kis-Katos 2014).

A final worry relating to the *third set of arguments* points to the limited importance and potential contestability of local elections (Bardhan and Mookherjee 2006). In addition, unclear divisions of responsibilities between national and subnational governments might allow local governments to shift the blame for not having spent resources in a needs-responsive manner to higher government levels (Arends 2020). Both factors are argued to weaken the accountability of local governments to citizens and thereby weaken the incentive to spend public funds in a needs-responsive fashion (Bardhan and Mookherjee 2006).

In sum, there are many different arguments for why fiscal decentralization might increase the responsiveness of public spending to citizens' wants and needs, but also a variety of factors that might prevent this important benefit from materializing, as summarized in Table 8 below. With this theoretical background in mind, let us now see how the factors discussed above have played out in the case of the FAIS, by discussing existing empirical evidence on the needs-responsiveness of FISM spending. These existing empirical studies will then form the basis for an evaluation of the needs-responsiveness of FISM spending for the post-reform period.

Argument in Favour	Potential Concerns
Information and flexibility advantages at the local level	Lack of human, institutional and financial resources at the local level
Greater participatory possibilities at the local level	Possibilities for interest capture by elite groups at the local level
Higher accountability of governments at the local level	Contestability and lacking importance of local elections; blame shifting

Table 8: Summary of Theoretical Arguments in Favour and Against Increases in Needs-Responsiveness due to Fiscal Decentralization

7.2. Empirical Evidence on the Needs-Responsiveness of FISM Spending

While empirical evaluations of the effectiveness of FAIS spending are already scarce, even fewer studies have looked at the needs-responsiveness of FAIS spending. To the best of the knowledge of the author, only two studies have attempted to generate evidence in this regard, out of which only one is based on a set-up that allows for conclusions regarding the needs-responsiveness of FISM spending specifically.

7.2.1. Wellenstein et al. (2006)

This study of the latter type has been conducted by Wellenstein et al. (2006) (in the following: WS). As part of a comprehensive paper which addresses many issues relating to the FAIS, the authors ask themselves how far FAIS spending is targeting infrastructure needs, focusing on the FISM part of the FAIS. To this end, the authors make use of an OLS model, regressing the infrastructure access rates for a given infrastructure service covered by the FISM in 2000 on the share of FISM resources spent on this service in 2000, 2002, and 2004, respectively. In addition, the authors control for municipal income as well as for the coverage rates of the other infrastructure services analysed, thus yielding the following model:

$$\text{(W) Log}\textit{FISM}_{imt+x} = ß_0 + ß_1 \text{ Log}\textit{Coverage}_{imt} + ß_2\text{Log}\textit{FISC}_{mt} + ß_{3\text{-I}} \text{ Log}\textit{OtherCoverage}_{-imt}$$

In this model, *FISM* represents the logged share of FISM resources spent by municipality m on infrastructure service i at time t, with i being drinking water, sanitation, and electricity, respectively. Since the authors use data from 2000, 2002, and 2004 x ϵ {0, 2, 4}. In addition, *Coverage* is a logged measure for access to infrastructure service i, measured by the share of the population of municipality m who has access to infrastructure service i at time t. *FISC* represents the logged per capita financial resources at the disposal of municipality m at time t. Finally, *Other Coverage* represents the logged share of the municipal population with access to those infrastructure services analysed, but not represented by the target regressor, at time t.

Based on this model, WS find that FISM spending on drinking water and electricity is at least mildly responsive to local infrastructure needs. That is, the authors find a 1% increase in access to drinking water to be associated with an average reduction of the share of FISM resources spent on drinking water by 0.13%-0.26%. In the case of electricity, a 1% increase in access is associated with a 0.41%-0.84% reduction, on average. However, in the case of sanitation, the authors did not find a significant association between infrastructure coverage rates and allocated FISM shares (Wellenstein et al. 2006).

In sum, WS conclude that even though the relationship between infrastructure needs and FISM spending shares indicates targeting in the cases of drinking water and electricity, this relationship is weak in the case of drinking water and non-existent in the case of sanitation (Wellenstein et al. 2006). Overall, these results thus paint a disappointing picture regarding the needs-responsiveness of FISM spending.

Thereby, WS's analysis supports the hypothesis presented above: That is, the lacking effectiveness of FISM spending, which has, initially, not been improved by the 2014-reform, might be explainable by pointing to the weak responsiveness of FISM spending to local needs, potentially hindered by the barriers listed in Table 8. However, WS's analysis seems to be a rather weak support for this explanation of the results found above for at least three reasons:

Firstly, quite some time has passed since the period analysed by WS, making an analysis based on more current data interesting. Especially, the 2014-reform has since then set out to improve the incentives for municipalities to spend FISM resources in a way that aligns with the goals of the fund, thus potentially also improving the needs-responsiveness of FISM spending. Thus, it will be insightful to see if WS's results also hold up when using data from the post-reform period. Secondly, WS only analyse three out of the eight infrastructure services covered by the FAIS, raising the question if the results might differ for the other infrastructure services.

Thirdly, WS's study uses a rather limited model, relating infrastructure coverage rates and FISM expenditure shares while only controlling for municipal income and other coverage rates.

However, authors such as Moreno-Jaimes (2011) make a case for other variables to be included in a model that is used for analysing the needs-responsiveness of FISM spending. These additional variables thus warrant consideration as potential additional controls.

Based on these three factors that prevent a direct usage of WS's results for explaining the above findings relating to the effectiveness of FISM spending and the 2014-reform, the following subsections will develop a new model building on (W). This model will not only be estimated using post-reform data and for more infrastructure services than those covered by WS, but also include a richer set of controls. These controls will be introduced in the next subsection, drawing on the second paper on the needs-responsiveness of FISM spending by Moreno-Jaimes (2011).

7.2.2. Moreno-Jaimes (2011)

Next to WS, Moreno-Jaimes' (2011) paper also aimed at analysing the needs-responsiveness of FISM spending. However, due to a lack of detailed FISM data, the author uses general public infrastructure expenditure data, making the analysis less tailored to the present research needs than the one by WS. Still, Moreno-Jaimes makes use of a range of controls useful for assessing the needs-responsiveness of FISM spending building on model (W) sketched above.

Firstly, the rate of population concentration is included to capture differences in marginal costs of closing infrastructure access gaps, which is likely to affect both public infrastructure investment decisions and coverage rates. That is, Moreno-Jaimes argues, it is reasonable to assume that municipalities with a higher population concentration face lower marginal costs when it comes to providing infrastructure services due to economies of scale. This holds especially when it comes to network infrastructure such as electricity (Kamiya et al. 2022). Connecting remote and sparsely populated areas to key infrastructure services, on the other hand, is associated with lower marginal costs (see also Arends 2020; Cleary 2007 and Diaz Cayeros et al. 2016).

Secondly, Moreno-Jaimes includes the rate of population growth to account for growing pressures on municipal infrastructure assets that might affect public infrastructure investment decisions while similarly being correlated with coverage rates. Finally, the author includes state dummies to account for unobservable factors that might affect public investment decisions.

7.3. Final Specification

Building on (W) and by including the controls discussed in the previous subsection, the following model emerges, which will be used in the following to generate empirical evidence on the responsiveness of FAIS spending for the post-reform period:

(III) $\text{Log}\mathit{FISM}_{\text{imt+x}} = ß_0 + ß_1 \text{ Log}\mathit{Gap}_{\text{imt}} + ß_2\text{Log}\mathit{FISC}_{\text{mt}} + ß_3\text{Log}\mathit{PopulationGrowth}_{\text{m(t-5)-t}} + ß_4\ \mathit{PopulationConcentration}_{\text{mt}} + ß_{5\text{-I}} \text{ Log}\mathit{OtherGaps}_{\text{-imt}} + \gamma_s + \varepsilon_{\text{mt}}$

In line with (W), logged municipal FISM expenditure shares are used as the dependent variable. However, to be able to generate evidence regarding the needs-responsiveness of FISM spending for the post-reform period using (III), t = 2015 and t = 2020 are chosen as the baseline years instead of t = 2000. To account for the fact that needs-responsive FISM allocation decisions should react to past observed infrastructure needs, several specifications are run using FISM expenditure shares at the time t+x.

Using FISM allocation data from t+x instead of t is also useful for preventing potential reverse causation. That is, while FISM allocation decisions should, in a needs-based setting, be at least partially caused by infrastructure needs, infrastructure coverage rates are also plausibly caused by FISM allocation decisions. However, this problem can be circumvented by using FISM expenditure shares from t+x: While policy-makers likely need some time to adjust their FISM allocation decisions to observed infrastructure needs, allocation decisions at time t+x will not cause infrastructure coverage rates at time t[16]. In this case, FISM expenditure data from 2016, 2017, 2018, and 2021 and coverage rates from 2015 and 2020 are used to this end.

The very detailed FISM expenditure data required to measure the dependent variable, which also has to include information on how municipalities allocated their assigned FISM resources across the FISM infrastructure categories is available from Bienestar, the responsible government agency for the FAIS, for 2014-2021[17]. Since this data covers all of the infrastructure services on which municipalities can spend their FISM resources, the infrastructure services analysed by WS (i.e. drinking water, sanitation, and electricity) are expanded to also include housing, health, and education.

[16] Still, for being fully able to account for potential reverse causality problems arising in this set up, an instrumental variable approach would be preferable, as discussed in section 8.2..

[17] The precise definitions of the FISM infrastructure categories changed slightly over time, with the most detailed aggregation available in 2020/2021. For comparability, all earlier FISM data was recoded according to the infrastructure category definitions of 2020/2021.

Turning to the right-hand side of the equation, a slight difference compared to (W) is that access gap measures instead of coverage rates are used for the target regressor as well as for controlling for the coverage rates in the other infrastructure sectors analysed. This is done to facilitate the interpretation of the results in the context of the discussion of needs-responsiveness, where "needs" are more naturally interpreted in terms of access gaps than coverage rates. However, the basic idea behind the model remains the same.

The data for measuring the variables *Gap* (the logged share of the population of municipality m without access to infrastructure service *i* in 2015/2020) and *Other Gaps* (the logged share of the population without access to the infrastructure services analysed other than *i* in 2015/2020) are taken from the Mexican Census data available from INEGI. Table 9 below offers an overview of the access gap measures employed for the infrastructure services covered by the present analysis[18].

Infrastructure Service Covered	Access Gap Measure
Drinking Water	Share of households without access to drinking water
Electricity	Share of households without access to electricity
Sanitation	Share of households without access to sanitation
Housing	Share of dwellings with a dirt floor
Health	Share of the population without access to health services
Education	Share of the population aged 15 or older who has not completed primary school

Table 9: Overview Access Gap Measures

Finally, data on the logged municipal income in 2015 and 2020 (*FISC*) is, again, taken from INEGI's State and Municipal Public Finance database. Data for the logged measure of the growth in the municipal population is available from the Census data, just as the data for the density (municipal population/square km) as a measure for the population concentration.

[18] Due to collinearity concerns, one of the two education outcome measures used in model I, II and IIA had to be chosen. However, as section 8.6.2. shows, the results are robust to the choice of either education measure.

7.4. Diagnostic Tests

Several tests were run to see if the assumptions behind a linear regression model hold up in the case of (III)[19], thereby ensuring the interpretability of the results presented in the next subsection.

To this end, firstly, the relationship between the predictors and the outcome variables was examined, which should be linear. When plotting the standardized residuals against the respective predictor variables, as shown in appendix A.6. (Figures A.6.i. – A.6.vii.), the residuals appear to be randomly scattered around the zero line, with no obvious non-random pattern emerging. This indicates that there is no noteworthy violation of the linearity assumption in the case of (III).[20]

Secondly, we turn to the homoscedasticity assumption, which assumes a constant variance for the error term conditional on the explanatory variables (Wooldridge 2013). This assumption can be tested using the Breusch-Pegan test (Wooldridge 2013). When doing so, the results, presented in appendix A.6. (Figures A.6.viii – A.6.xiv) indicate that the null-hypothesis of the test, i.e. constant variance, has to be rejected for all specifications. To accommodate this, robust standard errors are used for obtaining the results presented in the next subsection.

Thirdly, the variance inflation factor (VIF) is calculated for all specifications to detect potential issues of collinearity, which might entail problems such as large standard errors (Wooldridge 2013). As the results in appendix A.6. (Tables A.6.i. – A.6.vi.) show, none of the VIFs for the key predictor variables is near the commonly set threshold of 10. This indicates that collinearity issues are not likely to impede upon the interpretability of the results for the target regressors.

In sum, it seems that (III), when using robust standard errors, is likely to provide us with reliable insights regarding the needs-responsiveness of FISM allocations during the post-reform period, which we shall turn to now.

[19] The assumption of normality of residuals, which is important for valid hypothesis testing, is not tested here, as the sample size of N > 1000 is likely to be large enough to ensure that the residuals, qua Central Limit Theorem, are approximately normally distributed.

[20] However, the residual plots reveal that, in some cases, outliers might pose a problem to the interpretability of the results. This is addressed in the sensitivity analysis, where a robust regression is run to ensure that the results are not driven by outliers.

7.5. Estimation Results

The results from estimating (III) for the outcome variables summarized in Table 9 are reported in Tables 10-15 below:

	(1) Share FISM spent on Drinking Water	(2) Share FISM spent on Drinking Water	(3) Share FISM spent on Drinking Water	(4) Share FISM spent on Drinking Water
No Access Drinking Water	**.0387***	.0062	-.0022	-.0182
	(.0231)	(.0196)	(.0196)	(.029)
Municipal Income	.0518	.2217***	.1184*	.2104***
	(.0884)	(.0668)	(.0659)	(.08)
Density	.4253**	.1488*	.0053	-.2498*
	(.1862)	(.0827)	(.142)	(.1494)
Population Growth Rate	.0031	.0111	.0058	.012
	(.0085)	(.0074)	(.0067)	(.0086)
No Access Sanitation	.0003	.0325	.0308	.092**
	(.0235)	(.0204)	(.0227)	(.0408)
No Access Electricity	-.0295	-.0438	-.0289	.0232
	(.0337)	(.0273)	(.0255)	(.045)
Dirt Floor	-.0325	.0059	.0257	-.1697***
	(.0256)	(.0227)	(.0222)	(.0505)
No Access Health Care	-.0094	-.0341	-.0592	-.0244
	(.0585)	(.053)	(.0536)	(.0678)
Primary Education not Completed	-.0813	-.1457**	-.0087	-2.52***
	(.0962)	(.0589)	(.0655)	(.7709)
State Dummies	YES	YES	YES	YES
Constant	-2.835***	-4.2308***	-3.1936***	-4.6233***
	(.9452)	(.6578)	(.6936)	(.7669)
Observations	1513	1664	1558	1474
R-squared	.0702	.1356	.1558	.205

Robust standard errors are in parentheses
*** $p<.01$, ** $p<.05$, * $p<.1$

Table 10: Main Results Model III Drinking Water

Notes: All dependent variables refer to the logged share of the municipal FISM resources allocated to the infrastructure service in question. All target regressors and the remaining access gap measures refer to logged per capita shares. Municipal Income refers to the logged municipal income per capita in 2015 (2020 for the rightmost column). Density refers to the population per km2 of municipal land in 2015 (2020 for the rightmost column). Growth Rate refers to the logged population growth rate between 2010 and 2015 (2015 to 2020 for the rightmost column).

	(1) Share FISM spent on Drainage and Latrines	(2) Share FISM spent on Drainage and Latrines	(3) Share FISM spent on Drainage and Latrines	(4) Share FISM spent on Drainage and Latrines
No Access Sanitation	0	-.0088	.01	**-.1895*** **
	(.0278)	(.0255)	(.025)	(.0452)
Municipal Income	-.0109	-.1607*	-.1927***	.218**
	(.0787)	(.0839)	(.0743)	(.0917)
Density	-.3652	.0412	.3751	-.0011
	(.2876)	(.2389)	(.2491)	(.0887)
Population Growth Rate	.0008	.0072	-.0171**	.0088
	(.0058)	(.0086)	(.0074)	(.0088)
No Access Drinking Water	-.0323	-.0566**	-.0936***	-.0757**
	(.0244)	(.0242)	(.0216)	(.033)
No Access Electricity	-.0321	-.0284	-.0216	-.1365**
	(.0335)	(.0357)	(.0306)	(.0551)
Dirt Floor	-.0388	-.0553*	-.0429	.0267
	(.0306)	(.0306)	(.027)	(.0555)
No Access Health Care	.1308*	.1626**	.2016***	-.0209
	(.0692)	(.0656)	(.0634)	(.0762)
Primary Education not Completed	-.3722***	-.3578***	-.3703***	-.2002
	(.0912)	(.0846)	(.0749)	(1)
State Dummies	YES	YES	YES	YES
Constant	-2.8026***	-1.916**	-1.6437*	-7.677***
	(.9336)	(.8982)	(.8717)	(.9947)
Observations	1422	1467	1430	1203
R-squared	.1382	.184	.1858	.1642

Robust standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table 11: Main Results Model III Sanitation

Notes: All dependent variables refer to the logged share of the municipal FISM resources allocated to the infrastructure service in question. All target regressors and the remaining access gap measures refer to logged per capita shares. Municipal Income refers to the logged municipal income per capita in 2015 (2020 for the rightmost column). Density refers to the population per km2 of municipal land in 2015 (2020 for the rightmost column). Growth Rate refers to the logged population growth rate between 2010 and 2015 (2015 to 2020 for the rightmost column).

	(1) Share FISM spent on Electricity	(2) Share FISM spent on Electricity	(3) Share FISM spent on Electricity	(4) Share FISM spent on Electricity
No Access Electricity	.0153	.014	-.0406	**.1693*** **
	(.0304)	(.0317)	(.0325)	(.0592)
Municipal Income	.232***	.3231***	.3047***	.3322***
	(.0838)	(.082)	(.0771)	(.0921)
Density	.3686	.1751	.1281	.0145
	(.2323)	(.1329)	(.0854)	(.2676)
Population Growth Rate	.0034	.0019	.0103	-.0219
	(.0081)	(.012)	(.0091)	(.0142)
No Access Drinking Water	-.0546**	-.0507**	.009	-.0851**
	(.0241)	(.0245)	(.0231)	(.0366)
No Access Sanitation	.0593**	.0699***	.0253	.0125
	(.0271)	(.0264)	(.0269)	(.0496)
Dirt Floor	.0074	-.018	.0111	-.2932***
	(.0259)	(.0247)	(.026)	(.0612)
No Access Health Care	.0677	.0442	.0101	.0478
	(.0706)	(.0705)	(.0647)	(.0795)
Primary Education not Completed	-.2118***	-.287***	-.0658	-1.9032**
	(.0787)	(.0795)	(.0827)	(.8987)
State Dummies	YES	YES	YES	YES
Constant	-4.0249***	-5.1423***	-5.1145***	-5.7602***
	(.904)	(.8534)	(.8298)	(.8786)
Observations	1275	1334	1353	1124
R-squared	.1858	.1962	.1688	.2665

Robust standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table 12: Main Results Model III Electricity

Notes: All dependent variables refer to the logged share of the municipal FISM resources allocated to the infrastructure service in question. All target regressors and the remaining access gap measures refer to logged per capita shares. Municipal Income refers to the logged municipal income per capita in 2015 (2020 for the rightmost column). Density refers to the population per km2 of municipal land in 2015 (2020 for the rightmost column). Growth Rate refers to the logged population growth rate between 2010 and 2015 (2015 to 2020 for the rightmost column).

	(1) Share FISM spent on Housing	(2) Share FISM spent on Housing	(3) Share FISM spent on Housing	(4) Share FISM spent on Housing
Dirt Floor	.0017	-.022	.0171	**-.1144***
	(.0338)	(.0299)	(.0297)	(.0593)
Municipal Income	.7403***	.581***	.5491***	.7262***
	(.1674)	(.0832)	(.075)	(.0931)
Density	.2055	.2957	.2409	-.1917**
	(.2043)	(.1868)	(.1933)	(.0815)
Population Growth Rate	.0183	.0283***	.0141**	.0184
	(.0117)	(.0072)	(.0059)	(.012)
No Access Drinking Water	-.0037	-.0007	-.0378	-.1405***
	(.0294)	(.0255)	(.0243)	(.0391)
No Access Sanitation	.0184	.0081	-.0096	.153***
	(.0263)	(.0274)	(.0245)	(.0567)
No Access Electricity	-.062*	-.0401	-.0038	.069
	(.0352)	(.0329)	(.0343)	(.0635)
No Access Health Care	-.2181***	-.1861**	-.2137***	-.3171***
	(.0742)	(.0768)	(.0614)	(.0807)
Primary Education not Completed	-.1301	-.1344	-.0715	-2.2989**
	(.1023)	(.1002)	(.088)	(1.0975)
State Dummies	YES	YES	YES	YES
Constant	-8.3379***	-7.848***	-7.78***	-9.6425***
	(1.5948)	(.8425)	(.9119)	(.8764)
Observations	1185	1150	1118	941
R-squared	.2471	.2432	.2715	.3259

Robust standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table 13: Main Results Model III Housing

Notes: All dependent variables refer to the logged share of the municipal FISM resources allocated to the infrastructure service in question. All target regressors and the remaining access gap measures refer to logged per capita shares. Municipal Income refers to the logged municipal income per capita in 2015 (2020 for the rightmost column). Density refers to the population per km2 of municipal land in 2015 (2020 for the rightmost column). Growth Rate refers to the logged population growth rate between 2010 and 2015 (2015 to 2020 for the rightmost column).

	(1) Share FISM spent on Health	(2) Share FISM spent on Health	(3) Share FISM spent on Health	(4) Share FISM spent on Health
No Access to Health Care	.2491	.1129	-.1917	.1478
	(.2088)	(.1286)	(.121)	(.2149)
Municipal Income	.3897**	.4229**	.6397***	.6625**
	(.1791)	(.1707)	(.1745)	(.3348)
Density	1.5741***	1.1531***	.2718	1.1636
	(.4039)	(.4196)	(.8702)	(.8887)
Population Growth Rate	-.0044	.0064	.0265	-.0019
	(.0103)	(.0166)	(.0169)	(.0253)
No Access Drinking Water	-.0215	-.1001**	-.1016**	-.0324
	(.0434)	(.0418)	(.0466)	(.0976)
No Access Sanitation	-.0312	-.0597	.0183	-.0437
	(.0543)	(.0575)	(.0515)	(.1193)
No Access Electricity	-.0934	-.0394	-.074	-.0471
	(.0652)	(.0662)	(.0764)	(.1301)
Dirt Floor	-.0679	-.0469	-.0623	-.2685
	(.0568)	(.0519)	(.0561)	(.1722)
Primary Education not Completed	-.1371	-.347**	-.2464*	.3535
	(.1816)	(.167)	(.1417)	(2.0786)
State Dummies	YES	YES	YES	YES
Constant	-10.4213***	-9.8637***	-10.1961***	-11.2131***
	(1.7184)	(1.546)	(1.7045)	(2.739)
Observations	539	542	473	219
R-squared	.2297	.2575	.2653	.346

Robust standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table 14: Main Results Model III Health

Notes: All dependent variables refer to the logged share of the municipal FISM resources allocated to the infrastructure service in question. All target regressors and the remaining access gap measures refer to logged per capita shares. Municipal Income refers to the logged municipal income per capita in 2015 (2020 for the rightmost column). Density refers to the population per km2 of municipal land in 2015 (2020 for the rightmost column). Growth Rate refers to the logged population growth rate between 2010 and 2015 (2015 to 2020 for the rightmost column).

