# Urban Sprawl and Social Capital: Evidence from Indonesian Cities*

Andrea Civelli
*University of Arkansas*

Arya Gaduh
*University of Arkansas*

Alexander D. Rothenberg†
*Syracuse University*

Yao Wang
*Syracuse University*

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**Abstract**

We use detailed data from cities in Indonesia to study the relationship between urban sprawl and social capital. For identification, we combine instruments for density with controls for community averages of observed characteristics, which control for sorting on observables and unobservables. We find that lower density increases trust in neighbors and community participation in urban areas of Indonesia, but it is also associated with lower interethnic tolerance. Heterogeneity analysis suggests that these findings are not explained by differential opportunity costs, but are instead reflective of social forces, including overall ethnic diversity and crime rates.

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†Corresponding author: 426 Eggers Hall, Syracuse, NY 13244-1020. Email: adrothen@maxwell.syr.edu.

## 1 Introduction

In many developing countries, urbanization is proceeding at an astonishing pace. The number of people living in urban areas in Asia increased by more than a billion from 1980 to 2010, and that same figure for Africa is expected to triple between 2018 and 2050 (ADB, 2012; UN, 2019). As rural to urban migration and rising incomes attract millions to cities in lower-to-middle income countries (LMICs), many of those cities are sprawling rapidly. Globally on average, cities are expanding spatially at twice their population growth rates (Angel et al., 2011).

Rapid urban sprawl raises concerns that low-density development may lead to the loss of a sense of community or more generally, social capital. Critics of urban sprawl have argued that compact, dense urban areas are more likely to promote social interaction (Jacobs, 1961), and because sprawl increases commuting times, it raises opportunity costs for community participation and interactions with neighbors (Putnam, 2000). Moreover, when sprawling development in the urban periphery offers new opportunities for sorting, the clustering of like-minded individuals may increase political polarization (Bishop, 2009).[1] If lower density erodes social capital and a sense of community, policies to reduce sprawl and mitigate these negative social externalities may be justified (Brueckner and Largey, 2008).[2]

However, it is not clear that low-density development will necessarily erode social capital. For instance, an older tradition in sociology, associated with the works of Simmel (1903) and Wirth (1938), argues that urban life overloads the senses, leading urban residents to limit social interactions with neighbors to preserve their mental energy. Trust may be harder to sustain in denser communities as anonymous interactions among people with diverse backgrounds and little shared norms increase (Habyarimana et al., 2007). Moreover, when density is associated with higher crime levels, its negative impact on trust and social capital might become amplified. On the other hand, density could instead facilitate greater intergroup interactions which could foster mutual understanding (Bazzi et al., 2019).

Although correlates of density and social interaction have been well studied in the U.S. and Europe (e.g. Glaeser and Gottlieb, 2006; Brueckner and Largey, 2008), little is known about how low-density development affects social capital in cities from low- and middle-income countries (LMICs). In this paper, we revisit the relationship between density and social capital, using uniquely rich data from cities in Indonesia, a middle-income and ethnically diverse country that has experienced rapid industrialization. To study multiple dimensions of social capital, we use cross-sectional data from the 2012 National Socioeconomic Survey (*Survei Sosial Ekonomi Nasional*, or *Susenas*). This survey provides detailed measures of various aspects of social capital, including trust in neighbors, community participation, and interethnic tolerance. Such measures reflect both "bonding" social capital, or within-group trust, and "bridging" social capital, or greater ties across groups (Putnam, 2000). We also use similar measures from a panel of households in the Indonesia Family Life Survey (IFLS).

In studying how urban sprawl affects social capital, we confront two fundamental identification challenges: simultaneity and sorting. The first identification problem is that social capital and density may be determined simultaneously, and omitted, place-specific characteristics may drive correlations in

[1] Growing political polarization has been a feature of many LMICs with democratic governments, including Brazil, India, and Indonesia (Carothers and O'Donohue, 2019).

[2] Related theoretical work has also argued that sprawl may reduce social interactions and increase segregation between groups, impacting equilibrium levels of employment (Sato and Zenou, 2015; Picard and Zenou, 2018).

both variables. An example of this "simultaneity problem" is that unobserved geographic or natural amenities may both facilitate cooperation over the provision of local public goods and also attract more people. The second identification problem is that people who differ in their willingness to contribute to local social capital may sort differentially into areas with different degrees of density. For instance, people with a strong dislike of other ethnic groups may sort into more homogeneous areas which tend to be less dense. Both identification problems make it challenging to draw causal inferences from observed correlations between population density and social capital measures.