	(1) Share FISM spent on Education	(2) Share FISM spent on Education	(3) Share FISM spent on Education	(4) Share FISM spent on Education
Primary Education not Completed	-.1119	**-.1354***	**-.1579****	**-2.3747****
	(.102)	(.0711)	(.0701)	(.9826)
Municipal Income	.258**	-.0211	.1365	.5517***
	(.1102)	(.0929)	(.0882)	(.1245)
Density	.6033**	.5787*	-.4757**	.1456
	(.2803)	(.3016)	(.235)	(.55)
Population Growth Rate	.0191***	.0167**	.0026	.0036
	(.007)	(.008)	(.007)	(.009)
No Access Drinking Water	-.0258	-.0069	.0176	-.0905**
	(.0242)	(.0225)	(.0216)	(.0421)
No Access Sanitation	-.0361	.0142	-.0101	-.0674
	(.0252)	(.0227)	(.023)	(.0547)
No Access Electricity	-.0978	-.032	-.066**	-.131**
	(.0734)	(.0321)	(.0329)	(.0609)
Dirt Floor	.0158	-.0167	-.0296	.0206
	(.0407)	(.0282)	(.0282)	(.0723)
No Access Health Care	-.0301	-.0738	.0173	-.0952
	(.0677)	(.06)	(.0595)	(.0839)
State Dummies	YES	YES	YES	YES
Constant	-5.9027***	-2.8957***	-4.1588***	-9.9393***
	(1.1576)	(.865)	(.8709)	(1.1786)
Observations	1231	1244	1235	859
R-squared	.1632	.1567	.1634	.2287

Robust standard errors are in parentheses
*** p<.01, ** p<.05, * p<.1*

Table 15: Main Results Model III Education

Notes: All dependent variables refer to the logged share of the municipal FISM resources allocated to the infrastructure service in question. All target regressors and the remaining access gap measures refer to logged per capita shares. Municipal Income refers to the logged municipal income per capita in 2015 (2020 for the rightmost column). Density refers to the population per km2 of municipal land in 2015 (2020 for the rightmost column). Growth Rate refers to the logged population growth rate between 2010 and 2015 (2015 to 2020 for the rightmost column).

Given WS' results outlined above, one would not necessarily expect positive, significant coefficients for the target regressors that would point to a needs-responsive character of FISM allocation decisions. However, as discussed above, the 2014-reform as well as the inclusion of additional infrastructure services and control variables make it less clear if we can expect a result in line with WS when running (III).

Still, as can be seen in Tables 10-15 above, the results regarding the needs-responsiveness of FISM resource allocations for drinking water, sanitation, electricity, housing, health, and education confirm WS's conclusion that associations between FISM spending and local needs are weak, at best. That is, in most cases, no significant relationship between infrastructure access gaps and FISM allocation decisions can be derived from the results.

Exceptions to this missing relationship are found for one year in the cases of drinking water, sanitation, electricity, and housing and across three years in the case of education. However, most of these results indicate that FISM resources allocated to a given infrastructure service decrease, on average, if the respective infrastructure access gap increases. For instance, in the case of sanitation, a 10% increase in the share of households without access to sanitation is associated with a 1.9% average decrease in the share of FISM resources allocated to drainage and latrines one year later. The two notable exceptions are drinking water and electricity, where a positive relationship between access gaps and FISM expenditure shares is found for one year, thereby confirming WS's findings in this regard.

Education is the only outcome variable for which a persistent significant relationship between infrastructure access gaps and FISM allocation decisions is found. However, this relationship is, again, negative, indicating that a 1% increase in the share of the population without a completed basic education is associated with up to a 2.4% average decrease in FISM resources allocated to education.

In this specific case, however, this strong negative relationship could be explainable by the fact that education expenses are also covered explicitly by two other funds in Ramo 33 that, together, account for more than 52% of the resources of Ramo 33, as shown in Figure 1. As WS also hypothesize, this arrangement might imply that municipalities receive sufficient resources from other funds to satisfy their infrastructure needs regarding education. This, in turn, could lead them to spend more FISM resources on infrastructure services not covered by other funds, despite increasing education needs (Wellenstein et al. 2006).

Still, even if overlaps in fund intentions might be able to explain some of the results in Tables 10 – 15, the overall lacking, weak, or even negative association between infrastructure needs and FISM expenditure shares indicates a limited needs-responsiveness of FISM expenditures. This is especially striking since the results do not only confirm those of the pre-reform analysis conducted by WS but even seem to point to a lower responsiveness of FISM investments to local needs for the post-reform period.

These findings seem to provide grounds for hypothesizing about a potential mechanism behind the findings associated with the first and the second contribution of this thesis. There, we have seen that FISM spending has not been effective in alleviating extreme poverty and inequality in the period of 2005-2020 even though the 2014 reform has shown some emerging promise in this regard. With the results from above in mind, one potential explanation for this finding would indeed be a limited responsiveness of FISM spending to local infrastructure needs. That is, while municipalities are able to improve infrastructure access through FISM spending, them not spending their FISM resources where they are needed the most, as indicated by the results in Tables 10-15, would explain why FISM spending has not been associated with improvements regarding poverty and inequality.

Based on this explanation, policy measures aimed at increasing the needs-responsiveness of FISM spending would be a promising way for improving the effectiveness of FISM spending. Before turning to discuss potential policy measures in this regard, the next subsection discusses whether the findings in Tables 10-15 offer a good basis for such policy recommendations by showing their robustness to several sensitivity checks.

7.6. Sensitivity Analysis

This subsection discusses the sensitivity of the findings just discussed to (a) different measures of the dependent variable (b) different measures of the education target regressor and (c) outliers.

7.6.1. Robustness to Different Measures of the Dependent Variable

7.6.1.1. FISM Spending Excluding Urbanization

The analysis of the needs-responsiveness of FISM spending presented in this section focuses on FISM spending on drinking water, sanitation, electricity, housing, health, and education. However, as can be seen in Figure 2, only around 40% of all FISM resources were allocated to these infrastructure categories in 2021, while around 60% was used for the construction and maintenance of roads under the urbanization category. This omission of the largest FISM expenditure item, which is due to the unavailability of road accessibility data at the municipal level, might pose a problem for the present analysis. That is, municipalities might use FISM resources to react to access gaps in urbanization, which is likely to involve high investment costs, thus leaving less room to respond to gaps in other infrastructure sectors.

To see whether these concerns impact the results of the present analysis, model (III) is re-run focusing only on the FISM resources allocated to the infrastructure services analysed. That is, instead of using, for instance, the FISM resources spent on health as a share of the total FISM resources, the FISM resources spent on health as a share of the FISM resources spent on drinking water, sanitation, electricity, housing, health, and education is used. Thereby, the analysis captures whether FISM resources, within the categories in the focus of this study, are allocated based on infrastructure needs. Thereby, potential distortions due to the large share of FISM resources spent on urbanization can be avoided.

When looking at the results of this sensitivity check in appendix A.7. (Tables A.7.i. – A.7.vi.), it emerges that the results in Tables 10-15 are robust to this different measure of the dependent variable: Effect sizes and directions as well as significance levels are comparable to those found in the main analysis, with minor differences. Most interestingly, the negative effect in the case of the education specification is only found for one instead of three years, while the positive effect in the case of drinking water turns insignificant. However, results regarding other significant effects like the ones found in the cases of electricity, sanitation, and housing are retained.

7.6.1.2. Drainage and Sanitation Spending Coded Separately

As discussed in footnote 17, the detailed FISM expenditure data used in this analysis is, for comparability purposes, coded according to the definitions of the 2020/2021 infrastructure categories. And while these categories are more fine-grained than those in previous years, the spending on drainage and sanitation services is still defined as one expenditure category ("Drainage and Latrines"). This leads to the fact that model (III) could only be used to illuminate the needs-responsiveness for one of the two infrastructure services, in this case, sanitation.

However, doing so might yield misleading results if municipalities were to use the FISM resources that they allocate to the Drainage and Latrines category mainly to respond to drainage access gaps, not sanitation access gaps. This possibility is especially salient in light of the different coverage rates of the two infrastructure services, with 20% of the population lacking access to the drainage network in 2015, but only 6% to sanitation (see Table 1).

To see whether this influences the results, the expenditure item "Drainage and Latrines" is recoded into two separate categories, covering drainage and sanitation, respectively. This is possible by coding FISM expenditure in this category according to the expenditure subcategories also available from the Bienestar data. These subcategories give insights into whether spending is more closely associated with drainage or sanitation services. A detailed list of the subcategories of the Drainage and Latrines expenditure items and how they were sorted into a category for drainage and one for sanitation can be found in appendix A.7 (Table A.7.vii.).

As the results in appendix A.7. (Tables A.7.viii. – A.7.xiv.) show, the results for drainage and sanitation are largely robust to this modification, with the effects found in Tables 10-15 for the cases of electricity, housing, and education emerging again. However, the negative effect on sanitation found before in case of 2021 disappears, while a negative effect appears for the case of drainage for 2016. This speaks against the possibility that municipalities mainly focus on closing drainage access gaps based on the FISM resources that they choose to assign to the Drainage and Latrines category.

7.6.2. Robustness to Different Measures for the Education Target Regressor

In the first part of this analysis, where the effectiveness of FISM spending was analysed, two outcome measures relating to FISM spending on education were employed; the share of the population 15 years or older without a finished primary education and the illiteracy rate. However, since model (III) controls for infrastructure access gaps in other sectors, one of the two had to be chosen to prevent multi-collinearity issues. To see whether this choice might have influenced the results in Table 15, which are the only ones in which a persistent negative association between FISM spending and needs can be observed over a period of time, model (III) is re-run using the illiteracy rate instead of the primary education variable to measure the education infrastructure access gap.

The results of this exercise, which can be found in appendix A.7. (Tables A.7.xv. – A.7.xx), show that the results from Tables 10-15 are largely robust to using a different measure for the education access gap. The main difference is that the negative significant effect now only surfaces for one instead of three years, albeit with a similar magnitude as before. This indicates that the most remarkable result in Tables 10-15 did, to some extent, depend on the choice of the access gap measure and is not as strong when using an alternative measure. However, the main results for the other infrastructure services remain stable, the only exception being a negative effect of the health access gaps on FISM spending on health surfacing for 2018.

7.6.3. Robustness to Outliers

In section 7.4., residual plots were used to assess whether the linearity assumption behind regression model (III) holds up. While this was the case, the residual plots also revealed a few outliers in the data. That this might be an issue for the present analysis is also confirmed when looking at the leverage residual plots reported in appendix A.7. (Figures A.7.i. – A.7.vi.), which confirm the presence of data points that either have large residuals or high leverage. However, these plots also show that the observations with either high leverage or large residuals differ between infrastructure services, i.e. it is not the case that the same municipalities pose a problem across all specifications. Therefore, there is no indication of data entry errors or similar issues which would give reasons to exclude municipalities from the sample.

To still get a sense of the extent to which these outliers or leverage points might influence the results shown in Table 10-15, a robust form of model (III) is run, in which less well-behaved data points get less weight in the regression[21]. The results of the robust regression can be found in appendix A.7. (Tables A.7.xxi – A.7.xxvi). As becomes evident, the results do not differ heavily from those in Table 10-15: Negative effects in the case of education and sanitation persist, as does the positive effect in the case of electricity found for 2021. One remarkable difference arises in the case of health, where a positive effect is found for 2016. However, since the coefficient had already been positive, though not significant when looking at the original results, this change might also be driven by the different standard errors used in the robust regression (see footnote 21).

In sum, we have seen that the weak and often even negative relationship between infrastructure access gaps and FISM expenditure shares largely persists when using different measures for the dependent variables, a different measure for the education target regressor, and giving less weight to outliers. This increases the confidence in the results presented in Tables 10-15 and thus in the hypothesis formulated above. That is, lacking responsiveness of FISM spending to local infrastructure needs is a key driver behind the limited effectiveness of FISM spending when it comes to reducing extreme poverty and inequality, even in the short term after the 2014-reform.

Before formulating policy measures that appear to be promising when it comes to fostering more needs-responsive and thus more effective FISM spending, some limitations of the analyses discussed so far are outlined in the following section.

8. Limitations and Avenues for Future Research

Three major limitations must be borne in mind when discussing the results in this thesis and deriving policy recommendations from it: (1) Potential flaws in the 2020 Census data, (2) causal identification problems, and (3) limited informativeness regarding effects on the poor.

8.1. Limitation One: The 2020 Census Data

The usage of the 2020 Census data in the evaluation of the effectiveness of FISM spending in the first part of the present analysis underpinned the first contribution of this thesis. In addition, it allowed us to generate tentative evidence regarding the effects of the 2014-reform and to assess the needs-responsiveness of FISM spending for the post-reform period.

However, as already touched upon in footnote six, the quality of the 2020 Census data is far from undisputed. Firstly, this is because there was a major change in the methods used to collect

[21] In Stata, this can be done using the command "rreg" (see UCLA 2021). Unfortunately, this command is not compatible with the usage of robust standard errors, which were used for generating the results in Tables 10-15.

the data for the 2020 Census compared to previous years. Most importantly, this involved the usage of a Computer-Assisted Personal Interviewing system as the main enumeration method (Vielma Orozco et al. 2020). Although offering advantages over paper-based methods in many regards, this change in methods was, already in the run-up to the 2020 data collection, argued to pose significant challenges for INEGI. These risks were argued to arise mainly from staff needs and risks of technical failures (INEGI 2020a).

Secondly, the data collection for the 2020 Census was heavily impacted by the Covid-19 pandemic (Avila-Vera et al. 2020): Data was collected between March 2nd and March 27th 2020, thus exactly when the Covid-19 pandemic hit worldwide. Just as in other countries, Covid-19 related challenges in the collection of Census data are likely to have led to issues with data reliability such as undercounting of vulnerable and hard-to-reach groups (US Census Bureau 2022). This even led some authors to argue that the Mexican 2020 Census has been conducted in an incomplete fashion (Avila-Vera et al. 2020).

Both methodological changes and Covid-19-associated challenges might impede upon the quality of the 2020 Census data, potentially up to a point where the validity of the present results, which heavily rely on this data, would be questionable. To see whether this might be the case, future research could work towards assessing the quality of the data collected in the 2020 Census. This could be done through, for instance, data simulations to gauge the extend of a potential undercounting problem. Doing so will be highly important for ensuring the usability of this rich data set for a wide range of interesting research questions surrounding Mexico.

8.2. Limitation Two: Causal Identification

In the evaluation of policies, a typical challenge arises when it comes to the identification of the causal effects of policies on a given outcome: That is, we can only observe the outcome for each individual (or, say, municipality) in either the case where it is exposed to the policy of interest or the case in which it is not. This necessitates the comparison of distinct individuals when trying to identify causal effects, which are likely to, however, also differ regarding other characteristics than only the exposure to the policy (Imbens and Wooldridge 2009).

The same problem surfaces in the present analysis, especially since commonly used techniques for identifying causal effects despite the just sketched “identification problem” are not applicable in the context of the FAIS. For instance, it is not possible to randomly allocate FAIS resources across municipalities to evaluate the effectiveness of FAIS spending. Similarly, it is not the case that parts of Mexico have not introduced the 2014-FAIS reform, thus lending themselves to forming the comparison group in a difference-in-difference set up. This makes it likely that endogeneity concerns plague the results of the present analysis.

While techniques such as the fixed-effects method introduced above or the addition of a second set of controls in the construction of model (III) can deal with these endogeneity concerns to some extent, worries remain. For instance, private infrastructure investment might also drive the outcome measures analysed in the evaluation of FISM effectiveness but are likely to differ both across municipalities and across time. Further, the 2014-FAIS reform might have coincided with other changes over time, such as the increasing popularity of private-public partnerships at the local level, which might drive outcomes simultaneously to the 2014-reform. Finally, potential worries relating to the reverse causality issue plaguing an analysis of the needs-responsiveness of FISM spending might not completely be alleviated by the usage of lags in the presence of path dependences (cf. Moreno-Jaimes 2011).

To alleviate these potential concerns even in the face of restrictions relating to the usage of common identification strategies, future research could, for instance, focus on the development of suitable instrumental variables to further improve insights on important questions such as the needs-responsiveness of FISM spending.

8.3. Limitation Three: What can we Really Say about the Poor?

One of the characteristics of the FAIS that makes it unique among the funds subsumed under Ramo 33 is its explicit targeting of the extremely poor and marginalized in Mexico. That is, FAIS resources should be employed by subnational governments to construct social infrastructure with the goal of benefitting these groups. Therefore, it would only be natural for an evaluation of FAIS effectiveness and needs-responsiveness to focus on these groups instead of looking at the whole population.

However, the analyses presented above are performed at the municipality level, thus not making any claims specific to the target group of the FAIS when it comes to the effectiveness and needs-responsiveness of the FAIS. For instance, the analysis presented above reveals that FISM spending has had positive, though moderate effects on social infrastructure access rates at the municipal level. However, this result might trigger less positive associations if it was driven by increases in access of more advantaged parts of the municipal population.

Future research could generate more detailed insights in this regard by making use of more fine-grained data. For instance, the Mexican Census data is also available at the block level, thereby forming the basis for inquiries into the effectiveness and needs-responsiveness of FISM spending at a much lower level.[22] To this end, methods such as subgroup analyses or quantile regressions might be useful to gauge the extent to which, for instance, improvements in infrastructure access in the more disadvantaged parts of the municipalities drive the positive results on FISM effectiveness in this regard.

9. Policy Recommendations

The analysis presented above, albeit faced with the limitations just outlined, points to the conclusion that increasing the needs-responsiveness of FISM spending is key in aligning the fund with its goals, i.e. alleviating extreme poverty and thus inequality. To structure the discussion around policy measures that would be suitable for achieving this, it is helpful to think back to the barriers to needs-responsive decentralized public spending discussed in section 7.1.2. and summarized in Table 8. There, we have seen that, firstly, a lack of human, institutional and financial resources as well as, secondly, a lack of effective citizen participation and possibilities for interest capture at the local level might prevent needs-responsive decentralized public spending. A third set of barriers to needs-responsive spending is posed by limited accountability to both beneficiaries and higher-level governments.

And indeed, these factors also seem to play a role in the Mexican context. For example, WS explain their findings, which also point to a weak responsiveness of FISM expenditure decisions to local needs as follows: Firstly, they mention "[…] technical, budgetary […] and institutional issues" and secondly, they hypothesize that "limited accountability to beneficiaries or the federal government to motivate efficient spending" might play a role (Wellenstein et al. 2006, p. 206). Thereby, the authors indicate that two of the three barriers summarized in Table 8 might be at play in the Mexican context.

How could these two barriers to needs-responsive decentralized public spending be addressed by public policy? As WS suggest, *systematic evaluations and monitoring* can play a crucial role in this regard. Thereby, reliable information on the usage of FISM resources and the resulting improvements would be provided to both higher-level governments and citizens. Such information is likely to prove useful in improving both upward and downward accountability (Wellenstein et al. 2006).

However, such an approach would have to be accompanied by measures targeting the lack of institutional, financial, and human resources. This lack of resources already poses barriers to

[22] However, other data used in the present analysis such as the poverty and inequality data from CONEVAL is only available at the municipality level. This is why this level of analysis was chosen for the present analysis, in line with previous studies.

needs-responsive spending, especially for poor municipalities, and would probably do so even more in light of increased evaluations and monitoring. One way to do so would be to *increase the share of FISM resources that can be spent on "institutional development"*. Currently, 2% of the annual FISM resources allocated to municipalities can be spent in that manner. A slight increase of this share, coupled with guidance on how to use this money effectively to systematically build institutional and technical capacity at the local level, might prove helpful in tackling barriers in this regard.

When it comes to the barrier relating to financial capacity, another potential policy recommendation is brought up by RC, who, as we have briefly seen above, suggest an interesting modification to the FAIS allocation formula. Instead of allocating more resources to municipalities with a higher share of people living in extreme poverty, the authors suggest allocating FAIS resources partly on the basis of infrastructure investment gaps. As they argue, such a change would also have to be accompanied by formula changes tackling the perverse incentive problem. This could be achieved, for instance, by rewarding municipalities which display effective reductions in local social infrastructure gaps (Rodríguez-Castelán et al. 2020). Coupled with other measures to increase the fiscal capacity of municipalities suggested by the authors, this modification seems promising when it comes to removing financial barriers prohibiting needs-responsive FISM spending.

This suggestion is especially interesting in light of the results of the present analysis. As we have seen, the weak relationship between FISM allocations and local infrastructure needs found by WS also persists after the 2014-reform, where the allocation formula was adapted to improve incentives for municipalities. Since this evidence hints at the claim that this first modification of the allocation formula did not yet have the intended effect, a second modification might be an interesting way to go for public policy.

In addition to the two barriers identified by WS in the quote above, we have also seen that a lack of effective citizen participation and increased possibilities for interest capture might pose barriers to needs-responsive spending of decentralized public resources. And indeed, there seem to be reasons to believe that this is also one of the barriers preventing more needs-responsive decentralized spending in the case of Mexico. This would make measures aimed at increasing effective citizen participation another set of policy measures suitable for increasing the needs-responsiveness of FISM spending.

For instance, in one of the first studies on the FAIS published in 2005, Rocha Menocal presents qualitative evidence pointing to the conclusion that there has been little effective involvement of citizens when it comes to the planning, execution, and monitoring of FISM projects. This is especially striking since such citizen participation in FISM projects is mandated by the Law of Fiscal Coordination. However, it seems that such mandatory citizen participation has been more met with suspicion by the citizens instead of having led to their effective participation (Rocha Menocal 2005).

A second, later study on citizen participation in FISM projects sheds more light on why even the mandatory participation of citizens has not translated into needs-responsive FISM allocation patterns. In this study, Taguenca Belmonte and Lugo Néria (2020) analyse citizen participation in FISM projects in the state of Hidalgo for the years 2002-2009. To this end, they make use of survey data from municipal officials regarding their perception of citizen participation in FISM projects. The authors find that only a small share of municipalities seems to struggle with having no citizen participation at all in their FISM projects. Rather, the problem seems to be that citizens are, for a large part, only involved in the very early stages of FISM projects, such as the presentation of project proposals. However, when it comes to the project stages in which actual decisions on the usage of FISM resources are made, citizen participation is far less frequent (Taguenca Belmonte and Lugo Néria 2020).

These results suggest that while Mexican citizens indeed make use of the increased participatory possibilities at the local level, lacking citizen participation in the decisive stages of FISM projects might explain why FISM resources are not spent in a needs-responsive manner, as shown above. Thus, *ensuring that citizen participation is not only restricted to early stages of FISM projects* would be another way of increasing the needs-responsiveness of FISM allocations. Doing so might also counter suspicions regarding mandatory citizen participation once it becomes clear that citizens are involved in the actual decision making. This would also be a factor that could be addressed in the monitoring and evaluation processes discussed above.

In sum, often-cited barriers to needs-responsive decentralized public spending also seem to play a role in Mexico. Policy measures such as better monitoring and evaluations, further modifications of the FAIS allocation formula, increasing the share of FISM resources that can be spent on institutional development, or ensuring citizen participation at all stages of FISM projects might prove useful in tackling these barriers. Thereby, policy action can work towards increasing the responsiveness of FISM spending to local infrastructure needs and thus, FISM effectiveness.

10. Conclusion

Fiscal decentralization has seen a surge in popularity in countries around the globe over the past years, promising to increase the effectiveness of public spending through, amongst others, increasing the responsiveness of public expenditure to societal wants and needs. However, in the case of the "Fondo de Aportaciones para la Infraestructura Social" (FAIS), one of the large funds set up by Mexico during its fiscal decentralization process in the 1990s, past evaluations have pointed to, if at all, modest effects on target measures such as extreme poverty rates.

Still, a major reform of the FAIS allocation formula in 2014 aiming at removing "perverse incentives" in the past formula gives reason to believe that a re-evaluation of FAIS effectiveness which includes the post-2014 period might yield more promising results. Such an evaluation is, for the first time, presented in this thesis. However, just like previous evaluations, an analysis also based on data from after 2014 reveals positive, but moderate effects of FAIS spending on social infrastructure access, but no or even negative effects on poverty and inequality measures. In addition, when analysing potential changes in the effectiveness of FAIS spending in light of the 2014-reform, it emerges that the reform has not yet been able to reverse this trend, even though it shows promise in the mid- to long term.

In search of a potential mechanism driving these results for being able to ground policy recommendations, it emerges that lacking responsiveness of FAIS spending to local needs might play a central role. And indeed, empirical evidence on the needs-responsiveness of FAIS spending during the post-reform period presented in this thesis confirms that FAIS spending has not been responsive to local infrastructure needs during this period. Hence, the 2014 reform does not seem to have set the right incentives for municipalities to spend their municipal FAIS resources in a way that responds to the most pressing local infrastructure gaps. This mechanism might thus explain the lacking effectiveness of FAIS spending and the limited short-run effect of the 2014-reform when it comes to poverty and inequality alleviation.

To tackle this problem, potential policy interventions should thus focus on fostering an increased needs-responsiveness of FAIS spending. To this end, measures such as increased monitoring and evaluation, coupled with measures to improve the financial and institutional capacity of municipalities might prove to be helpful. However, the results presented in this thesis upon which these policy recommendations are built are subject to several limitations. Still, all of these limitations also provide interesting avenues for future research on the nexus of fiscal decentralization and the effectiveness and needs-responsiveness of public spending for the fascinating case of the FAIS.

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Appendix

Appendix 1 on Descriptive Statistics Outcome Measures Model I

Drinking Water

Year	N	Mean	SD	Min	Max
2005	2454	.775	0.207	0	1
2010	2453	.791	0.197	.04	1
2015	2457	.913	0.213	.003	1
2020	2469	.933	0.093	.081	1

Table A.1.i.: Descriptive Statistics Municipal Share of Population with Access to Drinking Water, by Year (Data Sources: INEGI 2005, 2010, 2015 and 2020b)

Drainage

Year	N	Mean	SD	Min	Max
2005	2454	.656	0.272	0	1
2010	2452	.74	0.240	0	1
2015	2457	.81	0.320	0	1
2020	2469	.858	0.193	.009	1

Table A.1.ii.: Descriptive Statistics Municipal Share of Population with Access to Drainage, by Year (Data Sources: INEGI 2005, 2010, 2015 and 2020b)

Electricity

Year	N	Mean	SD	Min	Max
2005	2454	.922	0.081	.283	1
2010	2456	.945	0.063	.291	1
2015	2457	.975	0.116	.086	1
2020	2469	.977	0.035	.082	1

Table A.1.iii: Descriptive Statistics Municipal Share of Population with Access to Electricity, by Year (Data Sources: INEGI 2005, 2010, 2015 and 2020b)

No Dirt Floor

Year	N	Mean	SD	Min	Max
2005	2454	.739	0.218	.042	.994
2010	2456	.862	0.117	.204	1
2015	2457	.914	0.210	.09	1
2020	2469	.916	0.090	.081	1

Table A.1.iv: Descriptive Statistics Municipal Share of Population with an Adequate Floor (no Dirt Floor), by Year (Data Sources: INEGI 2005, 2010, 2015 and 2020b)

Access Health Care

Year	N	Mean	SD	Min	Max
2005	2454	.299	0.221	0	.961
2010	2456	.613	0.175	.016	.968
2015	2457	.855	0.074	.413	1
2020	2469	.757	0.109	.067	.989

Table A.1.v.: Descriptive Statistics Municipal Share of Population with Access to Health Care, by Year (Data Sources: INEGI 2005, 2010, 2015 and 2020b)

Primary Education Completed

Year	N	Mean	SD	Min	Max
2005	2454	.118	0.041	.004	.242
2010	2456	.136	0.038	.038	.448
2015	2457	.899	0.052	.63	1
2020	2469	.129	0.039	.007	.414

Table A.1.vi.: Descriptive Statistics Municipal Share of Population with a Completed Primary Education, by Year (Data Sources: INEGI 2005, 2010, 2015 and 2020b)

Illiteracy

Year	N	Mean	SD	Min	Max
2005	2454	.106	0.065	.006	.392
2010	2456	.094	0.060	.004	.384
2015	2457	.114	0.065	0	.444
2020	2469	.072	0.051	.001	.346

Table A.1.vii: Descriptive Statistics Municipal Share of Population who is Analphabetic, by Year (Data Sources: INEGI 2005, 2010, 2015 and 2020b)

Extreme Poverty

Year	N	Mean	SD	Min	Max
2005	0	.	.	.	.
2010	2456	.38	0.214	.003	1.052
2015	2446	.368	0.230	.005	.991
2020	2466	.336	0.209	.01	1.042

Table A.1.viii: Descriptive Statistics Municipal Share of Population Living in Extreme Poverty, by Year (Data Sources: INEGI 2005, 2010, 2015 and 2020b)

Gini

Year	N	Mean	SD	Min	Max
2005	0	.	.	.	.
2010	2456	.424	0.045	.308	.659
2015	2446	.378	0.037	.282	.641
2020	2466	.343	0.035	.259	.64

Table A.1. ix: Descriptive Statistics Municipal Gini Coefficient, by Year (Data Sources: INEGI 2005, 2010, 2015 and 2020b)

Appendix 2 on Diagnostic Tests Model I

Testing for the Inclusion of Time Fixed Effects

When testing for the inclusion of time fixed effects in addition to entity fixed effects by running a joint test assessing whether all year dummies are equal to zero, the following results emerge:

Model I, Drinking Water

```
( 1)  2010.Year = 0
( 2)  2015.Year = 0
( 3)  2020.Year = 0
      F(  3,  2443) =   81.87
           Prob > F =    0.0000
```

Figure A.2.i..: Test Inclusion Time Fixed Effects, Model I, Drinking Water

Model I, Drainage

```
( 1)  2010.Year = 0
( 2)  2015.Year = 0
( 3)  2020.Year = 0
      F(  3,  2443) =   44.26
           Prob > F =    0.0000
```

Figure A.2.ii..: Test Inclusion Time Fixed Effects, Model I, Drainage

Model I, Electricity

```
( 1)  2010.Year = 0
( 2)  2015.Year = 0
( 3)  2020.Year = 0
      F(  3,  2443) =    4.00
           Prob > F =    0.0075
```

Figure A.2.iii..: Test Inclusion Time Fixed Effects, Model I, Electricity

Model I, Housing

```
( 1)  2010.Year = 0
( 2)  2015.Year = 0
( 3)  2020.Year = 0
      F(  3,  2443) =  155.73
           Prob > F =    0.0000
```

Figure A.2.iv..: Test Inclusion Time Fixed Effects, Model I, Housing

Model I, Health

```
( 1)  2010.Year = 0
( 2)  2015.Year = 0
( 3)  2020.Year = 0
      F(  3,  2443) =  976.16
           Prob > F =    0.0000
```

Figure A.2.v.: Test Inclusion Time Fixed Effects, Model I, Health

Model I, Primary School

```
( 1)  2010.Year = 0
( 2)  2015.Year = 0
( 3)  2020.Year = 0
      F(  3,  2443) =70305.19
           Prob > F =    0.0000
```

Figure A.2.vi.: Test Inclusion Time Fixed Effects, Model I, Primary School

Model I, Illiteracy

```
( 1)  2010.Year = 0
( 2)  2015.Year = 0
( 3)  2020.Year = 0
      F(  3,  2443) = 2685.26
           Prob > F =    0.0000
```

Figure A.2.vii.: Test Inclusion Time Fixed Effects, Model I, Illiteracy

Model I, Extreme Poverty
(1) 2015.Year = 0
(2) 2020.Year = 0
F(2, 2442) = 255.83
Prob > F = 0.0000

Figure A.2.viii.: Test Inclusion Time Fixed Effects, Model I, Extreme Poverty

Model I, Gini
(1) 2015.Year = 0
(2) 2020.Year = 0
F(2, 2442) = 1032.27
Prob > F = 0.0000

Figure A.2.ix.: Test Inclusion Time Fixed Effects, Model I, Gini Coefficient

Testing for the Preferability of a Fixed-Effects over a Random-Effects Model

When testing if a fixed effects is preferable in comparison to a random effects model using the Hausman test, the following results emerge:

Hausman (1978) specification test: Drinking Water, Model I

	Coef.
Chi-square test value	258.853
P-value	0

Table A.2.i.: Results Hausman Test, Drinking Water, Model I

Hausman (1978) specification test: Drainage, Model I

	Coef.
Chi-square test value	536.009
P-value	0

Table A.2.ii.: Results Hausman Test, Drainage, Model I

Hausman (1978) specification test: Electricity, Model I

	Coef.
Chi-square test value	180.693
P-value	0

Table A.2.iii.: Results Hausman Test, Electricity, Model I

Hausman (1978) specification test: Housing, Model I

	Coef.
Chi-square test value	420.52
P-value	0

Table A.2.iv.: Results Hausman Test, Housing, Model I

Hausman (1978) specification test: Health, Model I

	Coef.
Chi-square test value	522.595
P-value	0

Table A.2.v.: Results Hausman Test, Health, Model I

Hausman (1978) specification test: Primary Education, Model I

	Coef.
Chi-square test value	361.378
P-value	0

Table A.2.vi.: Results Hausman Test, Primary Education, Model I

Hausman (1978) specification test: Illiteracy, Model I

	Coef.
Chi-square test value	7105.116

P-value	0

Table A.2.vii.: Results Hausman Test, Illiteracy, Model I

Hausman (1978) specification test: Extreme Poverty, Model I

	Coef.
Chi-square test value	1697.864
P-value	0

Table A.2.viii.: Results Hausman Test, Extreme Poverty

Hausman (1978) specification test: Gini, Model I

	Coef.
Chi-square test value	538.073
P-value	0

Table A.2.ix.: Results Hausman Test, Gini Coefficient, Model I

Testing for Heteroskedasticity

When running the modified Wald test for groupwise heteroskedasticity in the residuals of a fixed effects model (Stata command: xttest3), the following results emerge:

1) **Drinking Water, Model I**

Modified Wald test for groupwise heteroskedasticity in fixed effect regression model

H0: sigma(i)^2 = sigma^2 for all i

chi2 (2444) = 5.0e+34

Prob>chi2 = 0.0000

Figure A.2.x.: Results Wald Test, Drinking Water, Model I

2) **Drainage, Model I**

Modified Wald test for groupwise heteroskedasticity in fixed effect regression model

H0: sigma(i)^2 = sigma^2 for all i

chi2 (2444) = 2.6e+36

Prob>chi2 = 0.0000

Figure A.2.xi.: Results Wald Test, Drainage, Model I

3) **Electricity, Model I**

Modified Wald test for groupwise heteroskedasticity in fixed effect regression model

H0: sigma(i)^2 = sigma^2 for all i

chi2 (2444) = 7.4e+36

Prob>chi2 = 0.0000

Figure A.2.xii.: Results Wald Test, Electricity, Model I

4) **Housing, Model I**

Modified Wald test for groupwise heteroskedasticity in fixed effect regression model

H0: sigma(i)^2 = sigma^2 for all i

chi2 (2444) = 8.0e+30

Prob>chi2 = 0.0000

Figure A.2.xiii.: Results Wald Test, Housing, Model I

5) **Health, Model I**

Modified Wald test for groupwise heteroskedasticity in fixed effect regression model

H0: sigma(i)^2 = sigma^2 for all i

chi2 (2444) = 2.5e+34

Prob>chi2 = 0.0000

Figure A.2.xiv.: Results Wald Test, Health, Model I

6) **Primary Education, Model I**

Modified Wald test for groupwise heteroskedasticity in fixed effect regression model

H0: sigma(i)^2 = sigma^2 for all i

chi2 (2444) = 3.2e+33

Prob>chi2 = 0.0000

Figure A.2.xv.: Results Wald Test, Primary Education, Model I

7) **Illiteracy, Model I**

Modified Wald test for groupwise heteroskedasticity in fixed effect regression model

H0: sigma(i)^2 = sigma^2 for all i

chi2 (2444) = 1.1e+35

Prob>chi2 = 0.0000

Figure A.2.xvi.: Results Wald Test, Illiteracy, Model I

8) **Extreme Poverty, Model I**

Modified Wald test for groupwise heteroskedasticity in fixed effect regression model

H0: sigma(i)^2 = sigma^2 for all i

chi2 (2443) = 3.2e+35

Prob>chi2 = 0.0000

Figure A.2.xvii.: Results Wald Test, Extreme Poverty, Model I

9) Gini, Model I

Modified Wald test for groupwise heteroskedasticity in fixed effect regression model

H0: sigma(i)^2 = sigma^2 for all i

chi2 (2443) = 2.2e+35

Prob>chi2 = 0.0000

Figure A.2.xviii.: Results Wald Test, Gini, Model I

Testing for Serial Correlation

When running the Wooldridge test for autocorrelation in panel data models, the following results emerge:

Drinking Water, Model I

H0: no first-order autocorrelation

F(1, 2164) = 2.296

Prob > F = 0.1299

Figure A.2.xix.: Results Wooldridge Test, Drinking Water, Model I

Drainage, Model I

H0: no first-order autocorrelation

F(1, 2161) = 81.655

Prob > F = 0.0000

Figure A.2.xx.: Results Wooldridge Test, Drainage, Model I

Electricity, Model I

H0: no first-order autocorrelation

F(1, 2167) = 147.292

Prob > F = 0.0000

Figure A.2.xxi.: Results Wooldridge Test, Electricity, Model I

Dirt Floor, Model I

H0: no first-order autocorrelation

F(1, 2167) = 2.703

Prob > F = 0.1003

Figure A.2.xxii.: Results Wooldridge Test, Dirt Floor, Model I

Access to Health Care, Model I

H0: no first-order autocorrelation

F(1, 2167) = 2976.259

Prob > F = 0.0000

Figure A.2.xxiii.: Results Wooldridge Test, Health Care, Model I

Primary Education, Model I

H0: no first-order autocorrelation

F(1, 2167) = 2239.854

Prob > F = 0.0000

Figure A.2.xxiv.: Results Wooldridge Test, Primary Education, Model I

Illiteracy, Model I

H0: no first-order autocorrelation

F(1, 2167) = 985.485

Prob > F = 0.0000

Figure A.2.xxv.: Results Wooldridge Test, Illiteracy, Model I

Extreme Poverty, Model I

H0: no first-order autocorrelation

F(1, 2160) = 7.838

Prob > F = 0.0052

Figure A.2.xxvi.: Results Wooldridge Test, Extreme Poverty, Model I

Gini, Model I

H0: no first-order autocorrelation

F(1, 2160) = 663.797

Prob > F = 0.0000

Figure A.2.xxvii.: Results Wooldridge Test, Gini Coefficient, Model I

Appendix 3 on Regression Results Model I

	(1) Drinking Water	(2) Drainage	(3) Electricity	(4) No Dirt Floor	(5) Health Care	(6) Primary Education	(7) Illiteracy	(8) Extreme Poverty	(9) Gini
FISM	.07983***	.15171***	.01975***	.11629***	.48349***	.14484***	.0129916	.0218679	.012164**
	(.012778)	(.020894)	(.0046136)	(.0123878)	(.0385794)	(.0148586)	(.0087058)	(.0301933)	(.0056341)
Municipal Income	.0231492	.0293102	.0102205*	.0350664*	.0241915	.0017227	-.0113828	-.008049	.0008316
	(.023591)	(.0308259)	(.006055)	(.0179167)	(.0434249)	(.0151382)	(.0070453)	(.0226941)	(.0051373)
Blue Collar	-.21923**	-.396386*	-.0386567	-.168739*	-.60918**	-.1696235	.0247108	-.1578924	-.070995*
	(.086554)	(.2178324)	(.0339098)	(.0860653)	(.239631)	(.1657442)	(.1354557)	(.2154535)	(.0416756)
White Collar	-.3190384	-1.47888*	-.4307444	-.6483688	.1526918	-1.15445*	-2.125***	1.5218516	1.0262***
	(.3078161)	(.7739149)	(.3868696)	(.5477546)	(1.172505)	(.6959757)	(.497131)	(1.70417)	(.286743)
Assets	-5.000e-07	-1.500e-06***	0	-8.000e-07***	-4.900e-06***	-3.500e-06***	-5.000e-07	2.400e-06**	4.000e-07***
	(3.000e-1)	(5.000e-07)	(0)	(3.000e-07)	(1.400e-06)	(1.300e-06)	(4.000e-07)	(1.100e-06)	(1.000e-07)
Productivity	-.0032995	-.0038599	.0002304	-.006163	-.0306096	-.0173213*	.0029786	-.0089533*	.005***
	(.0026186)	(.0066468)	(.0005017)	(.0038828)	(.0221271)	(.0094027)	(.0023888)	(.0049739)	(.0011888)
Population >15000	-.0382317	-.0610715*	.0057128	.0047973	-.15801***	-.06757***	-.02925**	.0368553	-.0043326
	(.029098)	(.0325018)	(.011516)	(.0236455)	(.0462961)	(.0225183)	(.0126372)	(.0356205)	(.0085824)
Population > 2500	.1096647	.0171664	-.0106189	.1121777**	.2777832	.0813766*	-.07544***	.0590379	-.0181877
	(.07145)	(.1158849)	(.0194472)	(.055115)	(.1716327)	(.0470303)	(.0247918)	(.0731222)	(.0174796)
Year Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
Constant	-.7492***	-1.2269***	-.1875***	-.9995***	-3.5723***	-2.718***	-2.366***	-1.8774***	-.89512***
	(.148304)	(.1856861)	(.0383141)	(.1034003)	(.2681769)	(.0857412)	(.0457404)	(.1554662)	(.0353864)
Observations	9279	9273	9283	9283	9274	9283	9283	6862	6866
R-squared	.1416449	.1420915	.051622	.1949281	.5397513	.9307213	.7292801	.3192653	.6939237

Clustered standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table A.3.i.: Regression Results Model I

Note. All dependent variables refer to logged per capita rates, except for the Gini coefficient, which is logged, but not a per capita measure. FISM and Municipal Income correspond to the logged average monthly per capita value of the four previous years and are expressed in real terms in January 2020 pesos. Blue and White Collar refer to the population share of blue- and white-collar workers. Assets refers to the total value of the assets owned by the economic units. Productivity is measured as output per worker. Population > 15000 and Population > 2500 are dummy variables which equal one for municipalities with more than 15000/2500 inhabitants and zero otherwise.

Appendix 4 on Regression Results Models II and IIA

Regression Results Model II

	(1) Drinking Water	(2) Drainage	(3) Electricity	(4) No Dirt Floor	(5) Health Care	(6) Primary Education	(7) Illiteracy	(8) Extreme Poverty	(9) Gini
FISM	.0046	.1821***	.0104**	.1099***	.4135***	-.5797***	-.1889***	-.0935***	-.0773***
	(.0125)	(.0234)	(.0045)	(.0139)	(.0453)	(.0311)	(.0116)	(.0322)	(.006)
0bn.Post2014									
1.Post2014	-.2759***	-.4014***	-.0575***	-.2535***	-.8004***	1.6241***	.4625***	-.5092***	-.1435***
	(.0276)	(.0397)	(.0116)	(.0224)	(.0576)	(.0534)	(.0259)	(.0506)	(.0095)
0bn.Post2014xFISM									
1.Post2014xFISM	.103***	.0868***	.0179***	.0528***	.2262***	-.0183	-.064***	.0384***	.0103***
	(.0074)	(.0111)	(.0031)	(.006)	(.0159)	(.0129)	(.0061)	(.0132)	(.0025)
Municipal Income	.0358**	.1426***	.0209***	.1326***	.6328***	-.1247***	-.1685***	-.0597***	-.0512***
	(.0157)	(.0231)	(.0041)	(.0132)	(.0376)	(.0311)	(.0112)	(.0232)	(.0061)
Blue Collar	-.0878**	-.1251	-.0207	-.1889*	-1.3701**	-3.2129**	-.7999	-.2527	-.1951***
	(.044)	(.1122)	(.0296)	(.1023)	(.6347)	(1.5914)	(.5091)	(.2064)	(.0532)
White Collar	-.0414	-1.3025**	-.4212	-.9892*	-3.2384**	-6.4301*	-3.1673***	1.2336	.503*
	(.2377)	(.5973)	(.3815)	(.5087)	(1.374)	(3.8743)	(1.211)	(1.7077)	(.301)
Assets	0***	0	0**	0	0***	0***	0**	0**	0
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
Output	.0003	.0013	.001	-.0033	-.0186	-.0322	-.0045	-.0089	.0045*
	(.0011)	(.0021)	(.0006)	(.0023)	(.02)	(.0431)	(.0136)	(.0058)	(.0024)
Population > 15000	-.0073	.0271	.0151	.0625***	.1486***	-.3111***	-.1681***	.0012	-.0462***
	(.0282)	(.0324)	(.0117)	(.0232)	(.0453)	(.0738)	(.0253)	(.0352)	(.01)
Population > 2500	.0983	.0339	-.0093	.1443**	.5261***	.23**	-.0746**	.044	-.0301
	(.0711)	(.1157)	(.019)	(.0566)	(.1888)	(.0958)	(.0341)	(.0769)	(.0224)
Constant	-.5651***	-1.8797***	-.2069***	-1.4296***	-6.0975***	.584***	-.8815***	-1.157***	-.2652***
	(.0957)	(.1372)	(.022)	(.072)	(.2279)	(.1463)	(.0506)	(.1549)	(.0389)
Observations	9279	9273	9283	9283	9274	9283	9283	6862	6866
R-squared	.1632	.1272	.0553	.1794	.4241	.39	.2559	.3139	.5954

Clustered standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table A.4.i.: Regression Results Model II

Note. All dependent variables refer to logged per capita rates, except for the Gini coefficient, which is logged, but not a per capita measure. FISM and Municipal Income correspond to the logged average monthly per capita value of the four previous years and are expressed in real terms in January 2020 pesos. Blue and White Collar refer to the population share of blue- and white-collar workers. Assets refers to the total value of the assets owned by the economic units. Productivity is measured as output per worker. Population > 15000 and Population > 2500 are dummy variables which equal one for municipalities with more than 15000/2500 inhabitants and zero otherwise. Post-2014 is a dummy equaling 1 for the post-reform period and 0 otherwise.