Prior research has confronted the simultaneity problem by instrumenting for population density. For example, Brueckner and Largey (2008) use terrain ruggedness in the urban fringe and population density at a higher level of aggregation to instrument for census tract density. We follow a similar approach, instrumenting population density in Indonesian communities using two sets of variables: (1) soil characteristics, which were determined millions of years ago and influenced historical settlement patterns; (2) satellite-derived measures of built up areas in 1975, when Indonesia was still in the process of industrializing. Although these instruments differ in their coverage, sources of variation, and exclusion restrictions, they both have a strong first-stage relationship with density.

However, previous studies of the relationship between sprawl and social capital have not adequately addressed the second identification challenge, namely that sorting could still be confounding estimates, even if simultaneity is addressed. To tackle sorting, we combine our instruments for density with controls for community-level averages of observed individual characteristics. We include a rich vector of 38 controls for observed population and demographic characteristics, computed from 2010 census microdata. Altonji and Mansfield (2018) show that under certain assumptions, these controls for sorting on observables will also control for sorting on unobservables. We show that by combining their approach — which obtains partial identification of group-level treatment effects — with instrumental variables, we can point-identify the effects of density unconfounded by sorting or simultaneity.

We find that reductions in density increase trust in neighbors and community participation, echoing the findings of Brueckner and Largey (2008). These results are robust to controlling for sorting and simultaneity using different sets of instruments. However, we also find that lower density is correlated with reduced intergroup tolerance and cooperation, suggesting a potential negative social externality of sprawl. This latter result is somewhat less robust than the findings on trust and community participation, suggesting that sorting may play more of a role in driving these findings. Our results are robust to different specifications, and we find similar results when we use different data to test these hypotheses.

Our finding that greater density reduces within-village trust and community participation contradicts the hypothesis that variation in these forms of social capital is driven by higher opportunity costs for social interactions (Putnam, 2000; Glaeser and Gottlieb, 2006). A heterogeneity analysis based on proxies for individual-level opportunity costs further rejects this hypothesis. For example, if opportunity costs were important, it would be harder for wealthy individuals to participate in low density, suburban communities, attenuating the negative relationship between density and community participation for those individuals. Instead, we find even more negative effects of density on social capital for wealthier individuals. This result is robust to using other proxies for greater opportunity costs of time at the individual level, such as being married, having higher education, or commuting using a private motor vehicle. We also find more negative effects of density in more expansive and more rapidly sprawling cities, further contradicting the opportunity costs hypothesis.

On the other hand, we find that the relationship between density and social capital is more pronounced in cities with greater ethnic diversity. In such cities, greater sprawl may facilitate sorting of similar individuals into homogenous ethnic enclaves, increasing aspects of bonding social capital like community trust and participation. However, at the same time, these homogenous communities may also weaken interethnic tolerance and erode bridging social capital. We also find more pronounced effects of density on social capital in higher crime cities. This provides support for the idea that density reduces social capital because crime in dense areas increases fear, undermining trust and community participation (Glaeser and Sacerdote, 1999).

To better understand why lower density communities have greater levels of trust and community participation, even after accounting for sorting, we study an evolutionary trust game, following Manapat et al. (2013). In the model, individuals from different ethnic groups interact repeatedly by playing trust games with different members of their community, either as an investor or a trustee. An investor's potential return from trusting a co-ethnic trustee exceeds that from trusting a non co-ethnic trustee. In very dense communities, interactions are more likely to be anonymous, and players are less likely to have information about what strategies their opponents will play. This reduces the overall level of trust in equilibrium. Simulation results confirm that less information weakens trust, an effect that is robust to differences in ethnic composition. We also use the model data to effectively control for sorting in estimating the relationship between density and trust outcomes as we do in the empirical work.

Since the groundbreaking work of Putnam (2000), a large empirical literature that spans multiple disciplines tries to estimate the impact of urban sprawl on social capital outcomes, but existing evidence is mixed. Many studies find a negative relationship between various aspects of urban sprawl and social capital, but these results are difficult to interpret because they do not adequately address challenges of causal inference.[3] More recent studies have attempted to address the endogeneity of sprawl measures, such as density, through the use of instrumental variables or other methods. Although these studies do not tackle sorting, they tend to find that social capital is lower in higher density communities.[4] Our estimates, which use both instruments for density and controls for sorting, represent a significant methodological improvement over prior research.

We also contribute to the scarce literature studying the relationship between urban sprawl and social capital in developing country cities. With worse traffic congestion and lower-quality public transportation infrastructure, the potential impact of sprawl on social capital in LMICs could be even larger than in high-income countries. The few existing quantitative empirical papers on sprawl and social capital in LMICs, including Hemani et al. (2017) on neighborhood forms and social capital in Assam, India, and Zhao (2013) on segregation and sprawl in Beijing, suffer from identification problems. Another body of research uses qualitative methods, such as Connell (1999) on social isolation and sprawl in in Manila, Philippines, Caldeira (2001) on social segregation and fear in Sao Paolo, Brazil, and Coy and Pöhler (2002) on gated communities in Latin American cities. Our paper represents some of the best

[3]Prominent examples include Freeman (2001) on U.S. cities in the early 1990s, Leyden (2003) on the effects of walkable neighborhoods in U.S. cities, Besser et al. (2008) on commuting times and socially oriented trips, Wood et al. (2008) and Wood et al. (2012) on the impact of neighborhood design and social interactions in Western Australia, and Glaeser and Sacerdote (2000) on the impact of living in large apartment buildings.