Regression Results Model IIA

	(1) Drinking Water	(2) Drainage	(3) Electricity	(4) No Dirt Floor	(5) Health Care	(6) Primary Education Complete	(7) Illiteracy	(8) Extreme Poverty	(9) Gini
FISM	-.0154	.1117***	.0074*	.1155***	.5995***	.0799***	-.0289***	-.0035	.011*
0bn.Year2015									
1.Year2015	-.1733***	.0181	-.0305	-.1656***	-.7749***	1.7483***	.753***	-.7842***	-.1852***
	(.0375)	(.0545)	(.0189)	(.0353)	(.0618)	(.02)	(.0251)	(.0532)	(.0088)
0bn.Year2015xFISM									
1.Year2015xFISM	.0749***	-.0265	.0108**	.0316***	.2437***	.0353***	-.1157***	.1062***	.0172***
	(.0104)	(.0166)	(.0053)	(.01)	(.0173)	(.0054)	(.0062)	(.0138)	(.0024)
0bn.Year2020									
1.Year2020	-.3489***	-.7417***	-.0852***	-.4004***	-1.5291***	-1.0061***	-.5495***	-.2237***	-.1667***
	(.0304)	(.0494)	(.0107)	(.0233)	(.077)	(.0287)	(.0208)	(.0599)	(.0103)
0bnYear2020xFISM									
1.Year2020xFISM	.1281***	.1923***	.0251***	.0804***	.2847***	.1985***	.0661***	-.0485***	-.0121***
	(.0073)	(.0118)	(.0025)	(.005)	(.0181)	(.0065)	(.0046)	(.0149)	(.0026)
Municipal Income	.0361**	.1475***	.0217***	.141***	.7014***	.1211***	-.0901***	-.0476**	-.006
	(.016)	(.0231)	(.0041)	(.0135)	(.0386)	(.0127)	(.0064)	(.0217)	(.005)
Blue Collar	-.1057**	-.1442	-.0146	-.0952	-.4573*	.0507	.1899**	-.2852	-.0965***
	(.0454)	(.108)	(.0257)	(.0625)	(.2582)	(.1094)	(.0799)	(.1951)	(.029)
White Collar	.1584	-.3888	-.3492	-.6241	-1.5582	-.3501	-.7519	-.5642	.6138**
	(.2539)	(.5936)	(.3891)	(.488)	(1.3104)	(.4413)	(.5292)	(1.6853)	(.2738)
Assets	0***	0*	0**	0**	0	0**	0	0*	0
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
Output	.0002	.0011	.001	-.0028*	-.0128	-.0115**	.0017	-.0092	.0049***
	(.0009)	(.003)	(.0006)	(.0016)	(.0098)	(.0051)	(.0026)	(.006)	(.0013)

Population >15000	-.0151	.0004	.0142	.0666***	.2376***	.0052	-.0871***	.0424	-.0034
	(.0282)	(.0328)	(.0115)	(.0232)	(.0469)	(.0193)	(.014)	(.0361)	(.0085)
Population > 2500	.1008	.042	-.009	.1422**	.4909***	.1049**	-.1081***	.054	-.0187
	(.0705)	(.1154)	(.019)	(.0567)	(.1826)	(.0471)	(.0239)	(.074)	(.0174)
Constant	-.4958***	-1.6576***	-.201***	-1.4943***	-7.1239***	-3.0686***	-1.8685***	-1.5658***	-.8528***
	(.099)	(.1349)	(.022)	(.0757)	(.2407)	(.0745)	(.0333)	(.1739)	(.0368)
Observations	9279	9273	9283	9283	9274	9283	9283	6862	6866
R-squared	.1707	.1709	.0575	.1849	.4693	.9355	.7644	.3458	.7047

Clustered standard errors are in parentheses

**** p<.01, ** p<.05, * p<.1*

Table A.4.ii: Regression Results Model IIA

Note. All dependent variables refer to logged per capita rates, except for the Gini coefficient, which is logged, but not a per capita measure. FISM and Municipal Income correspond to the logged average monthly per capita value of the four previous years and are expressed in real terms in January 2020 pesos. Blue and White Collar refer to the population share of blue- and white-collar workers. Assets refers to the total value of the assets owned by the economic units. Productivity as measured as output per worker. Population > 15000 and Population > 2500 are Dummy variables which equal one for municipalities with more than 15000/2500 inhabitants and zero otherwise. Year 2015 and Year 2020 are year dummies.

Appendix 5 on Sensitivity Analyses Models I, II and IIA

Robustness to Population Weighting

	(1) Drinking Water	(2) Drainage	(3) Electricity	(4) No Dirt Floor	(5) Health Care	(6) Primary Education	(7) Illiteracy	(8) Extreme Poverty	(9) Gini
FISM	.0707***	.0694***	.0063	.0757***	.3055***	.1482***	-.0045	.0754	.0375***
	(.0108)	(.0141)	(.0088)	(.0096)	(.0272)	(.0203)	(.0205)	(.0475)	(.0089)
Municipal Income	.0394**	.0242	-.0115	.0529***	.1855***	.0797***	-.0573*	.1382*	.0332***
	(.0183)	(.024)	(.0164)	(.0176)	(.0459)	(.0297)	(.0303)	(.0802)	(.0106)
Blue Collar	-.2228	-.2899*	-.1044*	-.1224	-.4993*	.0978	-.2755	-.3289	.0137
	(.1721)	(.1707)	(.0564)	(.162)	(.272)	(.3513)	(.5717)	(.9499)	(.0888)
White Collar	-1.5786**	-1.0355	-.0764	-.3839	1.5609	-1.9478*	-1.3821	-1.4241	.8814**
	(.7492)	(.682)	(.1538)	(.6844)	(1.0533)	(1.1415)	(1.1556)	(2.834)	(.4422)
Assets	0	0***	0	0***	0***	0***	0*	0**	0
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
Output	-.0144*	-.0122***	-.003***	-.0137***	-.0646***	-.0441***	-.0081	.0058	-.0008
	(.0074)	(.0047)	(.001)	(.0043)	(.0193)	(.0147)	(.0086)	(.0231)	(.0041)
Population >15000	-.0056	-.0047	-.0071	.0462*	.1877***	.069**	-.1204***	-.0048	-.007
	(.0271)	(.0297)	(.0131)	(.0237)	(.0458)	(.0345)	(.0419)	(.0411)	(.0088)
Population >2500	.1387*	.0829	-.0091	.1627***	.6507***	.2328***	-.1194***	.0866	-.0182
	(.0721)	(.1188)	(.0179)	(.0588)	(.199)	(.069)	(.0346)	(.0876)	(.0215)
Year Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
Constant	-.6246***	-.5348***	-.0054	-.7794***	-3.2353***	-2.9389***	-2.6222***	-3.6402***	-1.1165***
	(.1237)	(.1806)	(.1039)	(.1108)	(.2992)	(.162)	(.1717)	(.4491)	(.0553)
Observations	9279	9273	9283	9283	9274	9283	9283	6862	6866
R-squared	.1467	.1189	.099	.1616	.4833	.9588	.8137	.3126	.7545

Clustered standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table A.5.i.: Regression Results Population Weighting Model I

Note. Importance given to observations increases in municipality size, using population data from 2020. All dependent variables refer to logged per capita rates, except for the Gini coefficient, which is logged, but not a per capita measure. FISM and Municipal Income correspond to the logged average monthly per capita value of the four previous years and are expressed in real terms in January 2020 pesos. Blue and White Collar refer to the population share of blue- and white-collar workers. Assets refers to the total value of the assets owned by the economic units. Productivity is measured as output per worker. Population > 15000 and Population > 2500 are dummy variables which equal one for municipalities with more than 15000/2500 inhabitants and zero otherwise.

Model II:

	(1) Drinking Water	(2) Drainage	(3) Electricity	(4) No Dirt Floor	(5) Health Care	(6) Primary Education Completed	(7) Illiteracy	(8) Extreme Poverty	(9) Gini
FISM	.0233**	.0482***	.0169***	.0455***	.1043***	-.5863***	-.1253***	.232***	-.0045
	(.0095)	(.0104)	(.004)	(.0083)	(.0227)	(.0792)	(.0336)	(.0549)	(.012)
0bn.Post2014									
1.Post2014	-.1014***	-.119***	.0267**	-.091***	-.3765***	1.8063***	.8526***	-.3182***	-.1186***
	(.0147)	(.0178)	(.0112)	(.0182)	(.0333)	(.1043)	(.0566)	(.0816)	(.0118)
FISM									
0bnPost2014xFISM									
1.Post2014xFISM	.0592***	.0448***	-.0035	.0311***	.1574***	-.0225	-.1513***	-.0735***	-.0034
	(.0054)	(.0063)	(.0035)	(.0054)	(.0095)	(.0304)	(.0166)	(.0223)	(.0037)
Municipal Income	.0311***	.0877***	.0217***	.0926***	.4577***	-.4849***	-.3021***	.2534***	-.0254**
	(.0082)	(.0101)	(.0046)	(.0092)	(.0267)	(.0828)	(.0351)	(.0712)	(.0114)
Blue Collar	.0606	-.1697	-.1528***	-.2567	-2.2315***	-8.8361***	-3.4592***	-.1141	-.2825**
	(.1732)	(.1722)	(.0491)	(.1712)	(.3227)	(2.5615)	(1.2786)	(.9441)	(.1221)
White Collar	-.9408	-.6811	-.15	-.5611	-1.3109	-19.642***	-7.9576**	-.9776	-.0916
	(.6603)	(.6345)	(.1606)	(.6803)	(.8872)	(7.1606)	(3.1783)	(2.7324)	(.5223)
Assets	0**	0***	0	0**	0***	0***	0***	0**	0**
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
Output	-.0057	-.0015	-.0014	-.0093**	-.0502***	-.2023**	-.0817**	.0122	-.0117**
	(.005)	(.0032)	(.0012)	(.0038)	(.0182)	(.0816)	(.0349)	(.0239)	(.0055)
Population > 15000	-.0009	.0277	.0069	.0536**	.1978***	-.7385***	-.4101***	.0635*	-.0449***
	(.0268)	(.0284)	(.0113)	(.0231)	(.0435)	(.2376)	(.118)	(.0363)	(.0108)
Population > 2500	.1083	.0756	-.0002	.1618***	.6842***	.3384***	-.0363	.1225	-.0261
	(.0724)	(.1183)	(.0181)	(.0585)	(.1989)	(.1065)	(.0419)	(.0767)	(.0242)
Constant	-.4894***	-.8072***	-.1935***	-.8713***	-3.7666***	3.2403***	-.6035***	-4.7714***	-.6171***
	(.0873)	(.1289)	(.0305)	(.0751)	(.2369)	(.3483)	(.1489)	(.3818)	(.0568)
Observations	9279	9273	9283	9283	9274	9283	9283	6862	6866
R-squared	.1663	.1226	.0898	.1671	.4456	.4785	.4056	.3136	.6875

Clustered standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table A.5.ii.: Regression Results Population Weighting Model II

Note. Importance given to observations increases in municipality size, using population data from 2020. All dependent variables refer to logged per capita rates, except for the Gini coefficient, which is logged, but not a per capita measure. FISM and Municipal Income correspond to the logged average monthly per capita value of the four previous years and are expressed in real terms in January 2020 pesos. Blue and White Collar refer to the population share of blue- and white-collar workers. Assets refers to the total value of the assets owned by the economic units. Productivity is measured as output per worker. Population > 15000 and Population > 2500 are dummy variables which equal one for municipalities with more than 15000/2500 inhabitants and zero otherwise. Post-2014 is a dummy equaling 1 for the post-reform period and 0 otherwise

Model IIA:

	(1) Drinking Water	(2) Drainage	(3) Electricity	(4) No Dirt Floor	(5) Health Care	(6) Primary Education Completed	(7) Illiteracy	(8) Extreme Poverty	(9) Gini
FISM	.0095	.0344***	.0156***	.051***	.19***	-.0195	.0633***	.1613***	.0449***
	(.0091)	(.0109)	(.005)	(.0084)	(.0228)	(.0248)	(.0194)	(.0555)	(.0107)
0bn.Year2015									
1.Year2015	-.0383*	-.0086	.0457**	-.0748***	-.3828***	2.0585***	1.1731***	-.459***	-.132***
	(.0214)	(.0289)	(.0213)	(.0254)	(.0316)	(.0299)	(.0493)	(.0845)	(.0094)
0bn.Year2015xFISM									
1.Year2015xFISM	.0343***	.0038	-.0103	.027***	.1811***	.035***	-.2126***	-.0193	-.0017
	(.0086)	(.0112)	(.0075)	(.0083)	(.0098)	(.0074)	(.0132)	(.0225)	(.003)
0bn.Year2020									
1.Year2020	-.1518***	-.2455***	.0008	-.1377***	-.6842***	-.7011***	-.3629***	.0193	-.1817***
	(.0164)	(.019)	(.007)	(.0156)	(.0461)	(.0416)	(.0333)	(.114)	(.0156)
0bn.Year2020xFISM									
1.Year2020xFISM	.085***	.092***	.0049*	.0395***	.1715***	.2039***	.0309***	-.1321***	-.0114***
	(.0054)	(.0056)	(.0027)	(.0039)	(.0111)	(.0101)	(.0072)	(.0267)	(.0041)
Municipal Income	.025***	.0823***	.0213***	.0957***	.5015***	-.1908***	-.2006***	.1583**	.0349***
	(.0081)	(.0101)	(.0052)	(.0094)	(.0273)	(.0255)	(.0169)	(.0784)	(.0104)
Blue Collar	-.0696	-.2276	-.1448**	-.1401	-.8297***	.8861**	.1401	-.6758	-.0161
	(.1614)	(.1672)	(.0563)	(.1611)	(.2635)	(.3547)	(.506)	(.975)	(.0897)
White Collar	-.7443	-.0067	.0012	-.2189	1.3713*	1.0673	1.3294	-4.6451	.6042
	(.714)	(.7106)	(.17)	(.7173)	(.7617)	(1.1216)	(1.0097)	(2.8527)	(.4277)
Assets	0***	0	0*	0	0	0**	0	0	0
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
Output	-.0073	-.0015	-.0011	-.0073**	-.0274**	-.0418***	-.0204***	-.0129	-.0024
	(.005)	(.0031)	(.0011)	(.0033)	(.0123)	(.0108)	(.0076)	(.0214)	(.0041)
Population >15000	-.0182	.0099	.0052	.0602***	.3014***	-.056	-.1852***	.0435	-.0029
	(.0268)	(.0293)	(.0114)	(.0229)	(.0422)	(.0342)	(.0383)	(.0403)	(.0088)
Population > 2500	.113	.0801	.0002	.1596***	.6526***	.1276**	-.1078***	.103	-.0168
	(.0714)	(.1175)	(.0181)	(.0585)	(.1955)	(.0594)	(.0283)	(.0754)	(.0202)
Constant	-.4084***	-.7455***	-.1914***	-.9212***	-4.4283***	-1.2568***	-2.1975***	-3.9307***	-1.1415***

	(.0851)	(.1287)	(.0381)	(.0764)	(.2423)	(.1337)	(.0803)	(.4485)	(.0565)
Observations	9279	9273	9283	9283	9274	9283	9283	6862	6866
R-squared	.1857	.1548	.0961	.1705	.4998	.9622	.8911	.3411	.7575

Clustered standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table A.5.iii: Regression Results Population Weighting Model IIA

Note. Importance given to observations increases in municipality size, using population data from 2020. All dependent variables refer to logged per capita rates, except for the Gini coefficient, which is logged, but not a per capita measure. FISM and Municipal Income correspond to the logged average monthly per capita value of the four previous years and are expressed in real terms in January 2020 pesos. Blue and White Collar refer to the population share of blue- and white-collar workers. Assets refers to the total value of the assets owned by the economic units. Productivity as measured is output per worker. Population > 15000 and Population > 2500 are dummy variables which equal one for municipalities with more than 15000/2500 inhabitants and zero otherwise. Year 2015 and Year 2020 are year dummies.

Robustness to Different Measurement of the Target Regressor

Model I:

	(1) Drinking Water	(2) Drainage	(3) Electricity	(4) No Dirt Floor	(5) Health Care	(6) Primary Education Completed	(7) Illiteracy	(8) Extreme Poverty	(9) Gini
FISM	.0577***	.1152***	.0141***	.0969***	.4628***	.1431***	-.0009	.0204	.0129**
	(.0127)	(.0194)	(.0045)	(.0124)	(.0361)	(.0136)	(.0079)	(.0282)	(.0054)
Municipal Income	.0292	.0277	.0113*	.033*	-.0089	-.0025	-.009	-.0109	.0001
	(.0246)	(.0323)	(.0062)	(.0183)	(.0436)	(.0156)	(.0074)	(.0232)	(.0052)
Blue Collar	-.2255**	-.4007*	-.0389	-.1728**	-.6081**	-.1679	.0254	-.1254	-.0713*
	(.0906)	(.22)	(.0339)	(.0876)	(.2361)	(.1648)	(.1358)	(.2205)	(.0415)
White Collar	-.3622	-1.4241*	-.42	-.6057	.1841	-1.1674	-2.0795***	1.3838	1.0133***
	(.3283)	(.8045)	(.3906)	(.5628)	(1.1569)	(.711)	(.4963)	(1.7153)	(.2889)
Assets	0*	0***	0	0***	0***	0***	0	0**	0***
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
Output	-.0035	-.0033	.0002	-.0057	-.0283	-.0162*	.003	-.0086*	.0052***
	(.0031)	(.0071)	(.0005)	(.0041)	(.023)	(.0094)	(.0025)	(.005)	(.0012)
Population > 15000	-.0385	-.0661**	.0056	.0052	-.1633***	-.0737***	-.0315**	.0279	-.0051
	(.0299)	(.0336)	(.0118)	(.0245)	(.0472)	(.0224)	(.0131)	(.0352)	(.0087)
Population > 2500	.1065	.0207	-.0101	.1098**	.2771	.0757	-.0754***	.0582	-.0187
	(.0717)	(.1136)	(.0195)	(.0553)	(.1716)	(.0471)	(.0249)	(.0731)	(.0175)
Year Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
Constant	-.702***	-1.1015***	-.1743***	-.9238***	-3.3501***	-2.6867***	-2.3309***	-1.8527***	-.8938***
	(.1507)	(.1918)	(.0389)	(.1043)	(.2629)	(.0851)	(.0454)	(.1503)	(.0349)
Observations	9081	9075	9085	9085	9076	9085	9085	6700	6704
R-squared	.1381	.139	.051	.1912	.5431	.9316	.7265	.3195	.6909

Clustered standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table A.5.iv.: Regression Results Three-Year FISM Average Model I

Note. All dependent variables refer to logged per capita rates, except for the Gini coefficient, which is logged, but not a per capita measure. FISM and Municipal Income correspond to the logged average monthly per capita value of the three previous years and are expressed in real terms in January 2020 pesos. Blue and White Collar refer to the population share of blue- and white-collar workers. Assets refers to the total value of the assets owned by the economic units. Productivity is measured as output per worker. Population > 15000 and Population > 2500 are dummy variables which equal one for municipalities with more than 15000/2500 inhabitants and zero otherwise.

Model II:

	(1) Drinking Water	(2) Drainage	(3) Electricity	(4) No Dirt Floor	(5) Health Care	(6) Primary Education Completed	(7) Illiteracy	(8) Extreme Poverty	(9) Gini
FISM	-.0133	.1509***	.0057	.0949***	.4283***	-.5104***	-.1845***	-.0894***	-.075***
	(.0124)	(.0213)	(.0039)	(.0132)	(.0431)	(.0307)	(.0106)	(.0312)	(.0057)
0bn.Post2014									
1.Post2014	-.2755***	-.3649***	-.0557***	-.226***	-.5848***	1.7374***	.4703***	-.527***	-.1521***
	(.0285)	(.0405)	(.0118)	(.0232)	(.0599)	(.0567)	(.0257)	(.0529)	(.0098)
FISM									
0bn.Post2014xFISM									
1.Post2014xFISM	.1028***	.0819***	.0176***	.0482***	.1779***	-.0544***	-.0671***	.0406***	.0113***
	(.0073)	(.011)	(.0031)	(.0061)	(.0162)	(.0137)	(.006)	(.0136)	(.0025)
Municipal Income	.0468***	.1447***	.023***	.1313***	.5924***	-.1165***	-.1579***	-.0553**	-.0483***
	(.0168)	(.0243)	(.0043)	(.0138)	(.0392)	(.0313)	(.0112)	(.0236)	(.0062)
Blue Collar	-.0987**	-.1422	-.0219	-.199*	-1.4247**	-3.1102**	-.7545	-.1987	-.1841***
	(.0472)	(.1174)	(.0299)	(.1068)	(.6648)	(1.5593)	(.4914)	(.2085)	(.0485)
White Collar	-.0955	-1.2626**	-.4137	-.9632*	-3.3767**	-6.5723*	-3.138***	1.2176	.5549*
	(.2396)	(.6114)	(.3844)	(.5228)	(1.4062)	(3.7883)	(1.1698)	(1.717)	(.2965)
Assets	0***	0	0**	0	0***	0***	0**	0**	0
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
Output	.0005	.0028	.001*	-.0026	-.0168	-.0379	-.0065	-.009	.0042*
	(.0009)	(.0023)	(.0006)	(.0027)	(.0222)	(.044)	(.0137)	(.0056)	(.0022)
Population > 15000	-.0065	.0212	.0153	.0619***	.1293***	-.3036***	-.1618***	-.0013	-.0436***
	(.0289)	(.0332)	(.0119)	(.0239)	(.046)	(.0746)	(.0256)	(.0349)	(.01)
Population > 2500	.0963	.0349	-.0087	.1409**	.5229***	.2558***	-.0633*	.0474	-.0271
	(.0715)	(.1135)	(.0191)	(.0568)	(.1884)	(.0946)	(.0338)	(.0768)	(.0219)
Constant	-.5538***	-1.7853***	-.2013***	-1.3701***	-5.9533***	.29**	-.9565***	-1.191***	-.288***
	(.0963)	(.1386)	(.0217)	(.0711)	(.2273)	(.1469)	(.0501)	(.1521)	(.0381)
Observations	9081	9075	9085	9085	9076	9085	9085	6700	6704
R-squared	.16	.1226	.0545	.1748	.4211	.399	.2722	.3155	.5948

Clustered standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table A.5.v.: Regression Results Three-Year FISM Average Model II

Note. All dependent variables refer to logged per capita rates, except for the Gini coefficient, which is logged, but not a per capita measure. FISM and Municipal Income correspond to the logged average monthly per capita value of the three previous years and are expressed in real terms in January 2020 pesos. Blue and White Collar refer to the population share of blue- and white-collar workers. Assets refers to the total value of the assets owned by the economic units. Productivity is measured as output per worker. Population > 15000 and Population > 2500 are dummy variables which equal one for municipalities with more than 15000/2500 inhabitants and zero otherwise. Post-2014 is a dummy equaling 1 for the post-reform period and 0 otherwise.