[4]Examples of studies focusing on the United States and using instruments for density or other approaches to address the simultaneity problem include Glaeser and Gottlieb (2006), Brueckner and Largey (2008), and Nguyen (2010).

quantitative evidence on sprawl and social capital from a non-upper income context.[5]

The rest of this paper is organized as follows. Section 2 presents background information on urbanization and economic development in Indonesia. It also provides an overview of ethnic diversity and different aspects of social capital that are important for our analysis. Section 3 describes the different datasets we analyze. Section 4 explains how we define metropolitan areas, how we measure urban sprawl, and presents some evidence on correlates of sprawl. Section 5 describes our empirical strategy, extending the work of Altonji and Mansfield (2018), which enables us to address the two identification problems in studying the relationship between urban sprawl and social capital. Section 6 presents results of estimating the impact of population density on social capital from multiple datasets. Section 7 presents an evolutionary game theory model that sheds light on a key mechanism relating density to trust outcomes. Section 8 concludes.

## 2 Background

After a sustained period of economic growth and structural transformation since the late 1960s, Indonesia is now an upper-middle income economy. From 1970 to 1997 (immediately before the Asian Financial Crisis), per-capita GDP grew by approximately 4.4 percent a year, from just $772 in 1970 (in constant 2010 USD) to just over $2,400 in 1997. This sustained growth was accompanied by rapid structural change as agriculture's share of GDP rapidly declined, while the share of manufacturing and services grew dramatically (Hill, 1996).

As the structure of Indonesia's economy transformed, people increasingly migrated out of rural areas, leading to rapid urbanization. In the 1980s and 1990s, the country's urbanization rate grew by 3 percent a year—an even faster rate of urban growth than was experienced by many other East Asian countries, including China. Between 1990 and 2000, the rate of urban growth in Indonesia peaked, and the subsequent two decades saw much slower urban growth. The population living in urban areas more than doubled between 1970 and 2010, and today, about 151 million (or 56 percent) of Indonesians live in urban areas (Roberts et al., 2019). By 2045, when Indonesia will celebrate its centennial, approximately 220 million people are expected to live in urban areas, amounting to more than 70 percent of the population.

As urban growth continues, many Indonesian cities have experienced significant spatial expansion. Economic activities in the largest cities have sprawled well beyond their administrative borders, leading to the formation of agglomerations that span multiple districts.[6] This outward expansion has led to significant growth in the periphery of urban areas. Although the high economic productivity in urban cores attracted significant migration and growth, housing costs increased rapidly, and many urban residents relocated to the periphery. Indeed, between 2000 and 2010, about one-third of population growth in the peripheries of metro areas has come from migration (Roberts et al., 2019, Figure 1.12).

[5]In a recent paper, Muzayanah et al. (2020) also study sprawl and social capital outcomes in Indonesian cities using similar data as we do, but our methodologies differ substantially. As we do, they find that individuals living in higher density areas had lower levels of trust, were less likely to know their neighbors, and were less involved in community activities. But they do not look at interethnic tolerance, and they use multi-level logistic regression, failing to address any endogeneity issues.

[6]Roberts et al. (2019, Box 1.5) identified a total of 21 multidistrict metro areas, defined as metro areas whose labor markets span multiple districts.

Although variation in the extent of urban sprawl across cities is driven by geo-climatic and socio-economic characteristics, national development policies also played an important role (Civelli and Gaduh, 2018). For example, Indonesian policymakers have generally enacted policies favoring motor vehicles, including subsidizing the price of gasoline and investing in road construction, instead of making public transportation investments. At the same time, agencies responsible for managing land use and urban planning have generally been ineffective in implementing spatial plans and zoning regulations that could potentially limit sprawl (Rukmana, 2015).[7]

### 2.1 Social Capital and Diversity

Following Putnam (1995), we define social capital as the features of social life, including social networks, social norms, and trust, that enable community members to act together effectively to pursue shared objectives.[8] Using a set of indicators that capture this notion of social capital, Legatum Institute (2019a) ranked Indonesia 5th out of 167 countries.[9] Indonesia received this high ranking despite its ethno-religious diversity: it is one of the world's most diverse countries, with more than 1,200 self-identified ethnic groups whose members belong to one of six recognized religions.[10] In 2010, its national-level ethnic fractionalization index—the probability that any two residents, randomly-drawn from the national population, belong to different ethnicities—is around 0.81.