Modell IIA:

	(1) Drinking Water	(2) Drainage	(3) Electricity	(4) No Dirt Floor	(5) Health Care	(6) Primary Education Completed	(7) Illiteracy	(8) Extreme Poverty	(9) Gini
FISM	-.0274**	.1031***	.0041	.1042***	.6109***	.1043***	-.0267***	-.0372	.0071
	(.0121)	(.0214)	(.0037)	(.0134)	(.0477)	(.016)	(.0077)	(.0356)	(.006)
0bn.Year2015									
1.Year2015	-.1696***	.0539	-.0289	-.1284***	-.5126***	1.7907***	.7105***	-.7819***	-.1792***
	(.0375)	(.0543)	(.0186)	(.0347)	(.0642)	(.0214)	(.0252)	(.0558)	(.0089)
0bn.Year2015xFISM									
1.Year2015#FISM	.0735***	-.0328**	.0105**	.0246**	.1866***	.024***	-.1051***	.106***	.0159***
	(.0103)	(.0163)	(.0051)	(.0098)	(.0176)	(.0058)	(.0061)	(.0143)	(.0024)
0bn.Year2020									
1.Year2020	-.3649***	-.7525***	-.0866***	-.4051***	-1.4771***	-.9973***	-.5536***	-.2106***	-.1632***
	(.032)	(.0514)	(.0113)	(.0248)	(.0799)	(.0303)	(.0219)	(.0616)	(.0107)
0bn.Year2020#FISM									
1.Year2020#FISM	.1305***	.1946***	.0254***	.0821***	.2684***	.1909***	.0665***	-.0458***	-.0124***
	(.0074)	(.012)	(.0026)	(.0053)	(.0184)	(.0068)	(.0047)	(.0152)	(.0026)
Municipal Income	.0455***	.1425***	.0233***	.1383***	.6615***	.109***	-.0918***	-.0436*	-.0052
	(.0171)	(.0241)	(.0043)	(.014)	(.0402)	(.0132)	(.0067)	(.0223)	(.0051)
Blue Collar	-.1084**	-.1404	-.0146	-.0942	-.4546*	.0503	.1895**	-.251	-.0965***
	(.0471)	(.1067)	(.0256)	(.0615)	(.2476)	(.1082)	(.08)	(.1934)	(.029)
White Collar	.124	-.317	-.3394	-.5415	-1.3437	-.3596	-.7774	-.6597	.6093**
	(.2536)	(.597)	(.3918)	(.4927)	(1.2388)	(.4503)	(.5344)	(1.7013)	(.275)
Assets	0***	0*	0**	0**	0	0**	0	0	0
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
Output	.0001	.0018	.001*	-.0019	-.0085	-.0104**	.0012	-.0088	.0051***
	(.001)	(.0029)	(.0006)	(.0016)	(.0107)	(.005)	(.0024)	(.0062)	(.0013)
Population > 15000	-.0135	-.0026	.0145	.0663***	.218***	-.0041	-.0852***	.0277	-.0053
	(.0289)	(.0336)	(.0118)	(.0238)	(.0474)	(.0189)	(.0142)	(.036)	(.0087)
Population > 2500	.0999	.047	-.0083	.1385**	.4763***	.0989**	-.1036***	.0496	-.0197
	(.0708)	(.1128)	(.019)	(.0568)	(.1817)	(.0471)	(.0242)	(.0744)	(.0175)
Constant	-.4991***	-1.6121***	-.198***	-1.4422***	-6.9694***	-3.0892***	-1.8722***	-1.4486***	-.8413***

	(.0995)	(.1372)	(.0217)	(.0745)	(.2383)	(.0739)	(.0326)	(.1731)	(.0366)
Observations	9081	9075	9085	9085	9076	9085	9085	6700	6704
R-squared	.1683	.1701	.057	.1822	.4719	.9363	.7595	.3464	.7013

Clustered standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table A.5.vi.: Regression Results Three-Year FISM Average Model IIA

Note. All dependent variables refer to logged per capita rates, except for the Gini coefficient, which is logged, but not a per capita measure. FISM and Municipal Income correspond to the logged average monthly per capita value of the three previous years and are expressed in real terms in January 2020 pesos. Blue and White Collar refer to the population share of blue- and white-collar workers. Assets refers to the total value of the assets owned by the economic units. Productivity is measured as output per worker. Population > 15000 and Population > 2500 are dummy variables which equal one for municipalities with more than 15000/2500 inhabitants and zero otherwise. Year 2015 and Year 2020 are year dummies.

Appendix 6 on Diagnostic Tests Model III

Testing for Linearity

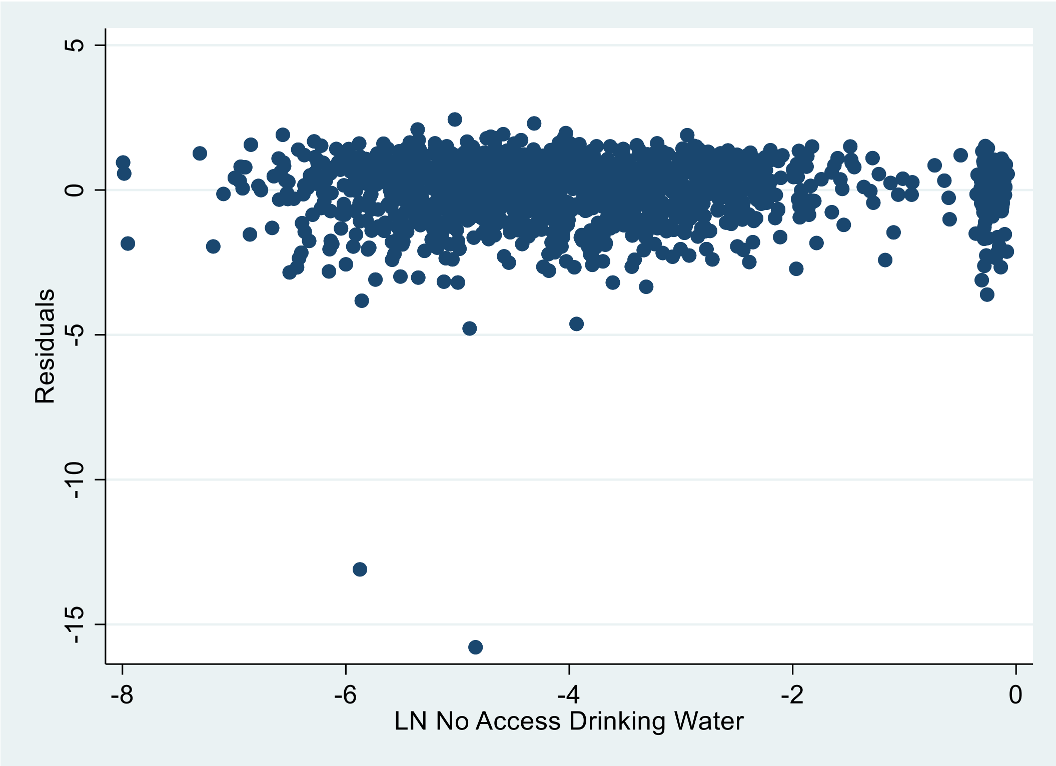

Figure A.6.i: Standardized Residual Plot Drinking Water, Model III, 2016

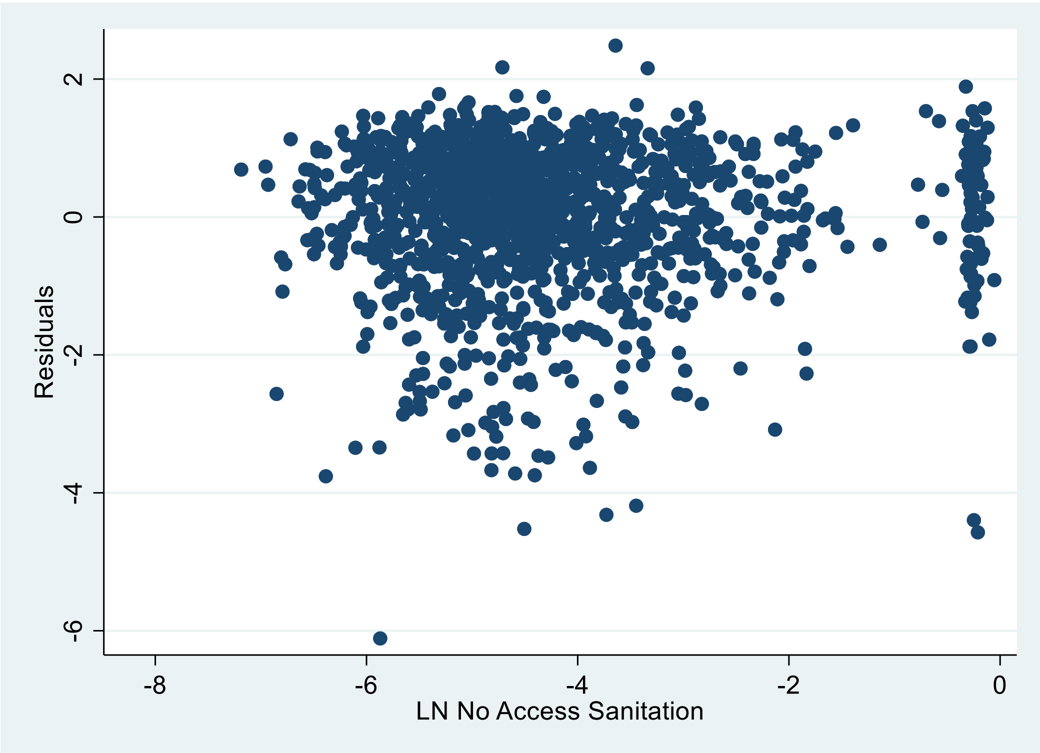

Figure A.6.ii: Standardized Residual Plot Sanitation, Model III, 2016

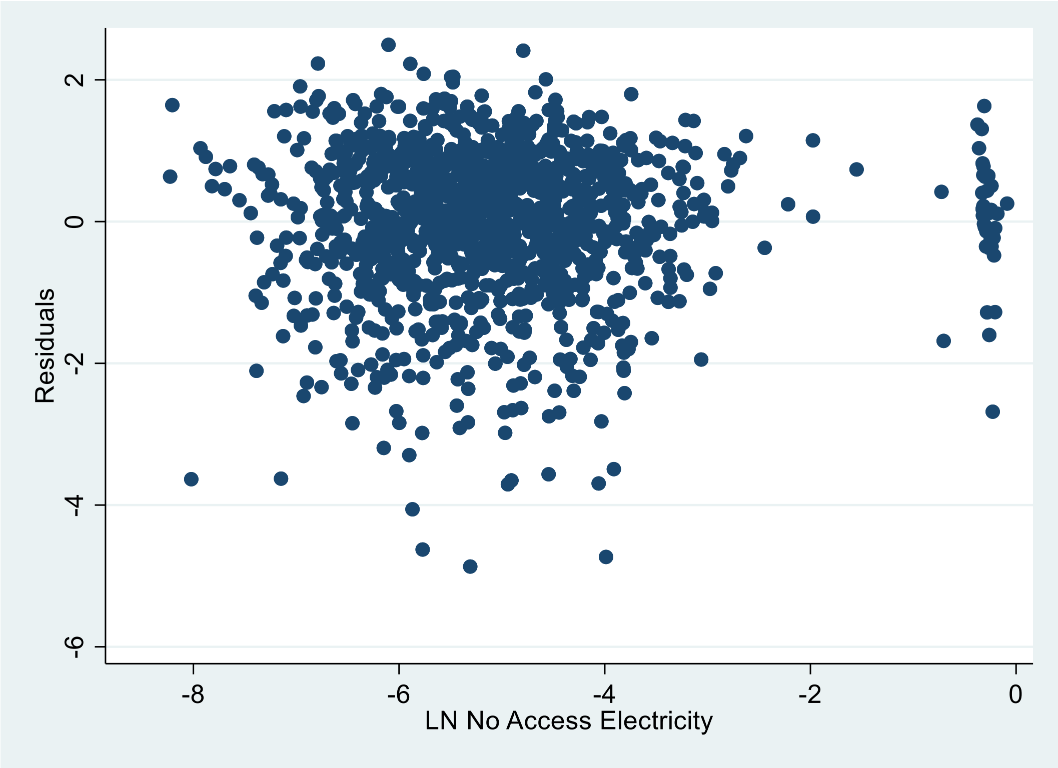

Figure A.6.iii.: Standardized Residual Plot Electricity, Model III, 2016

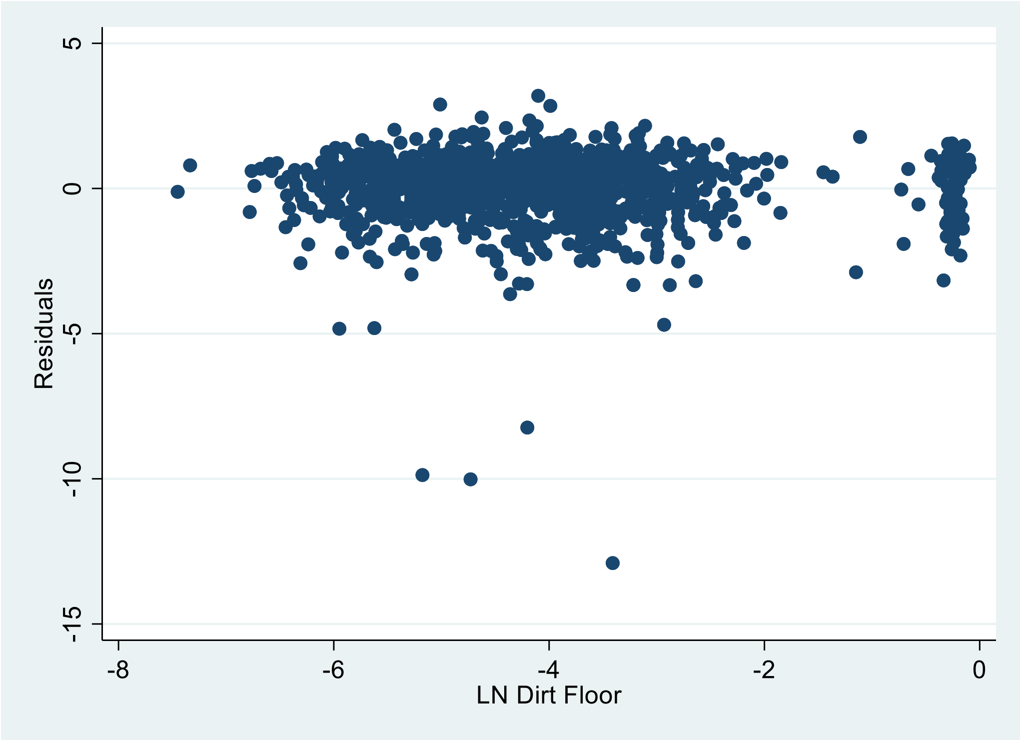

Figure A.6.iv: Standardized Residual Plot Housing, Model III, 2016

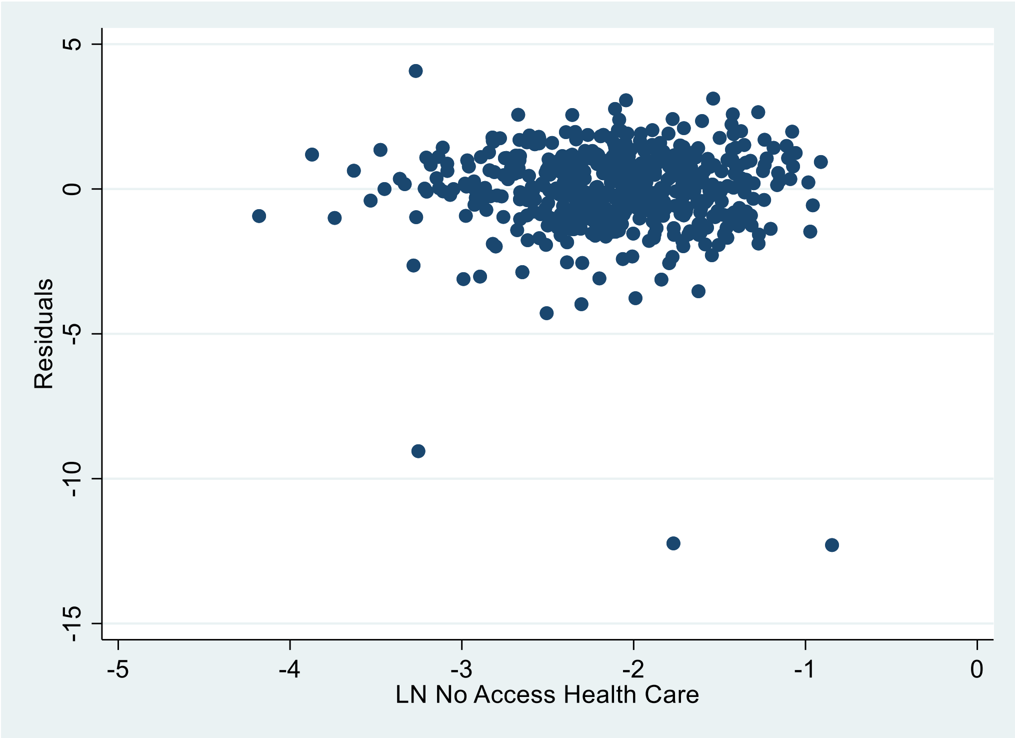

Figure A.6.v: Standardized Residual Plot Health, Model III, 2016

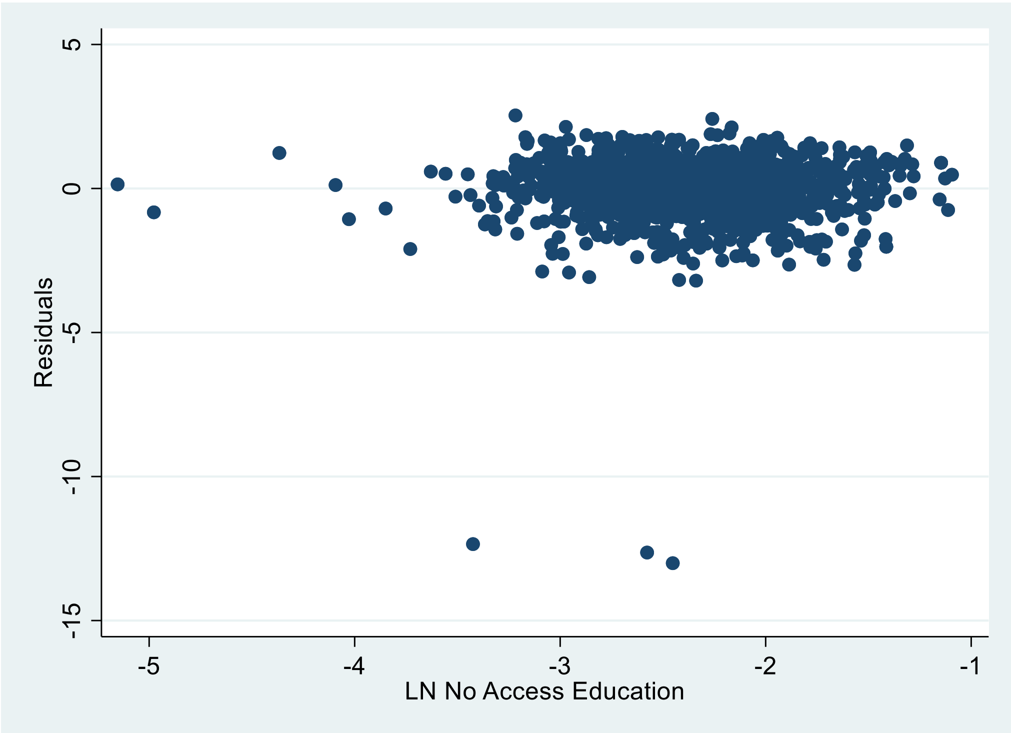

Figure A.6.vi: Standardized Residual Plot Education, Model III, 2016

Testing for Heteroskedasticity

Drinking Water

Breusch Pagan/Cook Weisberg test for heteroskedasticity
Assumption: Normal error terms
Variable: Fitted values of LnShareFISMWater
H0: Constant variance
chi2(1) = 24.98
Prob > chi2 = 0.0000
Figure A.6.vii: Results Breusch Pagan Test, Drinking Water

Sanitation
Breusch Pagan/Cook Weisberg test for heteroskedasticity
Assumption: Normal error terms
Variable: Fitted values of LnShareFISMDrain
H0: Constant variance
chi2(1) = 10.33
Prob > chi2 = 0.0013
Figure A.6.viii: Results Breusch Pagan Test, Sanitation

Electricity
Breusch Pagan/Cook Weisberg test for heteroskedasticity
Assumption: Normal error terms
Variable: Fitted values of LnShareFISMElec
H0: Constant variance
chi2(1) = 17.57
Prob > chi2 = 0.0000
Figure A.6.ix: Results Breusch Pagan Test, Electricity

Housing
Breusch Pagan/Cook Weisberg test for heteroskedasticity
Assumption: Normal error terms
Variable: Fitted values of LnShareFISMHous
H0: Constant variance
chi2(1) = 379.81
Prob > chi2 = 0.0000
Figure A.6.x: Results Breusch Pagan Test, Housing

Health
Breusch Pagan/Cook Weisberg test for heteroskedasticity
Assumption: Normal error terms
Variable: Fitted values of LnShareFISMHealth
H0: Constant variance
chi2(1) = 129.63
Prob > chi2 = 0.0000
Figure A.6.xi: Results Breusch Pagan Test, Health

Education
Breusch Pagan/Cook Weisberg test for heteroskedasticity
Assumption: Normal error terms
Variable: Fitted values of LnShareFISMEduc
H0: Constant variance
chi2(1) = 318.88
Prob > chi2 = 0.0000
Figures A.6.xii: Results Breusch Pagan Test, Education

Testing for Collinearity

Results Variance Inflation Factor (VIF) for Model III:

Drinking Water

VIF		1/VIF
No Access Drinking Water	1.82	0.55
Municipal Income	1.69	0.59
Density	1.81	0.55
Growth Rate	1.19	0.837
No Access Sanitation	1.72	0.58
No Access Electricity	1.98	0.5
Dirt Floor	1.88	0.53
No Access Health	1.55	0.64
No Access Education	2.1	0.49
State Dummies		
5.310		

Table A.6.i.: Variance Inflation Factor, Model III (Drinking Water), 2016 FISM Data

Sanitation

VIF		1/VIF
No Access Sanitation	1.88	0.53
Municipal Income	1.66	0.60
Density	1.61	0.62
Growth Rate	1.19	0.84
No Access Water	1.89	0.53
No Access Electricity	2.03	0.49
Dirt Floor	1.87	0.53
No Access Health	1.63	0.61
No Access Education	1.95	0.51
State Dummies		
Mean VIF 8.17		

Table A.6.ii: Variance Inflation Factor, Model III (Sanitation), 2016 FISM Data

Electricity

VIF		1/VIF
No Access Electricity	2.04	0.48
Municipal Income	1.83	0.53
Density	1.68	0.47
Growth Rate	1.23	0.80
No Access Water	1.77	0.50
No Access Sanitation	1.79	0.46
Dirt Floor	1.90	0.50
No Access Health	1.54	0.64
No Access Education	1.84	0.47
State Dummies		
Mean VIF 6.4		

Table A.6.iii: Variance Inflation Factor, Model III (Electricity), 2016 FISM Data

Housing

VIF		1/VIF
Dirt Floor	2.08	0.48
Municipal Income	1.88	0.53
Density	2.09	0.48
Growth Rate	1.24	0.81
No Access Water	1.97	0.51
No Access Sanitation	1.78	0.56
No Access Electricity	2.1	0.49
No Access Health	1.57	0.64
No Access Education	2.15	0.47

State Dummies	
Mean VIF 8.55	

Table A.6.iv: Variance Inflation Factor, Model III (Housing), 2016 FISM Data

Health

VIF		1/VIF
No Access Health	1.71	0.58
Municipal Income	1.93	0.52
Density	1.76	0.57
Growth Rate	1.32	0.76
No Access Water	1.74	0.58
No Access Sanitation	1.97	0.50
No Access Electricity	2.37	0.42
Dirt Floor	1.94	0.51
No Access Education	2.03	0.49
State Dummies		
Mean VIF 14.530		

Table A.6.v.: Variance Inflation Factor, Model III (Health), 2016 FISM Data

Education

VIF		1/VIF
No Access Education	1.94	0.52
Municipal Income	1.89	0.53
Density	1.80	0.56
Growth Rate	1.26	0.79
No Access Water	1.73	0.58
No Access Sanitation	1.74	0.57
No Access Electricity	1.97	0.51
Dirt Floor	1.83	0.55
No Access Health	1.62	0.62
State Dummies		
Mean VIF 8.730		

Table A.6.vi.: Variance Inflation Factor, Model III (Education), 2016 FISM Data

Appendix 7 on Sensitivity Analyses Model III

Robustness to Different Measures of the Dependent Variable: Excluding Urbanization Spending

	(2016) Share FISM spent on Drinking Water	(2017) Share FISM spent on Drinking Water	(2018) Share FISM spent on Drinking Water	(2021) Share FISM spent on Drinking Water
No Access Drinking Water	.0349	.0033	-.0001	.0301
	(.0224)	(.0195)	(.0194)	(.0269)
Municipal Income	.0394	.1684***	.088	.0258
	(.0801)	(.0647)	(.0651)	(.0767)
Density	.33*	.1224	.0214	-.2621*
	(.1775)	(.0748)	(.123)	(.156)
Population Growth Rate	.0007	.0043	.0053	.0033
	(.0076)	(.0072)	(.0064)	(.0074)
No Access Sanitation	-.0041	.0242	.0243	.0323
	(.0223)	(.0204)	(.0223)	(.0386)
No Access Electricity	-.0158	-.0366	-.0253	.0117
	(.0334)	(.0276)	(.0255)	(.0426)
Dirt Floor	-.0401	.0046	.0248	-.1241***
	(.026)	(.022)	(.0219)	(.0479)
No Access Health Care	-.0126	-.042	-.0577	.02
	(.0583)	(.0513)	(.0533)	(.0638)
Primary Education not Completed	-.058	-.0837	.0395	-1.1226
	(.0944)	(.0573)	(.0649)	(.7173)
State Dummies	YES	YES	YES	YES
Constant	-2.136**	-3.382***	-2.2635***	-1.656**
	(.8632)	(.6473)	(.7133)	(.7476)
Observations	1513	1664	1558	1474
R-squared	.0724	.131	.1426	.1609

Robust standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table A.7.i.: Regression Results FISM Spending Excluding Urbanization Spending, Drinking Water

Notes: FISM spending shares are calculated as the share of FISM resources spent on a given infrastructure service as a share of all FISM resources except those spent on urbanization. All target regressors and the remaining access gap measures refer to logged per capita shares. Municipal Income refers to the logged municipal income per capita in 2015 (2020 for the rightmost column). Density refers to the population per km2 of municipal land in 2015 (2020 for the rightmost column). Growth Rate refers to the logged population growth rate between 2010 and 2015 (2015 to 2020 for the rightmost column).