Indonesia's high ranking on the social capital index amidst its national diversity may appear to contradict an extensive empirical literature documenting the negative association between ethnic diversity and social capital (e.g. Alesina and La Ferrara, 2002, 2000; Costa and Kahn, 2003; Putnam, 2007). However, these contradictions disappear once we look at the local level. First, despite its national diversity, most Indonesian communities are very homogeneous, explained in part by the nation's archipelagic geography, which has separated ethnic groups by vast waterways for centuries. The median Indonesian village has a very low ethnic fractionalization index of 0.04. Second, the negative association between diversity and social capital resurfaces when we look at variations within Indonesia (Mavridis, 2015; Gaduh, 2016). Ethnic and religious tensions between groups have occasionally sparked violent conflicts throughout Indonesian history (see, e.g., Bertrand, 2004) and such conflicts are more likely when ethnoreligous groups are residentially clustered (Barron et al., 2009). Finally, the extent to which local diversity negatively affects social capital depends on whether diversity makes local inter-group competition more salient (Bazzi et al., 2019).

A variety of socio-cultural institutions foster social interactions at the local level, particularly in rural

[7]In a review of its experiences with urban planning, Rukmana (2015) finds that only 8 percent of the land permitted for housing in West Java was complaint with spatial plans. He argued that spatial planning was used to accommodate new development and to benefit real estate developers connected to the late Suharto's regime, rather than to control undesirable development.

[8]This definition is consistent with DiPasquale and Glaeser (1999), who argue that while social capital does not directly enter the utility function, it enhances the ability of neighbors to enjoy private investments in local amenities, such as community organizations, social groups, or local public goods.

[9]The Legatum Institute uses survey responses to construct a country-level social capital index that captures "the personal and family relationships, social networks and the cohesion a society experiences when there is high institutional trust, and people respect and engage with one another" (Legatum Institute, 2019b, p.7). The index is aggregated from the following sub-indices: (i) personal and family relationships; (ii) social networks; (iii) interpersonal trust; (iv) institutional trust; and (v) civic and social participation. Data for the social capital index come primarily, but not entirely, from the Gallup survey.

[10]The Indonesian government only recognizes six belief systems to be religions: (1) Buddhism; (2) Catholicism; (3) Confucianism; (4) Hinduism; (5) Islam; and (6) Protestantism.

areas. For example, "*Gotong royong*" is a norm of mutual and reciprocal assistance rooted in village, agrarian societies across Indonesia (Bowen, 1986). It encourages collective activities at the community level, such as mutual insurance, public good provision, collective work (e.g., harvesting), as well as celebrations (births and weddings) and commiserations (funerals) (see, e.g., Koentjaraningrat, 1985). Many of these social activities are organized by social, religious, or village-government organizations in the communities. Others, such as mutual insurance through *arisan* (i.e., rotating savings and credit association or ROSCA), were often developed organically by individual members.

Local-level institutions, and the social capital they generate, can help fill in some of the gaps in public goods left by the Indonesian government, both in rural and urban communities (Woolcock and Narayan, 2000; Bebbington et al., 2006). Many ethnic and religious institutions can naturally be found in both rural and urban communities. However, as cities expand into previously rural communities, the melding of rural and urban communities — what McGee (1991) describes as "*desakota*" (village-city) — means that some of the social institutions originating in rural areas (e.g., collective maintenance of public goods, mutual insurance) can also be found in many of Indonesia's urban communities (Beard and Dasgupta, 2006). Moreover, there is evidence that social interactions remain vibrant in these urban communities (Jellinek, 1991; Wilhelm, 2011). Miguel et al. (2006) found that rapid industrialization in Indonesia was positively associated with social capital within these industrializing regions, albeit at the cost of decreased social capital in neighboring regions.

# 3 Data

To study the relationship between social capital and urban sprawl in Indonesia, we combine several high-quality data sources. These include social capital measures from household survey data, population census data, and geospatial datasets. We briefly describe each of these data sources in turn.

**Social Capital Measures.** Our primary source of social capital outcomes is the 2012 National Socioeconomic Survey (*Survei Sosial Ekonomi Nasional*, or *Susenas*). The 2012 *Susenas* contains a detailed module that asked household-head respondents several questions about different aspects of social capital. These variables, described and summarized in Table 1, have been grouped into three broad categories. Panel A lists the set of questions asks about how well individuals trust their immediate neighbors, an important dimension of local social capital. Panel B lists the set of questions to measure participation in community activities and trust in community leadership. Panel C includes measures of tolerance in intergroup relations.