	(2016) Share FISM spent on Drainage and Latrines	(2017) Share FISM spent on Drainage and Latrines	(2018) Share FISM spent on Drainage and Latrines	(2021) Share FISM spent on Drainage and Latrines
No Access Sanitation	-.006	-.0108	.002	-.2177***
	(.0276)	(.025)	(.0248)	(.0437)
Municipal Income	-.0521	-.19**	-.2362***	-.0792
	(.076)	(.0831)	(.0732)	(.0902)
Density	-.4225	.0033	.3682	.0027
	(.2993)	(.2388)	(.2449)	(.1433)
Population Growth Rate	-.0023	.0041	-.0171**	.0027
	(.0059)	(.0086)	(.0074)	(.0084)
No Access Drinking Water	-.0353	-.0568**	-.0892***	-.04
	(.0239)	(.0237)	(.0212)	(.0317)
No Access Electricity	-.014	-.0198	-.0158	-.1334**
	(.0332)	(.0344)	(.0297)	(.0551)
Dirt Floor	-.038	-.0503*	-.0389	.0448
	(.0295)	(.0293)	(.0271)	(.0537)
Health Care	.1353**	.1804***	.1981***	.072
	(.0675)	(.0639)	(.0633)	(.0769)
Primary Education not Completed	-.3183***	-.2993***	-.3318***	.4625
	(.0891)	(.0819)	(.0725)	(.9299)
State Dummies	YES	YES	YES	YES
Constant	-1.8413**	-1.1824	-.8265	-3.534***
	(.8158)	(.8698)	(.8432)	(1.0566)
Observations	1422	1467	1430	1203
R-squared	.116	.1638	.1753	.1975

Robust standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table A.7.ii: Regression Results FISM Spending Excluding Urbanization Spending, Sanitation

Notes: FISM spending shares are calculated as the share of FISM resources spent on a given infrastructure service as a share of all FISM resources except those spent on urbanization. All target regressors and the remaining access gap measures refer to logged per capita shares. Municipal Income refers to the logged municipal income per capita in 2015 (2020 for the rightmost column). Density refers to the population per km2 of municipal land in 2015 (2020 for the rightmost column). Growth Rate refers to the logged population growth rate between 2010 and 2015 (2015 to 2020 for the rightmost column).

	(2016) Share FISM spent on Electricity	(2017) Share FISM spent on Electricity	(2018) Share FISM spent on Electricity	(2021) Share FISM spent on Electricity
No Access Electricity	.025	.0259	-.0349	.1271**
	(.0299)	(.0323)	(.0327)	(.0557)
Municipal Income	.203**	.28***	.2486***	.1277
	(.0807)	(.08)	(.0768)	(.0904)
Density	.2245	.1729	.0866	-.1235
	(.221)	(.1189)	(.0797)	(.2477)
Population Growth Rate	.0003	-.0013	.0114	-.0276**
	(.0067)	(.0117)	(.0088)	(.0134)
No Access Drinking Water	-.0514**	-.0554**	.0083	-.063*
	(.0237)	(.0246)	(.023)	(.0357)
No Access Sanitation	.055**	.0646**	.0211	-.0235
	(.0261)	(.0258)	(.0261)	(.0484)
Dirt Floor	.004	-.017	.0151	-.1975***
	(.0258)	(.0248)	(.0256)	(.059)
No Access Health Care	.0731	.0392	-.0141	.0761
	(.0681)	(.0683)	(.0646)	(.0771)
Primary Education not Completed	-.1567**	-.2371***	-.029	-.7279
	(.0745)	(.0774)	(.0803)	(.8735)
State Dummies	YES	YES	YES	YES
Constant	-3.0885***	-4.4129***	-4.141***	-2.7343***
	(.9102)	(.844)	(.8681)	(.853)
Observations	1275	1334	1353	1124
R-squared	.1691	.1786	.1657	.216

Robust standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table A.7.iii: Regression Results FISM Spending Excluding Urbanization Spending, Electricity

Notes: FISM spending shares are calculated as the share of FISM resources spent on a given infrastructure service as a share of all FISM resources except those spent on urbanization. All target regressors and the remaining access gap measures refer to logged per capita shares. Municipal Income refers to the logged municipal income per capita in 2015 (2020 for the rightmost column). Density refers to the population per km2 of municipal land in 2015 (2020 for the rightmost column). Growth Rate refers to the logged population growth rate between 2010 and 2015 (2015 to 2020 for the rightmost column).

	(2016) Share FISM spent on Housing	(2017) Share FISM spent on Housing	(2018) Share FISM spent on Housing	(2021) Share FISM spent on Housing
Dirt Floor	.0118	-.007	.0184	-.0799*
	(.0324)	(.0291)	(.0295)	(.0471)
Municipal Income	.6616***	.5258***	.5014***	.4818***
	(.1681)	(.0812)	(.0728)	(.0758)
Density	.1457	.2368	.1868	-.1242
	(.198)	(.1779)	(.1938)	(.081)
Population Growth Rate	.0153	.0241***	.0135**	.0046
	(.0114)	(.0065)	(.0056)	(.0102)
No Access Drinking Water	-.0013	-.0168	-.0352	-.0737**
	(.0287)	(.0248)	(.0237)	(.0313)
No Access Sanitation	.0141	-.0015	-.0176	.1337***
	(.0257)	(.0268)	(.0242)	(.0481)
No Access Electricity	-.0531	-.0309	.0033	.0116
	(.0346)	(.032)	(.0336)	(.0514)
No Access Health Care	-.2387***	-.2122***	-.2166***	-.255***
	(.0738)	(.075)	(.06)	(.0641)
Primary Education not Completed	-.0981	-.0846	-.0287	-.9372
	(.1008)	(.0968)	(.0859)	(.9557)
State Dummies	YES	YES	YES	YES
Constant	-7.3552***	-7.085***	-6.9774***	-6.2806***
	(1.6001)	(.809)	(.8804)	(.706)
Observations	1185	1150	1118	941
R-squared	.2181	.2096	.259	.3

Robust standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table A.7.iv.: Regression Results FISM Spending Excluding Urbanization Spending, Housing

Notes: FISM spending shares are calculated as the share of FISM resources spent on a given infrastructure service as a share of all FISM resources except those spent on urbanization. All target regressors and the remaining access gap measures refer to logged per capita shares. Municipal Income refers to the logged municipal income per capita in 2015 (2020 for the rightmost column). Density refers to the population per km2 of municipal land in 2015 (2020 for the rightmost column). Growth Rate refers to the logged population growth rate between 2010 and 2015 (2015 to 2020 for the rightmost column).

	(2016) Share FISM spent on Health	(2017) Share FISM spent on Health	(2018) Share FISM spent on Health	(2021) Share FISM spent on Health
No Access Health Care	.2094	.0781	-.1819	.1002
	(.2102)	(.1289)	(.1181)	(.2235)
Municipal Income	.3662**	.3896**	.5713***	.5514
	(.1767)	(.1711)	(.1685)	(.3488)
Density	1.5603***	.9944***	.1241	.5504
	(.3994)	(.383)	(.845)	(.8021)
Population Growth Rate	-.0029	.0074	.0254	-.0232
	(.0097)	(.0167)	(.0166)	(.0182)
No Access Drinking Water	-.0294	-.1061**	-.0935**	-.0725
	(.0441)	(.0412)	(.0463)	(.101)
No Access Sanitation	-.0331	-.0442	.0197	-.1457
	(.0554)	(.0574)	(.0518)	(.1231)
No Access Electricity	-.0626	-.0406	-.0729	-.1022
	(.0653)	(.0634)	(.0744)	(.1478)
Dirt Floor	-.0797	-.0423	-.0658	-.0142
	(.0554)	(.0506)	(.0549)	(.1783)
Primary Education not Completed	-.119	-.2838*	-.2091	1.2507
	(.1768)	(.1656)	(.1383)	(2.0539)
State Dummies	YES	YES	YES	YES
Constant	-9.8218***	-9.1567***	-9.1328***	-8.2684***
	(1.708)	(1.5392)	(1.6406)	(2.8762)
Observations	539	542	473	219
R-squared	.2223	.2405	.2542	.3316

Robust standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table A.7.v.: Regression Results FISM Spending Excluding Urbanization Spending, Health

Notes: FISM spending shares are calculated as the share of FISM resources spent on a given infrastructure service as a share of all FISM resources except those spent on urbanization. All target regressors and the remaining access gap measures refer to logged per capita shares. Municipal Income refers to the logged municipal income per capita in 2015 (2020 for the rightmost column). Density refers to the population per km2 of municipal land in 2015 (2020 for the rightmost column). Growth Rate refers to the logged population growth rate between 2010 and 2015 (2015 to 2020 for the rightmost column).

	(2016) Share FISM spent on Education	(2017) Share FISM spent on Education	(2018) Share FISM spent on Education	(2021) Share FISM spent on Education
Primary Education not Completed	-.0556	-.055	-.1194*	-1.3158
	(.1018)	(.0722)	(.069)	(.9622)
Municipal Income	.2183**	-.0489	.0967	.2698**
	(.1101)	(.0924)	(.0861)	(.1196)
Density	.5175*	.5012*	-.5455**	-.0041
	(.2773)	(.3031)	(.2223)	(.6125)
Population Growth Rate	.0163**	.0127	.0042	-.0035
	(.0068)	(.008)	(.0067)	(.0093)
No Access Drinking Water	-.0286	-.0094	.014	-.0736*
	(.0246)	(.0225)	(.0209)	(.0421)
No Access Drainage	-.0326	.0031	-.0114	-.1029*
	(.0256)	(.023)	(.0238)	(.053)
No Access Electricity	-.0937	-.0191	-.0579*	-.1343**
	(.0737)	(.0315)	(.0324)	(.059)
Dirt Floor	.0244	-.0248	-.0307	.0915
	(.0421)	(.0282)	(.0282)	(.0723)
No Access Health Care	-.0267	-.0585	-.0023	-.1021
	(.0683)	(.0603)	(.0579)	(.0855)
State Dummies	YES	YES	YES	YES
Constant	-5.0073***	-2.3212***	-3.5713***	-6.23***
	(1.1149)	(.8553)	(.8415)	(1.107)
Observations	1231	1244	1235	859
R-squared	.1578	.1548	.1503	.2133

Robust standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table A.7.vi.: Regression Results FISM Spending Excluding Urbanization Spending, Education

Notes: FISM spending shares are calculated as the share of FISM resources spent on a given infrastructure service as a share of all FISM resources except those spent on urbanization. All target regressors and the remaining access gap measures refer to logged per capita shares. Municipal Income refers to the logged municipal income per capita in 2015 (2020 for the rightmost column). Density refers to the population per km2 of municipal land in 2015 (2020 for the rightmost column). Growth Rate refers to the logged population growth rate between 2010 and 2015 (2015 to 2020 for the rightmost column).

Robustness to Different Measures of the Dependent Variable: Drainage and Sanitation Coded Separately

Drainage and Latrines Subcategories and Recoding

Subcategories Drainage and Latrines	English Translation	Recoded Into
Drenaje Pluvial	Storm Drainage	Drainage
Drenaje Sanitario	Sanitary Drainage	Drainage
Lineas de Conduccion	Pipes	Drainage
Planta de Tratamiento de Aguas Residuales	Residual Water Treatment Plant	Drainage
Pozos de Absorcion	Absorption Wells	Drainage
Conexion a la red de drenaje o fosa septica	Connection to the Drainage Network or septic tank	Drainage
Sanitarios Secos/Letrinas	Dry Toilets/Latrines	Sanitation
Tanques Septicos Conectado a Fosa Septica o Drenaje	Septic Tanks connected to the drainage network	Drainage
Sanitarios con Biodigestores	Toilets with biodigesters	Sanitation

Table A.7.vii.: Drainage and Latrines Subcategories and Recoding (Data Sources: Secretaría de Bienestar 2016/2017/2018/2021)

Regression Results Recoded FISM Data

	(2016) Share FISM spent on Drinking Water	(2017) Share FISM spent on Drinking Water	(2018) Share FISM spent on Drinking Water	(2021) Share FISM spent on Drinking Water
No Access Drinking Water	.0363	.0002	-.0031	-.015
	(.0234)	(.0198)	(.0198)	(.0298)
Municipal Income	.0527	.2086***	.117*	.2132***
	(.0894)	(.0673)	(.0659)	(.0803)
Density	.4277**	.1555*	.006	-.2604*
	(.1857)	(.0834)	(.1421)	(.1505)
Population Growth Rate	.0027	.0107	.0058	.0116
	(.0085)	(.0074)	(.0067)	(.0087)
No Access Drainage	.0148	.0357*	.0059	-.0382
	(.0231)	(.0195)	(.0193)	(.0624)
No Access Sanitation	-.0053	.0207	.029	.1278*
	(.0252)	(.0215)	(.0231)	(.0672)
No Access Electricity	-.03	-.0493*	-.0299	.0286
	(.0338)	(.0276)	(.0259)	(.0457)
Dirt Floor	-.0351	-.0018	.0245	-.169***
	(.0258)	(.0231)	(.0225)	(.0506)
No Access Health Care	.017	-.0225	-.0565	-.0237
	(.0613)	(.0533)	(.0537)	(.0679)
Primary Education not Completed	-.085	-.1625***	-.0111	-2.5768***
	(.0974)	(.0598)	(.0659)	(.7779)
State Dummies	YES	YES	YES	YES
Constant	-2.7755***	-4.1268***	-3.1799***	-4.6343***
	(.9591)	(.6615)	(.6936)	(.767)
Observations	1513	1664	1558	1474
R-squared	.0704	.1372	.1558	.2052

Robust standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table A.7.viii.: Regression Results Drainage and Sanitation Separate, Drinking Water

Notes: All dependent variables refer to the logged share of the municipal FISM resources allocated to the infrastructure service in question. All target regressors and the remaining access gap measures refer to logged per capita shares. Municipal Income refers to the logged municipal income per capita in 2015 (2020 for the rightmost column). Density refers to the population per km2 of municipal land in 2015 (2020 for the rightmost column). Growth Rate refers to the logged population growth rate between 2010 and 2015 (2015 to 2020 for the rightmost column).

	(2016) Share FISM spent on Drainage	(2017) Share FISM spent on Drainage	(2018) Share FISM spent on Drainage	(2021) Share FISM spent on Drainage
No Access Drainage	-.0661**	-.018	.0169	.0839
	(.0266)	(.024)	(.0221)	(.0716)
Municipal Income	-.0393	-.1558*	-.1955***	.2133**
	(.0833)	(.0841)	(.0744)	(.0918)
Density	-.4235	.0375	.3768	.0217
	(.3184)	(.2394)	(.2488)	(.0915)
Population Growth Rate	.0025	.0075	-.0171**	.0097
	(.006)	(.0085)	(.0074)	(.0088)
No Access Drinking Water	.0028	-.0535**	-.0958***	-.0811**
	(.0246)	(.0246)	(.0218)	(.0335)
No Access Sanitation	.0104	-.0015	.0036	-.2672***
	(.0306)	(.0277)	(.0266)	(.0769)
No Access Electricity	-.0294	-.0254	-.0246	-.1515***
	(.0356)	(.0354)	(.031)	(.0574)
Dirt Floor	-.0577*	-.0521*	-.0465*	.0269
	(.0324)	(.0315)	(.0273)	(.0557)
No Access Health Care	.1809**	.1553**	.2097***	-.0235
	(.0767)	(.0663)	(.0655)	(.0765)
Primary Education not Completed	-.3153***	-.3515***	-.3763***	-.0471
	(.1018)	(.0841)	(.075)	(1.0238)
State Dummies	YES	YES	YES	YES
Constant	-2.5173***	-1.9576**	-1.6169*	-7.6695***
	(.9666)	(.9006)	(.8738)	(.9935)
Observations	1344	1467	1430	1203
R-squared	.1786	.1843	.1862	.1649

Robust standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table A.7.ix: Regression Results Drainage and Sanitation Separate, Drainage

Notes: All dependent variables refer to the logged share of the municipal FISM resources allocated to the infrastructure service in question. All target regressors and the remaining access gap measures refer to logged per capita shares. Municipal Income refers to the logged municipal income per capita in 2015 (2020 for the rightmost column). Density refers to the population per km2 of municipal land in 2015 (2020 for the rightmost column). Growth Rate refers to the logged population growth rate between 2010 and 2015 (2015 to 2020 for the rightmost column).

	(2016) Share FISM spent on Sanitation	(2017) Share FISM spent on Sanitation	(2018) Share FISM spent on Sanitation	(2021) Share FISM spent on Sanitation
No Access Sanitation	.0567	.0591	.0572	.1402
	(.0591)	(.0635)	(.0641)	(.3438)
Municipal Income	1.0279***	.2432	.5611**	.998***
	(.2222)	(.2248)	(.2255)	(.3337)
Density	-.2719	3.8961***	2.5631	-.9182
	(1.4246)	(1.4907)	(1.8123)	(5.7023)
Population Growth Rate	-.0154	-.0108	.0231	.0378
	(.0262)	(.0247)	(.0247)	(.0253)
No Access Drinking Water	-.1502**	-.1447***	-.1024**	.0854
	(.0624)	(.0519)	(.0518)	(.1127)
No Access Drainage	.0236	.0643	.009	.1004
	(.0672)	(.0681)	(.0727)	(.3062)
No Access Electricity	.0108	-.1055	-.112	-.0382
	(.0738)	(.0918)	(.0949)	(.2176)
Dirt Floor	.0353	.0436	.0201	.0246
	(.0636)	(.0596)	(.0596)	(.2121)
No Access Health Care	.0459	-.1213	-.0512	.2909
	(.1519)	(.1634)	(.1718)	(.1858)
Primary Education not Completed	-.5313***	-.109	-.1878	-9.651**
	(.1834)	(.2162)	(.2234)	(3.8796)
State Dummies	YES	YES	YES	YES
Constant	-12.0083***	-6.0072***	-8.8324***	-11.4985***
	(2.1044)	(2.0816)	(2.0876)	(2.9362)
Observations	271	244	229	141
R-squared	.4592	.4774	.4846	.554

Robust standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table A.7.x.: Regression Results Drainage and Sanitation Separate, Sanitation

Notes: All dependent variables refer to the logged share of the municipal FISM resources allocated to the infrastructure service in question. All target regressors and the remaining access gap measures refer to logged per capita shares. Municipal Income refers to the logged municipal income per capita in 2015 (2020 for the rightmost column). Density refers to the population per km2 of municipal land in 2015 (2020 for the rightmost column). Growth Rate refers to the logged population growth rate between 2010 and 2015 (2015 to 2020 for the rightmost column).

	(2016) Share FISM spent on Electricity	(2017) Share FISM spent on Electricity	(2018) Share FISM spent on Electricity	(2021) Share FISM spent on Electricity
No Access Electricity	.0222	.0156	-.0347	.1711***
	(.0301)	(.0319)	(.0326)	(.0616)
Municipal Income	.2719***	.3278***	.3157***	.3327***
	(.0838)	(.0824)	(.0776)	(.092)
Density	.3493	.1723	.1205	.0122
	(.2345)	(.1329)	(.0852)	(.2688)
Population Growth Rate	.0034	.002	.0103	-.022
	(.008)	(.0119)	(.009)	(.0143)
No Access Drinking Water	-.0468**	-.0478*	.0152	-.0844**
	(.0238)	(.0245)	(.0232)	(.0371)
No Access Drainage	-.0669**	-.0168	-.0401*	-.0112
	(.0284)	(.0254)	(.0239)	(.0673)
No Access Sanitation	.0882***	.0763***	.0402	.0228
	(.0304)	(.028)	(.0281)	(.0726)
Dirt Floor	.0223	-.0145	.0185	-.2927***
	(.0262)	(.0246)	(.0261)	(.0616)
No Access Health Care	.0865	.0368	-.0092	.0483
	(.0746)	(.0713)	(.066)	(.0796)
Primary School not Completed	-.1676**	-.2787***	-.0546	-1.918**
	(.0802)	(.0794)	(.083)	(.9035)
State Dummies	YES	YES	YES	YES
Constant	-4.2398***	-5.1838***	-5.2381***	-5.7592***
	(.9065)	(.8585)	(.8341)	(.8791)
Observations	1275	1334	1353	1124
R-squared	.191	.1965	.1704	.2665

Robust standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table A.8.xi: Regression Results Drainage and Sanitation Separate, Electricity

Notes: All dependent variables refer to the logged share of the municipal FISM resources allocated to the infrastructure service in question. All target regressors and the remaining access gap measures refer to logged per capita shares. Municipal Income refers to the logged municipal income per capita in 2015 (2020 for the rightmost column). Density refers to the population per km2 of municipal land in 2015 (2020 for the rightmost column). Growth Rate refers to the logged population growth rate between 2010 and 2015 (2015 to 2020 for the rightmost column).