Our main specifications include responses to these questions for roughly 20,000 households living over 1,900 communities (*desa* or *kelurahan*). The community is the lowest administrative unit in Indonesia and comprises our main spatial unit of analysis.[11] Our sample of *Susenas* data contains observations that span 27 of Indonesia's 34 provinces. Our main analysis focuses on estimates of the mean effects of density on these outcomes, following Kling et al. (2007) as described below. Because most social capital responses are recorded on a 4 or a 5 point scale, we also use models that account for the ordered nature of these limited dependent variables in our analysis. In addition, the *Susenas* data also contain many mea-

[11] According to Census data, the communities in our sample had an average population of 9,766 in 2000 and 11,462 in 2010.

sures useful for individual-level controls, including age, education, marital status, employment sector, and employment status.

**Community-Level Demographic Characteristics.** We construct community-level demographic characteristics with data from the 2000 and 2010 Population Censuses. The census data allow us to construct multiple measures of average characteristics at the community level, including the size of the local population, the share of community members with different levels of educational attainment, and the share with different types of marital or migration status. The data also include questions on ethnicity, religion, and census block information that we can use to construct diversity and segregation measures.[12] As we describe below, community-averages of individual-level characteristics, which are calculated from these data, are crucial for our empirical strategy.

**Soil Quality Data.** We use data from SoilGrids to measure the characteristics of soils prevalent in Indonesian communities. SoilGrids is a global dataset that combines soil profile input data from roughly 150,000 sites with machine learning algorithms to provide global, 250-meter resolution predictions of many standard soil properties (Hengl et al., 2017).[13] These properties include (1) bulk density; (2) water content; (3) sand content; (4) clay content; (5) texture classification; and (6) soil taxonomy information.[14] Although measures of organic carbon content and soil pH are also available, we did not use these measures in our analysis, because they can be directly manipulated by human activity. We also only used measures for soil characteristics at a depth of 60 cm or more, as these capture variation in the subsoils and parent material of soils which were largely determined millions of years ago. Because we collected a large vector of soil characteristics, we use post-double-selection lasso techniques to select the appropriate soil variables in the analysis, as we describe below.

**Global Human Settlements Data.** To measure changes in the built up extent of areas in Indonesia, and to provide a baseline measure of population density before the industrialization period, we rely on data from the Global Human Settlement Layer (GHSL), produced by the European Commission's Joint Research Centre (JRC). These data were created by applying machine learning techniques to 40 years of Landsat satellite imagery to measure the locations and intensity of human settlements, including buildings and physical infrastructure (Pesaresi et al., 2016). More specifically, the 1975 GHS-BUILT grid contains estimates of built up areas based on data from Landsat 1's Multispectral Scanner (MSS) sensor. Coverage gaps and incomplete metadata information mean that for the 1975 epoch, large portions of Indonesia, including the entire island of Sumatra and portions of West Java, are missing.[15] To calculate sprawl measures for Indonesian cities and to measure the spatial extent of urban areas, we also use

[12]Note that because of regional conflicts in Aceh, Maluku, and Papua, the Census data in 2000 were estimated using population models.

[13]Hengl et al. (2017) harmonize characteristics information from soil samples collected across all 7 continents and multiple countries, and they train machine learning algorithms to predict those characteristics using covariates derived from remote sensing data. These covariates include: (1) information from digital elevation maps (e.g. slope, profile curvature); (2) long-term averages of MODIS observations (e.g. Enhanced Vegetation Index, NIR (band 4) and MIR (band 7) bands, land surface temperature, and snow cover); (3) land cover classes from GlobCover30; (4) average global precipitation; and (5) lithologic units (based on the Global Lithological Map, GLiM).

[14]The data we use are publicly available and stored on Google Earth Engine (`https://earthengine.google.com/`).

[15]Note that in measuring human settlements and instrumenting for density, we only use the GHS-BUILT grids from GHSL, and we refer to GHS-BUILT and GHSL interchangeably. Appendix Figure A.1 depicts the GHSL 1975 built up area data for communities in Indonesia. Locations with a larger percentage of built up areas are shaded in darker blue. The red portions of this figure indicate areas where the 1975 data are missing.

GHS-BUILT grids from 1990, 2000, and 2014, where coverage is considerably improved.[16]

**Geospatial Data on Administrative Boundaries and Topography.** Our analysis relies on administrative boundary shapefiles that identify community borders. These datasets are created by Indonesia's national statistical agency, *Badan Pusat Statistik* (BPS). We use these boundaries in combination with data from the *Harmonized World Soil Database (HWSD)* to construct basic topographic characteristics (e.g., ruggedness, slope, and elevation).

**Indonesia Family Life Survey (IFLS).** Another source of social capital outcomes comes from the Indonesia Family Life Survey (IFLS). The IFLS is a national longitudinal survey, representative of 83 percent of Indonesia's population, and it tracks more than 30,000 individuals in 5 waves over a 19 year period. These individuals are observed in more than 300 communities, which are located in 13 of Indonesia's 27 provinces. Although earlier IFLS data were collected, we only use data from wave 4 (2007) and wave 5 (2014), as the social capital model was only introduced in 2007.[17] The IFLS also contains detailed individual and household-level modules that we use to construct demographic and household characteristic controls. As we describe below, we use the IFLS panel data in two ways: (1) as cross-sections to confirm our main *Susenas* results; and (2) as individual-level panel data in a different approach to address sorting.

## 4 Measuring Urban Areas and Sprawl

To study the relationship between social capital and urban sprawl, we focus only on communities that comprise Indonesia's metropolitan areas. Although BPS provides rural and urban definitions, such measures often reflect political boundaries and do not capture their full economic borders. In the absence of reliable government definitions, there is no unambiguous way to classify urban areas and to determine which areas are part of which cities. This is a notoriously difficult problem, and multiple approaches for classifying urban areas and assigning geographic units to different cities have been suggested in the literature (e.g. Chomitz et al., 2005; Uchida and Nelson, 2010; Duranton, 2015).[18]

We adopt a morphological approach to city definitions (see Burchfield et al., 2006). We begin by identifying cities using a list of 83 urban regions in Indonesia—i.e., the set of administrative areas containing populations of 100,000 or more people in 2010—from the World Bank's East Asia and Pacific Urban Expansion (EAP-UE) maps project. We then carve out the actual physical boundaries of each city from the broader administrative areas in the EAP-UE identified urban regions. To do so, we identify the physical extent of urban areas based on patterns of high density built-up areas in 2000, as measured with 30-meter resolution GHS-BUILT data. For any built-up pixel in a map, its urban development density is defined as the percentage of built up space in the immediate square kilometer surrounding it.

We classify a city's *core area* as consisting of those built-up pixels that lie within the administrative boundaries of a metropolitan region and are surrounded by land that is more than 50 percent built-

[16]For our sample of urban areas in Indonesia, most of the input data for the 1975 GHSL come from Landsat tiles collected from 1972-1976, while most of the input data for the 1990 GHSL come from Landsat tiles collected in 1989-1990 (as shown in Gutman et al., 2013, Figure 3). More recent GHSL data are covered by annual Landsat data.

[17]IFLS 3 (2000) actually contains some community participation variables, but because it did not contain variables on trust and interethnic tolerance, we did not use it in the analysis.

[18]For a nice review of how different approaches may be used to define urban areas in Indonesia, see Bosker et al. (2019).

up. Typically, our definition of an urban core identifies a large, compact block of pre-existing built-up areas that correspond to the inner part of a city. However, smaller satellite centers that satisfy the core classification criteria might also arise around the main core.

Around this high-density core, and within the administrative boundaries of the metropolitan region, we define the *urban fringe* of the city— where an urban spatial expansion occurs between earlier years and 2014—using a 20-kilometer buffer area.[19] Appendix Figures A.3 and A.4 provide an illustration of the core-fringe identification for the metropolitan area of Bandar Lampung, which includes both the city (*kota*) of Bandar Lampung and the surrounding district (*kabupaten*) of Lampung Selatan. It is worth noting that in this procedure, the core of the metropolitan area does not necessarily match the administrative boundaries of the *kota*. Similarly, the metropolitan area is smaller than the simple union of the two administrative units. A more detailed description of the figure is left for the Appendix.

This approach identifies 80 urban metropolitan areas in Indonesia out of the 83 metropolitan areas initially listed by the EAP-UE project. The remaining 3 areas were dropped because they either lacked a well-identified core or did not exhibit sufficiently strong urban expansion in 2014. Figure 1 illustrates the geographic distribution of these 80 metropolitan areas. Half of these areas are located on the Inner Islands of Java and Bali, a quarter are on Sumatra, and the remaining quater are in other parts of the Outer Islands.[20]

The largest metropolitan area is Greater Jakarta (*Jabodetabekpunjur*), the economic and political center of Indonesia, which is a megacity of over 30 million people. Three other cities have more than 2 million inhabitants—these are Bandung, Surabaya, and Medan—while others have between 100,000 and 2 million people.[21] In our analysis below, we only include communities in our sample if they are part of at least one metro area, based on our definitions. A total of 20,717 communities are in our sample (out of 75,267 total in Indonesia), but only 2,233 communities from 76 metro areas were surveyed by the *Susenas* in 2012.