	(2016) Share FISM spent on Housing	(2017) Share FISM spent on Housing	(2018) Share FISM spent on Housing	(2021) Share FISM spent on Housing
Dirt Floor	-.0043	-.0185	.0168	-.1118*
	(.0345)	(.0304)	(.03)	(.0602)
Municipal Income	.7283***	.5836***	.5491***	.7253***
	(.1711)	(.0836)	(.075)	(.0932)
Density	.2011	.2946	.2412	-.1827**
	(.2055)	(.1867)	(.1935)	(.0843)
Population Growth Rate	.0182	.0284***	.0141**	.0187
	(.0116)	(.0073)	(.0059)	(.0121)
No Access Drinking Water	-.0086	.0032	-.0382	-.1443***
	(.0296)	(.0262)	(.025)	(.0405)
No Access Drainage	.0352	-.0244	.0023	.0423
	(.0307)	(.0337)	(.0255)	(.0991)
No Access Sanitation	0	.0191	-.0106	.1121
	(.031)	(.0325)	(.0273)	(.1067)
No Access Electricity	-.0658*	-.0375	-.0042	.0631
	(.0352)	(.033)	(.0343)	(.0655)
No Access Health Care	-.23***	-.1923**	-.2131***	-.3172***
	(.0833)	(.0765)	(.0614)	(.0809)
Primary Education not Completed	-.1747*	-.1234	-.0726	-2.232**
	(.1033)	(.1009)	(.0886)	(1.0964)
State Dummies	YES	YES	YES	YES
Constant	-8.368***	-7.8644***	-7.7805***	-9.6347***
	(1.5955)	(.8444)	(.9122)	(.8777)
Observations	1185	1150	1118	941
R-squared	.2483	.2436	.2715	.326

Robust standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table A.7.xii: Regression Results Drainage and Sanitation Separate, Housing

Notes: All dependent variables refer to the logged share of the municipal FISM resources allocated to the infrastructure service in question. All target regressors and the remaining access gap measures refer to logged per capita shares. Municipal Income refers to the logged municipal income per capita in 2015 (2020 for the rightmost column). Density refers to the population per km2 of municipal land in 2015 (2020 for the rightmost column). Growth Rate refers to the logged population growth rate between 2010 and 2015 (2015 to 2020 for the rightmost column).

	(2016) Share of FISM spent on Health	(2017) Share of FISM spent on Health	(2018) Share of FISM spent on Health	(2021) Share of FISM spent on Health
No Access Health Care	.103	.0832	-.2057*	.1533
	(.2179)	(.1316)	(.123)	(.2144)
Municipal Income	.3961**	.4396**	.6609***	.6677**
	(.1796)	(.1712)	(.1751)	(.3349)
Density	1.5282***	1.1221***	.2495	1.1686
	(.4079)	(.4141)	(.8674)	(.8817)
Population Growth Rate	-.0025	.0084	.0261	-.0017
	(.0104)	(.0165)	(.0169)	(.0253)
No Access Drinking Water	-.0083	-.0872**	-.0955**	-.0407
	(.044)	(.0428)	(.0471)	(.0985)
No Access Drainage	-.0906*	-.0608	-.0532	.1269
	(.0489)	(.0465)	(.0482)	(.2326)
No Access Sanitation	-.0035	-.0403	.0346	-.1617
	(.0586)	(.0584)	(.0537)	(.2557)
No Access Electricity	-.0785	-.0246	-.0623	-.0626
	(.0657)	(.0678)	(.0756)	(.1312)
Dirt Floor	-.0494	-.039	-.0526	-.276
	(.0591)	(.0516)	(.0571)	(.1738)
Primary Education not Completed	-.123	-.3366**	-.2237	.5267
	(.1852)	(.166)	(.1426)	(2.1402)
State Dummies	YES	YES	YES	YES
Constant	-10.71***	-9.9989***	-10.3899***	-11.3034***
	(1.7174)	(1.552)	(1.7097)	(2.7426)
Observations	539	542	473	219
R-squared	.231	.2598	.2672	.3472

Robust standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table A.7.xiii: Regression Results Drainage and Sanitation Separate, Health

Notes: All dependent variables refer to the logged share of the municipal FISM resources allocated to the infrastructure service in question. All target regressors and the remaining access gap measures refer to logged per capita shares. Municipal Income refers to the logged municipal income per capita in 2015 (2020 for the rightmost column). Density refers to the population per km2 of municipal land in 2015 (2020 for the rightmost column). Growth Rate refers to the logged population growth rate between 2010 and 2015 (2015 to 2020 for the rightmost column).

	(2016) Share FISM spent on Education	(2017) Share FISM spent on Education	(2018) Share FISM spent on Education	(2021) Share FISM spent on Education
Primary Education not Completed	-.1613*	-.1456**	-.1734**	-2.2211**
	(.0967)	(.0716)	(.0696)	(.9901)
Municipal Income	.215**	-.0286	.128	.5513***
	(.1079)	(.0936)	(.089)	(.1245)
Density	.615**	.5786*	-.4703**	.1423
	(.27)	(.3016)	(.2366)	(.551)
Population Growth Rate	.0186***	.0164**	.0024	.0042
	(.0068)	(.008)	(.007)	(.009)
No Access Drinking Water	-.0383	-.0114	.0119	-.097**
	(.0252)	(.0229)	(.0219)	(.0417)
No Access Drainage	.0844***	.0209	.0332	.0788
	(.0254)	(.024)	(.0226)	(.1006)
No Access Sanitation	-.068***	.007	-.021	-.1436
	(.0254)	(.0244)	(.0235)	(.116)
No Access Electricity	-.1066	-.0339	-.0707**	-.1395**
	(.0743)	(.0322)	(.0332)	(.0619)
Dirt Floor	.0007	-.0213	-.0361	.0208
	(.0392)	(.0287)	(.0287)	(.0723)
No Access Health Care	-.0154	-.0646	.0319	-.0948
	(.0728)	(.0609)	(.0606)	(.0839)
State Dummies	YES	YES	YES	YES
Constant	-5.5923***	-2.8346***	-4.0811***	-9.9457***
	(1.1452)	(.8723)	(.88)	(1.1799)
Observations	1231	1244	1235	859
R-squared	.1694	.1573	.165	.2292

Robust standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table A.7.xiv: Regression Results Drainage and Sanitation Separate, Education

Notes: All dependent variables refer to the logged share of the municipal FISM resources allocated to the infrastructure service in question. All target regressors and the remaining access gap measures refer to logged per capita shares. Municipal Income refers to the logged municipal income per capita in 2015 (2020 for the rightmost column). Density refers to the population per km2 of municipal land in 2015 (2020 for the rightmost column). Growth Rate refers to the logged population growth rate between 2010 and 2015 (2015 to 2020 for the rightmost column).

Robustness to Different Measures for the Education Target Regressor

	(2016)	(2017)	(2018)	(2021)
	Share FISM spent on Drinking Water	Share FISM spent on Drinking Water	Share FISM spent on Drinking Water	Share FISM spent on Drinking Water
No Access Drinking Water	.0386*	.0052	-.0022	-.0299
	(.0232)	(.0196)	(.0196)	(.029)
Municipal Income	.0584	.2297***	.1184*	.2946***
	(.0872)	(.0675)	(.0663)	(.0778)
Density	.4275**	.1572*	.0057	-.1694
	(.1863)	(.0831)	(.1419)	(.1506)
Population Growth Rate	.0028	.0112	.0058	.0124
	(.0085)	(.0074)	(.0067)	(.0086)
No Access Sanitation	.0014	.0312	.0307	.1446***
	(.0238)	(.0204)	(.0228)	(.0416)
No Access Electricity	-.0291	-.0443	-.0291	.0432
	(.034)	(.0276)	(.0254)	(.047)
Dirt Floor	-.03	.0091	.0257	-.1503***
	(.0257)	(.0228)	(.0226)	(.0519)
No Access Health Care	-.0189	-.047	-.0596	.0007
	(.0604)	(.0542)	(.0549)	(.0663)
Illiteracy Rate	-.0974	-.1372**	-.0062	-.1868***
	(.0868)	(.0669)	(.0723)	(.0668)
State Dummies	YES	YES	YES	YES
Constant	-2.9516***	-4.3239***	-3.1911***	-5.431***
	(.9145)	(.6836)	(.712)	(.7951)
Observations	1513	1664	1558	1474
R-squared	.0703	.135	.1558	.2033

Robust standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table A.7.xv.: Regression Results Illiteracy Rate as Education Outcome Measure, Drinking Water

Notes: All dependent variables refer to the logged share of the municipal FISM resources allocated to the infrastructure service in question. All target regressors and the remaining access gap measures refer to logged per capita shares. Municipal Income refers to the logged municipal income per capita in 2015 (2020 for the rightmost column). Density refers to the population per km2 of municipal land in 2015 (2020 for the rightmost column). Growth Rate refers to the logged population growth rate between 2010 and 2015 (2015 to 2020 for the rightmost column).

	(2016) Share FISM spent on Drainage and Latrines	(2017) Share FISM spent on Drainage and Latrines	(2018) Share FISM spent on Drainage and Latrines	(2021) Share FISM spent on Drainage and Latrines
No Access Sanitation	.0054	-.003	.0159	-.1657***
	(.0275)	(.0252)	(.025)	(.0457)
Municipal Income	.016	-.1313	-.1759**	.2542***
	(.0783)	(.0839)	(.0737)	(.0926)
Density	-.3882	.0518	.4043*	.0123
	(.2906)	(.2358)	(.241)	(.0864)
Population Growth Rate	-.0002	.0066	-.0176**	.0084
	(.0058)	(.0084)	(.0075)	(.0089)
No Access Drinking Water	-.0338	-.0571**	-.0937***	-.079**
	(.0242)	(.0241)	(.0215)	(.033)
No Access Electricity	-.0251	-.0204	-.0144	-.1156**
	(.0337)	(.0351)	(.0296)	(.0559)
Dirt Floor	-.0242	-.0392	-.0271	.0464
	(.0306)	(.0306)	(.0267)	(.0566)
No Access Health Care	.087	.0943	.1205*	-.0228
	(.0711)	(.0674)	(.066)	(.0753)
Illiteracy Rate	-.4686***	-.4776***	-.489***	-.1335*
	(.0875)	(.0828)	(.0776)	(.0703)
State Dummies	YES	YES	YES	YES
Constant	-3.3279***	-2.5491***	-2.2007**	-8.2128***
	(.9425)	(.9157)	(.8788)	(1.044)
Observations	1422	1467	1430	1203
R-squared	.1436	.1907	.1949	.1661

Robust standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table A.7.xvi.: Regression Results Illiteracy Rate as Education Outcome Measure, Sanitation

Notes: All dependent variables refer to the logged share of the municipal FISM resources allocated to the infrastructure service in question. All target regressors and the remaining access gap measures refer to logged per capita shares. Municipal Income refers to the logged municipal income per capita in 2015 (2020 for the rightmost column). Density refers to the population per km2 of municipal land in 2015 (2020 for the rightmost column). Growth Rate refers to the logged population growth rate between 2010 and 2015 (2015 to 2020 for the rightmost column).

	(2016) Share FISM spent on Electricity	(2017) Share FISM spent on Electricity	(2018) Share FISM spent on Electricity	(2021) Share FISM spent on Electricity
No Access Electricity	.0257	.0216	-.0327	.1998***
	(.0304)	(.0318)	(.0325)	(.0613)
Municipal Income	.283***	.3474***	.3218***	.407***
	(.0828)	(.0825)	(.0775)	(.0921)
Density	.3796*	.1889	.1375	.1056
	(.2287)	(.1309)	(.0839)	(.2855)
Population Growth Rate	.0023	.0007	.0096	-.0211
	(.0077)	(.0118)	(.0089)	(.0143)
No Access Drinking Water	-.0538**	-.0509**	.0105	-.089**
	(.0238)	(.0245)	(.0229)	(.0368)
No Access Sanitation	.0707***	.0733***	.0336	.0671
	(.027)	(.0265)	(.0269)	(.0514)
Dirt Floor	.0293	-.0058	.0211	-.2597***
	(.0263)	(.0248)	(.0261)	(.0629)
No Access Health Care	.0147	-.0134	-.0346	.0433
	(.0702)	(.0719)	(.0647)	(.0827)
Illiteracy Rate	-.4423***	-.3992***	-.2202**	-.2548***
	(.086)	(.0899)	(.0858)	(.0868)
State Dummies	YES	YES	YES	YES
Constant	-5.0268***	-5.7098***	-5.664***	-6.6824***
	(.9139)	(.8856)	(.8452)	(.9308)
Observations	1275	1334	1353	1124
R-squared	.1976	.201	.1726	.27

Robust standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table A.7.xvii.: Regression Results Illiteracy Rate as Education Outcome Measure, Electricity

Notes: All dependent variables refer to the logged share of the municipal FISM resources allocated to the infrastructure service in question. All target regressors and the remaining access gap measures refer to logged per capita shares. Municipal Income refers to the logged municipal income per capita in 2015 (2020 for the rightmost column). Density refers to the population per km2 of municipal land in 2015 (2020 for the rightmost column). Growth Rate refers to the logged population growth rate between 2010 and 2015 (2015 to 2020 for the rightmost column).

	(2016) Share FISM spent on Housing	(2017) Share FISM spent on Housing	(2018) Share FISM spent on Housing	(2021) Share FISM spent on Housing
Dirt Floor	.0018	-.0174	.0164	-.1244**
	(.0348)	(.0302)	(.0299)	(.0586)
Municipal Income	.7405***	.5934***	.5475***	.7709***
	(.172)	(.0843)	(.0752)	(.0899)
Density	.2016	.2961	.239	-.1433*
	(.204)	(.1856)	(.1932)	(.0817)
Population Growth Rate	.0186	.0282***	.0142**	.0189
	(.0116)	(.0073)	(.0059)	(.0119)
No Access Drinking Water	-.0052	-.0007	-.0394	-.1487***
	(.0292)	(.0254)	(.0242)	(.0396)
No Access Sanitation	.0143	.0092	-.0119	.1934***
	(.0259)	(.0275)	(.0246)	(.0571)
No Access Electricity	-.0649*	-.0374	-.0063	.0724
	(.0352)	(.0332)	(.0345)	(.0647)
No Access Health Care	-.2169***	-.2082***	-.2081***	-.3082***
	(.0723)	(.0793)	(.0628)	(.0818)
Illiteracy Rate	-.0662	-.1812	-.0211	-.065
	(.1286)	(.1151)	(.1022)	(.0943)
State Dummies	YES	YES	YES	YES
Constant	-8.2086***	-8.1121***	-7.6556***	-9.9363***
	(1.7004)	(.8982)	(.9292)	(.9302)
Observations	1185	1150	1118	941
R-squared	.2464	.2438	.2711	.3233

Robust standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table A.8.xviii: Regression Results Illiteracy Rate as Education Outcome Measure, Housing

Notes: All dependent variables refer to the logged share of the municipal FISM resources allocated to the infrastructure service in question. All target regressors and the remaining access gap measures refer to logged per capita shares. Municipal Income refers to the logged municipal income per capita in 2015 (2020 for the rightmost column). Density refers to the population per km2 of municipal land in 2015 (2020 for the rightmost column). Growth Rate refers to the logged population growth rate between 2010 and 2015 (2015 to 2020 for the rightmost column).

	(2016) Share FISM spent on Health	(2017) Share FISM spent on Health	(2018) Share FISM spent on Health	(2021) Share FISM spent on Health
No Access Health Care	.2076	.0305	-.2277*	.127
	(.2139)	(.1326)	(.128)	(.2253)
Municipal Income	.421**	.4636***	.6473***	.6658**
	(.179)	(.1683)	(.1753)	(.3302)
Density	1.5709***	1.0864***	.2571	1.1675
	(.402)	(.3964)	(.8659)	(.889)
Population Growth Rate	-.0042	.0069	.0262	-.0023
	(.0103)	(.0163)	(.0168)	(.0252)
No Access Drinking Water	-.0187	-.0964**	-.1019**	-.0281
	(.0431)	(.0418)	(.0469)	(.098)
No Access Sanitation	-.0204	-.0484	.0156	-.0437
	(.0568)	(.058)	(.0517)	(.1173)
No Access Electricity	-.0822	-.0297	-.0723	-.0329
	(.0664)	(.0662)	(.0767)	(.1385)
Dirt Floor	-.0592	-.0336	-.057	-.2632
	(.0567)	(.0513)	(.0557)	(.1703)
Illiteracy Rate	-.2835	-.5045***	-.2477	-.0573
	(.2293)	(.1805)	(.1603)	(.2004)
State Dummies	YES	YES	YES	YES
Constant	-11.0636***	-10.6956***	-10.36***	-11.4343***
	(1.7848)	(1.548)	(1.7455)	(2.7846)
Observations	539	542	473	219
R-squared	.2313	.262	.2647	.3461

Robust standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table A.7.xix: Regression Results Illiteracy Rate as Education Outcome Measure, Health

Notes: All dependent variables refer to the logged share of the municipal FISM resources allocated to the infrastructure service in question. All target regressors and the remaining access gap measures refer to logged per capita shares. Municipal Income refers to the logged municipal income per capita in 2015 (2020 for the rightmost column). Density refers to the population per km2 of municipal land in 2015 (2020 for the rightmost column). Growth Rate refers to the logged population growth rate between 2010 and 2015 (2015 to 2020 for the rightmost column).

	(2016) Share FISM spent on Education	(2017) Share FISM spent on Education	(2018) Share FISM spent on Education	(2021) Share FISM spent on Education
Illiteracy Rate	-.1483	-.1095	-.1242	-.2769***
	(.106)	(.0833)	(.0803)	(.0963)
Municipal Income	.2708**	-.0185	.1359	.6198***
	(.1103)	(.0936)	(.0888)	(.1248)
Density	.5999**	.5757*	-.4748**	.4171
	(.2817)	(.3021)	(.2365)	(.5463)
Population Growth Rate	.0189***	.0169**	.0026	.0026
	(.0069)	(.008)	(.0069)	(.0089)
No Access Drinking Water	-.0259	-.0078	.0168	-.1013**
	(.0241)	(.0225)	(.0216)	(.042)
No Access Sanitation	-.0336	.0127	-.0119	-.0006
	(.0253)	(.0228)	(.0232)	(.0545)
No Access Electricity	-.0961	-.0332	-.0679**	-.0882
	(.0735)	(.0322)	(.0329)	(.063)
Dirt Floor	.0206	-.015	-.0279	.036
	(.0398)	(.0287)	(.0289)	(.0712)
No Access Health Care	-.0444	-.0818	.008	-.1272
	(.0676)	(.0624)	(.0623)	(.0854)
State Dummies	YES	YES	YES	YES
Constant	-6.1181***	-2.8918***	-4.1166***	-10.8695***
	(1.1737)	(.8966)	(.8929)	(1.2483)
Observations	1231	1244	1235	859
R-squared	.1638	.1557	.1618	.2322

Robust standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table A.7.xx: Regression Results Illiteracy Rate as Education Outcome Measure, Education

Notes: All dependent variables refer to the logged share of the municipal FISM resources allocated to the infrastructure service in question. All target regressors and the remaining access gap measures refer to logged per capita shares. Municipal Income refers to the logged municipal income per capita in 2015 (2020 for the rightmost column). Density refers to the population per km2 of municipal land in 2015 (2020 for the rightmost column). Growth Rate refers to the logged population growth rate between 2010 and 2015 (2015 to 2020 for the rightmost column).

Robustness to Outliers

Leverage Residual Plots

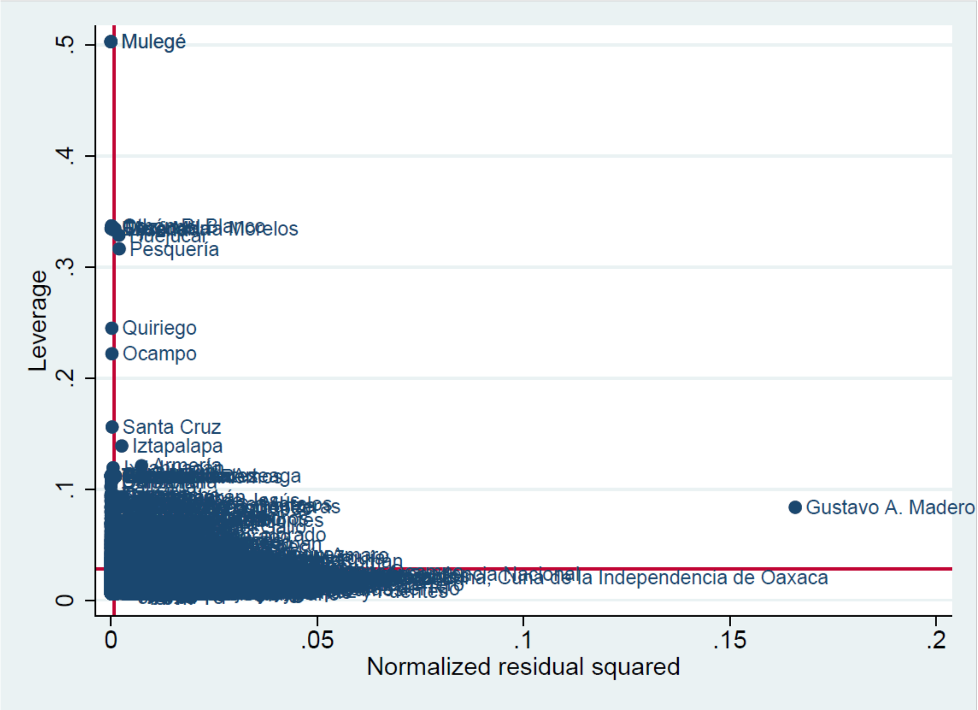

Figure A.7.i.: Leverage Residual Plot Model III Drinking Water, 2016 FISM Expenditure Data

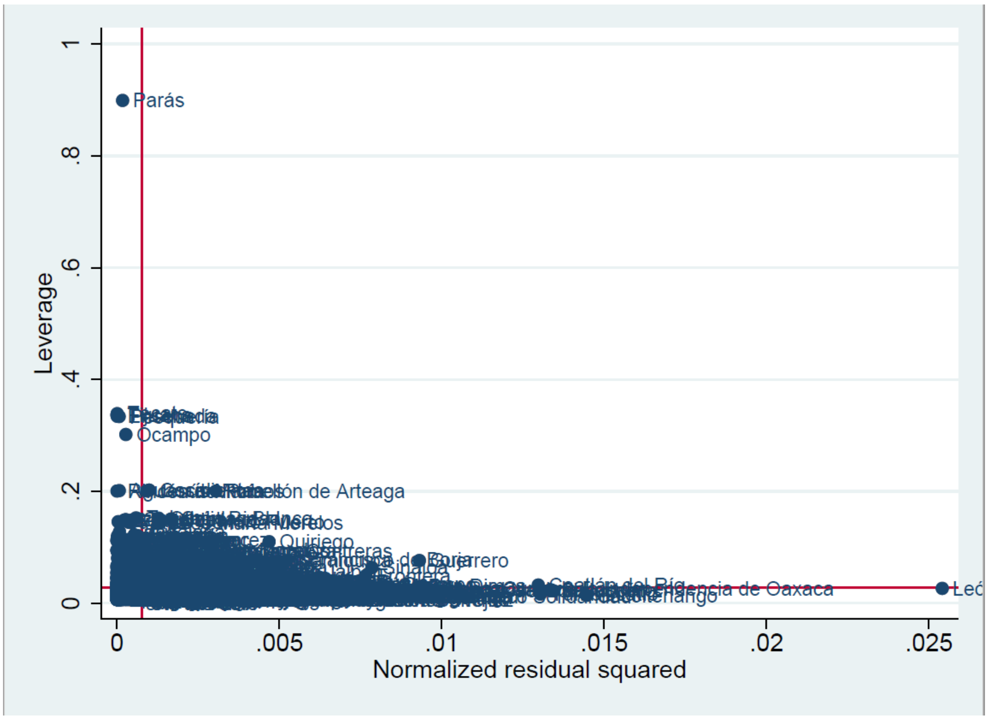

Figure A.7.ii: Leverage Residual Plot Model III Sanitation, 2016 FISM Expenditure Data