### 4.1 Measuring Sprawl and its Correlates

According to the GHSL data, 0.46 percent of Indonesia consisted of built up areas in 1990. By 2014, that figure had nearly doubled, increasing to 0.75 percent. To measure the extent of urban sprawl in various cities in Indonesia, we use the metropolitan area definitions in Figure 1 to construct a sprawl measure. Following Burchfield et al. (2006), we define a measure of sprawl as the share of open space in the immediate square kilometer around each pixel in the fringe that was newly built up in 2014. The sprawl index for the urban area is the average of those sprawl measures for these pixels. It provides a direct

[19] Burchfield et al. (2006) choose a 20-kilometer fringe because it contains almost 100 percent of the new developments around built-up areas in the U.S. at the beginning of their sample. Visual inspection of maps produced in our analysis confirms that this also holds for the spatial expansion of cities in Indonesia from 2000 to 2014.

[20] The concentration of metropolitan areas in the Inner Islands is not unexpected, and it closely reflects the differences in economic and urban development across the regions of the arcipelago. The Inner Islands are the most densely populated part of Indonesia, with a land area of around 8 percent of its total, but with 60 percent of its population. The Inner Islands are also more urban with around 70 percent of the country's urban population residing there in 2007 (World Bank, 2012, Table 2.3).

[21] Greater Jakarta, the world's second-most populated metropolitan area and the location of the country's capital (DKI Jakarta), is part of the Inner Islands. Modern economic activity has always been concentrated in the Inner Islands, with economic activities contributing about two-thirds of GDP in 2004 (Hill et al., 2009). The economic structure of the Inner and Outer Islands economies are also quite different, as manufacturing and services are concentrated on the Inner Islands, while agriculture is still predominant in the Outer Islands.

measure of the undeveloped land in the square kilometer surrounding an average urban development.

Figure 2 illustrates significant variation in the extent of urban sprawl across metropolitan areas. The sprawl index ranges from a minimum of 65.8 to a maximum of 92.3, with the mean equal to 80.3 and the standard deviation equal to 6.1. Metropolitan areas in the Outer Islands, where the share of urban land cover is still quite low and cities can grow into more rural and underdeveloped areas, are typically less compact. The index is generally lower for major cities like Jakarta and Bandung, as one might expect.

Urban sprawl is neither a recent phenomenon for Indonesia's metro areas, nor has it been uniform over time. Using the GHS-BUILT data for 1990, we also construct a sprawl index for urban areas between 1990 and 2000, and compare it to the sprawl index between 2000 and 2014. Figure 3 illustrates the scatter plot of the indexes for these two periods relative to the 45-degree line, where cities would fall if they experienced the same amount of sprawl over the two periods. While sprawl is positively correlated between the two periods, the pace of sprawl increased in the 2000's, as most cities lie above the 45-degree line. The effect is most pronounced for the cities with the smallest levels of sprawl in the 1990-2000 period.

Urban sprawl is also inversely related to the area of the urban core at baseline, as Figure 4 illustrates. On the $x$-axis, we plot the log urban core surface area (measured in 2000).[22] The size of the core can be interpreted as a proxy of the volume of the economic and business activity of a city. The inverse relationship between urban sprawl and baseline log urban core area is fairly linear, providing some evidence that larger and busier cities constitute a stronger force of attraction towards the center of the metropolitan area. Similar evidence is obtained by replacing the core size with the core population, as illustrated by Figure A.2 in the Appendix.

As cities sprawl, density falls and new housing constructed in the periphery offers increased opportunities for sorting. Figure 5 plots the relationship between a community's distance to the central business district (CBD) and several community-level variables measured from 2010 Census data.[23] The figure uses only data for communities that comprise the cores and peripheries of urban areas, our main analysis sample. Estimated local polynomial regression lines for the relationships are reported in red, along with confidence bands in gray. Panel A shows that population density declines substantially as distance to the CBD increases. Panel B plots the relationship between ethnic fractionalization and distance to the CBD, where fractionalization measures the probability that two community residents belong to different ethnic groups.[24] This figure shows that communities located farther from the center of the city are more ethnically homogeneous. Ethnic fractionalization is highest at the cores of metropolitan areas, but it displays a sharp decline of about 50% in the first 10km from the CBD, flattening out after that. Panel C shows that religious fractionalization declines in a similar way as distance to the CBD increases, tapering off again after a distance of 10 km. Panel D plots the relationship between city-level sprawl and ethnic segregation, using the Alesina and Zhuravskaya (2011) segregation measure applied to com-

[22]The Jakarta urban area has a surface of 1,144 km$^2$, while most other Indonesian cities are smaller than 100 km$^2$.

[23]Distance to the CBD is defined as the crow-flies distance between the centroid of the urban core polygon and the community's centroid, measured in kilometers.

[24]Formally, let $c$ index communities, and let $g$ index groups. The fractionalization index for community $c$ can be written as:

$$ELF_c = 1 - \sum_g \pi_{g,c}$$

where $\pi_{g,c}$ is the share of group $g$ in the population of community $c$.

munities in each city's urban core and periphery.[25] Ethnic segregation increases moderately as sprawl increases, suggesting that sprawling cities may provide more opportunities for sorting by ethnicity.