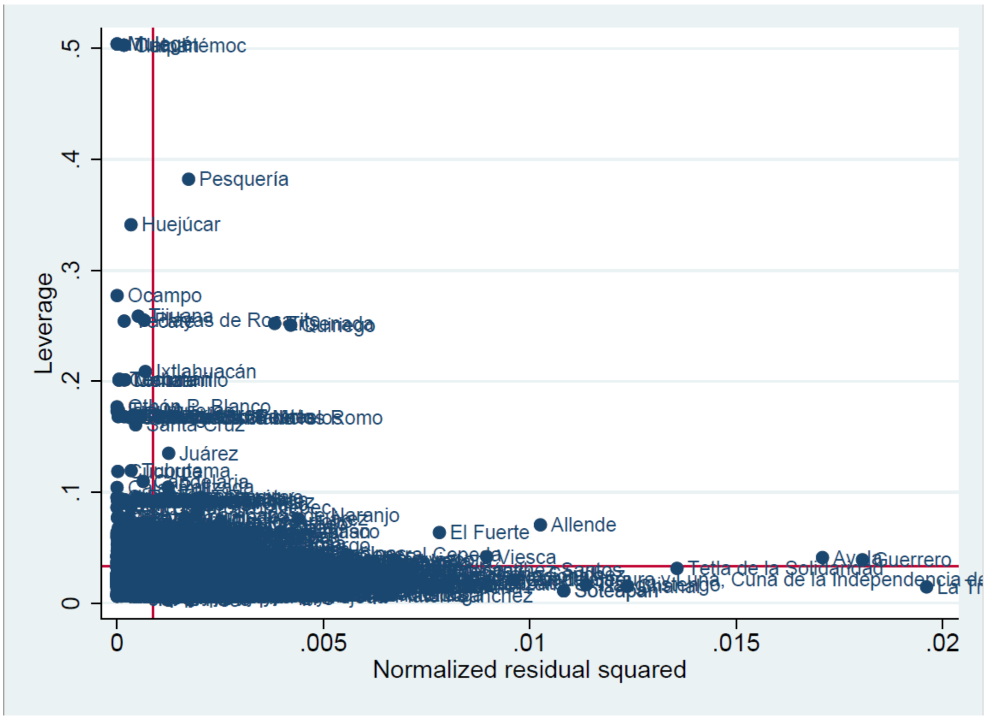

Figure A.7.iii.: Leverage Residual Plot Electricity, 2016 FISM Expenditure Data

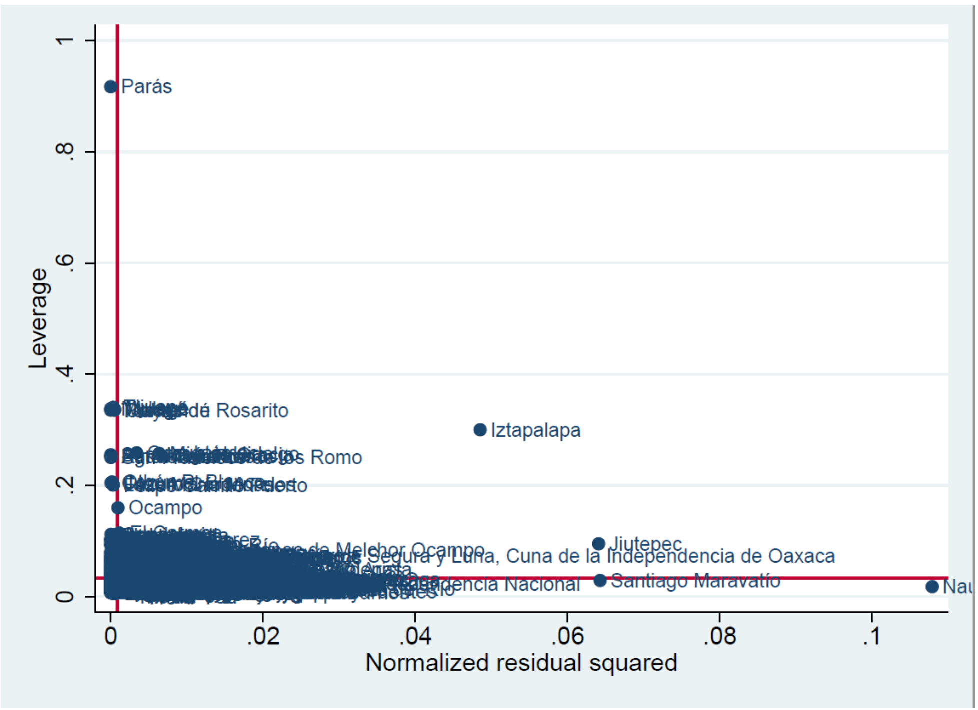

Figure A.7.iv.: Leverage Residual Plot Model III Housing, 2016 FISM Expenditure Data

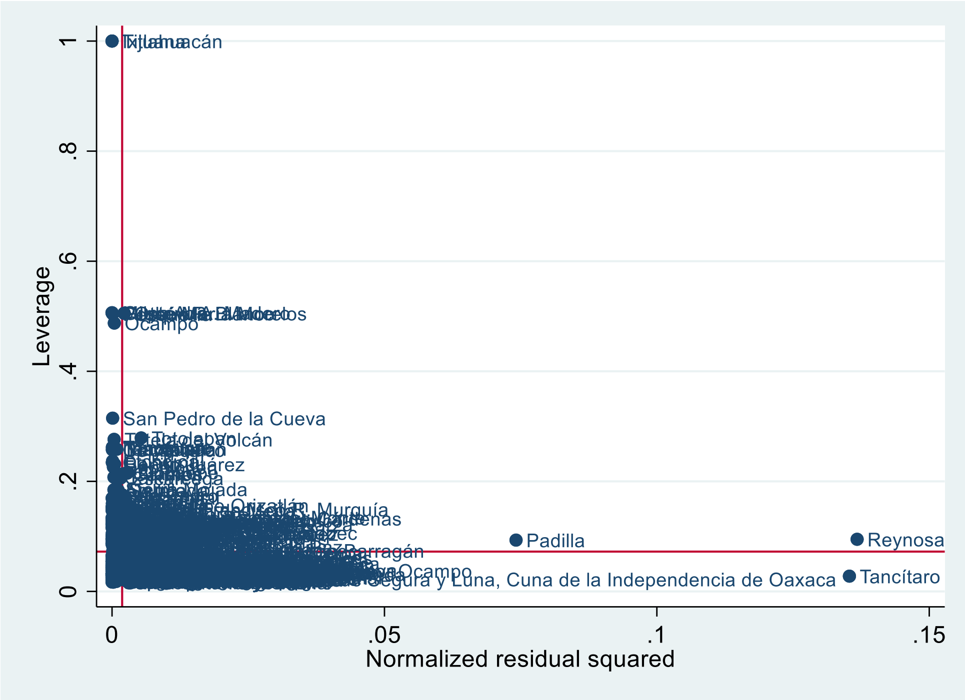

Figure A.7.v: Leverage Residual Plot Model III Health, 2016 FISM Expenditure Data

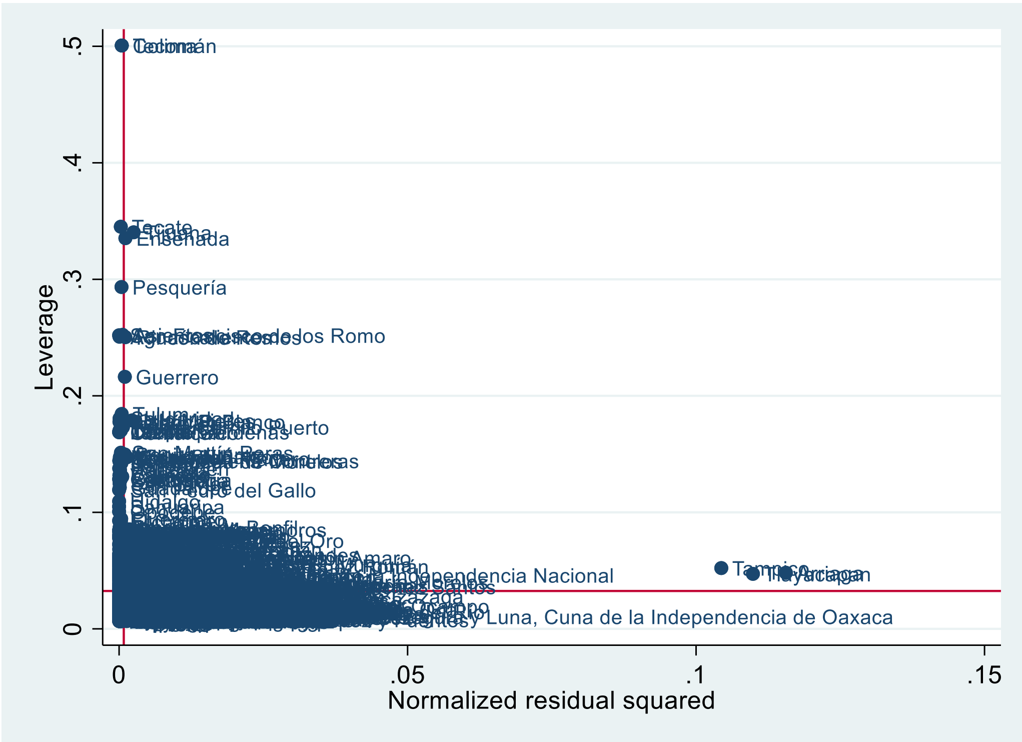

Figure A.7.vi: Leverage Residual Plot Model III Education, 2016 FISM Expenditure Data

Regression Results Robust Regression

	(2016) Share FISM spent on Drinking Water	(2017) Share FISM spent on Drinking Water	(2018) Share FISM spent on Drinking Water	(2021) Share FISM spent on Drinking Water
No Access Drinking Water	.0197	.0141	-.0194	-.0276
	(.0201)	(.0184)	(.0182)	(.0317)
Municipal Income	.0745	.2478***	.0563	.1914**
	(.0664)	(.0651)	(.0611)	(.0834)
Density	.3306	.0724	.0594	-.188
	(.2061)	(.1177)	(.1134)	(.1265)
Population Growth Rate	-.0005	.011	.0044	.0085
	(.0062)	(.0074)	(.0067)	(.0081)
No Access Sanitation	-.0045	.0234	.0327	.0958**
	(.0222)	(.0205)	(.021)	(.0428)
No Access Electricity	-.0223	-.0229	-.016	.0098
	(.0267)	(.025)	(.0252)	(.0484)
Dirt Floor	-.0149	.004	.035	-.1436***
	(.0236)	(.0212)	(.0218)	(.0489)
No Access Health	.0307	-.0285	-.054	-.0216
	(.0571)	(.0517)	(.0518)	(.0697)
Primary Education not Completed	-.1541**	-.1591***	-.0696	-2.8123***
	(.0721)	(.0614)	(.0603)	(.7835)
State Dummies	YES	YES	YES	YES
Constant	-3.087***	-4.3434***	-2.7012***	-4.3825***
	(.7067)	(.685)	(.6578)	(.8106)
Observations	1513	1664	1558	1474
R-squared	.1057	.1433	.1607	.1896

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table A.7.xxi: Regression Results Robust Regression, Drinking Water

Notes: Outliers and high leverage points are given less weight in the regression. All dependent variables refer to the logged share of the municipal FISM resources allocated to the infrastructure service in question. All target regressors and the remaining access gap measures refer to logged per capita shares. Municipal Income refers to the logged municipal income per capita in 2015 (2020 for the rightmost column). Density refers to the population per km2 of municipal land in 2015 (2020 for the rightmost column). Growth Rate refers to the logged population growth rate between 2010 and 2015 (2015 to 2020 for the rightmost column).

	(2016) Share FISM spent on Drainage and Sanitation	(2017) Share FISM spent on Drainage and Sanitation	(2018) Share FISM spent on Drainage and Sanitation	(2021) Share FISM spent on Drainage and Sanitation
No Access Sanitation	-.0079	-.0089	-.0097	-.1604***
	(.0236)	(.0226)	(.0225)	(.0463)
Municipal Income	-.0429	-.2464***	-.1768***	.2101**
	(.0687)	(.0711)	(.0676)	(.096)
Density	-.3229	-.1558	.1449	.0213
	(.2319)	(.2123)	(.2183)	(.148)
Population Growth Rate	.0016	.0021	-.0101	.0096
	(.0064)	(.0077)	(.0071)	(.0088)
No Access Drinking Water	-.0366*	-.0665***	-.0872***	-.0607*
	(.0209)	(.02)	(.0198)	(.0349)
No Access Electricity	-.0288	-.0148	-.0029	-.1678***
	(.028)	(.0276)	(.0265)	(.0551)
Dirt Floor	-.0077	-.0325	-.0299	.0178
	(.024)	(.0231)	(.0228)	(.0533)
No Access Health Care	.1696***	.1787***	.1948***	-.0068
	(.059)	(.0563)	(.0572)	(.0808)
Primary School not Completed	-.4156***	-.3572***	-.3224***	.2559
	(.0723)	(.0679)	(.0674)	(.9678)
State Dummies	YES	YES	YES	YES
Constant	-2.2617***	-.7302	-1.2093*	-7.5573***
	(.7649)	(.7463)	(.7335)	(.9693)
Observations	1422	1467	1430	1203
R-squared	.1705	.204	.185	.1681

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table A.7.xxii.: Regression Results Robust Regression, Sanitation

Notes: Outliers and high leverage points are given less weight in the regression. All dependent variables refer to the logged share of the municipal FISM resources allocated to the infrastructure service in question. All target regressors and the remaining access gap measures refer to logged per capita shares. Municipal Income refers to the logged municipal income per capita in 2015 (2020 for the rightmost column). Density refers to the population per km2 of municipal land in 2015 (2020 for the rightmost column). Growth Rate refers to the logged population growth rate between 2010 and 2015 (2015 to 2020 for the rightmost column).

	(2016) Share FISM spent on Electricity	(2017) Share FISM spent on Electricity	(2018) Share FISM spent on Electricity	(2021) Share FISM spent on Electricity
No Access to Electricity	.0128	.0151	-.0204	.1885***
	(.0301)	(.0321)	(.0297)	(.0558)
Municipal Income	.1975**	.2756***	.2864***	.254***
	(.0785)	(.0776)	(.0752)	(.0971)
Density	.1781	.1205	.1077	.0911
	(.2319)	(.1233)	(.1261)	(.2172)
Population Growth Rate	.0059	.0138	.0056	-.0075
	(.007)	(.0091)	(.0082)	(.0092)
No Access Drinking Water	-.0576**	-.052**	.0037	-.0824**
	(.0227)	(.0234)	(.0231)	(.0374)
No Access Sanitation	.0508*	.0639**	.0425	-.0313
	(.0261)	(.0259)	(.0258)	(.0505)
Dirt Floor	.006	-.0161	.0029	-.2586***
	(.0267)	(.0259)	(.0258)	(.0581)
No Access Health Care	.0138	.0528	.0559	.0535
	(.0641)	(.0662)	(.0664)	(.08)
Primary School not Completed	-.1606**	-.2121***	-.1367*	-2.6466***
	(.0775)	(.0794)	(.0742)	(.9132)
State Dummies	YES	YES	YES	YES
Constant	-3.709***	-4.4749***	-4.78***	-5.0804***
	(.8526)	(.8307)	(.7982)	(.926)
Observations	1275	1334	1353	1124
R-squared	.2043	.1973	.1754	.2687

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table A.7.xxiii: Regression Results Robust Regression, Electricity

Notes: Outliers and high leverage points are given less weight in the regression. All dependent variables refer to the logged share of the municipal FISM resources allocated to the infrastructure service in question. All target regressors and the remaining access gap measures refer to logged per capita shares. Municipal Income refers to the logged municipal income per capita in 2015 (2020 for the rightmost column). Density refers to the population per km2 of municipal land in 2015 (2020 for the rightmost column). Growth Rate refers to the logged population growth rate between 2010 and 2015 (2015 to 2020 for the rightmost column).

	(2016) Share FISM spent on Housing	(2017) Share FISM spent on Housing	(2018) Share FISM spent on Housing	(2021) Share FISM spent on Housing
Dirt Floor	.0065	-.0262	-.0049	-.0974
	(.028)	(.0267)	(.0269)	(.0608)
Municipal Income	.5421***	.5343***	.5271***	.7661***
	(.074)	(.077)	(.0706)	(.0971)
Density	.2596	.2873	.1317	-.1982
	(.1751)	(.1875)	(.1604)	(.1334)
Population Growth Rate	.0147	.0221***	.0073	.0231***
	(.0091)	(.0073)	(.0068)	(.0086)
No Access Drinking Water	-.0082	-.0142	-.0492**	-.1323***
	(.0233)	(.0232)	(.0222)	(.0391)
No Access Sanitation	-.0101	-.0259	-.0052	.1387**
	(.025)	(.0253)	(.0245)	(.0562)
No Access Electricity	-.0428	-.045	.0028	.0754
	(.0321)	(.0312)	(.0302)	(.0603)
No Access Health Care	-.1591**	-.198***	-.1633***	-.2839***
	(.0632)	(.0637)	(.0629)	(.0824)
Primary Education not Completed	-.1409	-.1025	-.1027	-2.0891*
	(.0858)	(.0833)	(.0802)	(1.1396)
State Dummies	YES	YES	YES	YES
Constant	-6.5392***	-7.5373***	-7.3642***	-9.827***
	(.8652)	(.8147)	(.7631)	(.9336)
Observations	1185	1150	1118	941
R-squared	.2773	.2929	.2887	.3507

Standard errors are in parentheses
**** $p<.01$, ** $p<.05$, * $p<.1$*

Table A.7.xxiv: Regression Results Robust Regression, Housing

Notes: Outliers and high leverage points are given less weight in the regression. All dependent variables refer to the logged share of the municipal FISM resources allocated to the infrastructure service in question. All target regressors and the remaining access gap measures refer to logged per capita shares. Municipal Income refers to the logged municipal income per capita in 2015 (2020 for the rightmost column). Density refers to the population per km2 of municipal land in 2015 (2020 for the rightmost column). Growth Rate refers to the logged population growth rate between 2010 and 2015 (2015 to 2020 for the rightmost column).

	(2016) Share FISM spent on Health	(2017) Share FISM spent on Health	(2018) Share FISM spent on Health	(2021) Share FISM spent on Health
No Access Health Care	.3483***	.1895	-.1903	.1032
	(.1272)	(.1323)	(.1437)	(.2576)
Municipal Income	.2697*	.4497***	.6615***	.6922*
	(.1572)	(.1682)	(.1939)	(.3632)
Density	1.3033***	1.1146**	1.3051*	1.2504
	(.4125)	(.4839)	(.7158)	(1.1512)
Population Growth Rate	-.0082	.0108	.0279*	-.0063
	(.0114)	(.0154)	(.016)	(.0243)
No Access Drinking Water	-.0636	-.0966**	-.1151**	-.0079
	(.0421)	(.042)	(.051)	(.11)
No Access Sanitation	-.0217	-.0633	.0138	-.036
	(.0501)	(.0535)	(.0574)	(.1491)
No Access Electricity	-.0986	-.0706	-.0505	-.0596
	(.0624)	(.0645)	(.0723)	(.154)
Dirt Floor	-.055	-.0437	-.07	-.2988
	(.0526)	(.0525)	(.062)	(.1893)
Primary Education not Completed	-.0707	-.2967**	-.2968*	.5628
	(.1621)	(.1503)	(.1596)	(2.5765)
State Dummies	YES	YES	YES	YES
Constant	-7.2685***	-9.9932***	-12.8342***	-11.6302***
	(1.5573)	(1.7554)	(2.2221)	(3.2374)
Observations	538	542	471	218
R-squared	.2811	.2668	.2707	.3115

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

Table A.7.xxv: Regression Results Robust Regression, Health

Notes: Outliers and high leverage points are given less weight in the regression. All dependent variables refer to the logged share of the municipal FISM resources allocated to the infrastructure service in question. All target regressors and the remaining access gap measures refer to logged per capita shares. Municipal Income refers to the logged municipal income per capita in 2015 (2020 for the rightmost column). Density refers to the population per km2 of municipal land in 2015 (2020 for the rightmost column). Growth Rate refers to the logged population growth rate between 2010 and 2015 (2015 to 2020 for the rightmost column).

	(2016) Share FISM spent on Education	(2017) Share FISM spent on Education	(2018) Share FISM spent on Education	(2021) Share FISM spent on Education
Primary Education not Completed	-.1774**	-.1067	-.1152*	-2.3683**
	(.0732)	(.0702)	(.0627)	(1.065)
Municipal Income	.2208***	.0116	.0278	.5762***
	(.0751)	(.0796)	(.0706)	(.1245)
Density	.3952	.4287*	-.2659	.0528
	(.2691)	(.2546)	(.1994)	(.5072)
Population Growth Rate	.0161**	.014*	.0031	-.0014
	(.0063)	(.0077)	(.0072)	(.0093)
No Access Drinking Water	-.0049	-.006	.0035	-.1157***
	(.0203)	(.0204)	(.0185)	(.0393)
No Access Sanitation	-.0487**	.02	.0043	-.0501
	(.0232)	(.0234)	(.0208)	(.0556)
No Access Electricity	-.0203	-.0531*	-.0391	-.103*
	(.0286)	(.0277)	(.0253)	(.0613)
Dirt Floor	-.0322	-.0163	-.0136	-.0272
	(.0241)	(.0236)	(.0226)	(.0659)
No Access Health Care	.0416	-.0486	.0093	-.1039
	(.06)	(.0588)	(.0538)	(.0901)
State Dummies	YES	YES	YES	YES
Constant	-5.4007***	-3.11***	-2.8801***	-10.3254***
	(.8345)	(.8404)	(.747)	(1.1809)
Observations	1231	1244	1235	859
R-squared	.1991	.1567	.1571	.2404

Standard errors are in parentheses
**** $p<.01$, ** $p<.05$, * $p<.1$*

Table A.7.xxvi: Regression Results Robust Regression, Education

Notes: Outliers and high leverage points are given less weight in the regression. All dependent variables refer to the logged share of the municipal FISM resources allocated to the infrastructure service in question. All target regressors and the remaining access gap measures refer to logged per capita shares. Municipal Income refers to the logged municipal income per capita in 2015 (2020 for the rightmost column). Density refers to the population per km2 of municipal land in 2015 (2020 for the rightmost column). Growth Rate refers to the logged population growth rate between 2010 and 2015 (2015 to 2020 for the rightmost column).

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