# 5 Empirical Strategy

In this section, we present our empirical approach to address the two key identification challenges that confound estimates of the relationship between density and social capital: (1) the simultaneous determination of density and social capital by unobservable place-specific variables and (2) sorting of individuals with lower or higher costs to contributing to social capital. Our empirical strategy builds on the control function approach of Altonji and Mansfield (2018) for bounding the variance of group-level treatment effects in the presence of sorting into groups, adding instruments to point identify group treatment effects. We describe key features of the procedure here but leave many details for Appendix B.

## 5.1 Sorting into Communities

Let $i$ index households and let $v \in \{1, ..., V\}$ index the discrete set of communities that comprises metropolitan areas in Indonesia. Household $i$'s consumer surplus from choosing to live in community $v$ is given by the following expression:

$$U_i(v) = \mathbf{W}_i \mathbf{A}_v - P_v + \varepsilon_{iv}\,, \tag{1}$$

where $\mathbf{A}_v$ represents a $(K \times 1)$ vector of amenities that characterize community $v$, $P_v$ is the price of living in community $v$, and $\varepsilon_{iv}$ is an idiosyncratic component specific to individual $i$'s tastes for living in community $v$. The term $\mathbf{W}_i$ represents a $(1 \times K)$ vector of weights capturing household $i$'s willingness to pay for different components of the amenity vector.

We partition $\mathbf{W}_i$ into three components: (1) $\mathbf{X}_i$, a vector of individual-level observables that influence social capital outcomes; (2) $\mathbf{X}_i^U$, a vector of individual-level unobservables that affect social capital outcomes; and (3) $\mathbf{Q}_i$, a vector of variables (observed and unobserved) that may influence preferences over amenities and sorting but have no impact on social capital outcomes:

$$\mathbf{W}_i = \mathbf{X}_i \boldsymbol{\Theta} + \mathbf{X}_i^U \boldsymbol{\Theta}^U + \mathbf{Q}_i \boldsymbol{\Theta}^Q\,,$$

where $\boldsymbol{\Theta}$, $\boldsymbol{\Theta}^U$, and $\boldsymbol{\Theta}^Q$ are the respective willingness to pay coefficients.

[25] Let $c$ index cities, let $v = 1, ..., V^c$ index communities within city $c$, and let $k = 1, ..., K$ index ethnic groups. The Alesina and Zhuravskaya (2011) segregation measure, a squared coefficient of variation between community ethnic group shares and the shares of ethnic groups in the city's population, is defined as follows:

$$S_c = \frac{1}{K-1} \sum_{k=1}^{K} \sum_{v=1}^{V^c} \frac{n_v}{N_c} \frac{(\pi_{k,v} - \pi_k^c)^2}{\pi_k^c}$$

where $K$ is the number of ethnic groups, $V^c$ is the number of communities in city $c$, $n_v$ is community $v$'s population, $N_c$ is the population of city $c$, $\pi_{k,v}$ is the share of ethnic group $k$ in community $v$, and $\pi_k^c$ is the share of ethnic group $k$ in city $c$'s population. If each community in city $c$ were comprised of a separate group, the index would be equal to 1, reflecting full segregation. If each community in city $c$ had ethnic group shares that were equal to the city's overall ethnic shares, the index would be equal to zero, reflecting perfect integration.

We assume that households take $P_v$ and $\mathbf{A}_v$ as given when making their location decisions, and that households choose the community that maximizes (1) using all information available to them. This information set includes housing prices in different locations, the vectors of amenities in those locations, the full set of individual weights, $\mathbf{W}_i$, and realizations of the idiosyncratic component, $\varepsilon_{iv}$ for all $v \in \{1, ..., V\}$.

Altonji and Mansfield (2018) prove that given this setup and under a relatively weak set of additional assumptions, the community-level expectation of individual-level unobservables that influence the social capital outcome, denoted by $\mathbf{X}_v^U$, is linearly dependent on group-level observables, $\mathbf{X}_v$. The intuition behind this argument is that sorting creates two vector-valued mappings: (1) a mapping between group level averages of observables in community $v$ and the amenities in that community, $\mathbf{X}_v = \mathbf{f}(\mathbf{A}_v)$; and (2) a mapping between group-level averages of unobservables in community $v$ and amenities, $\mathbf{X}_v^U = \mathbf{f}^U(\mathbf{A}_v)$. The authors provide conditions under which the first mapping, $\mathbf{f}$, is invertible, so we can write: $\mathbf{X}_v^U = \mathbf{f}^U\left(\mathbf{f}^{-1}(\mathbf{X}_v)\right)$. Under an additional assumption, the relationship between $\mathbf{X}_v^U$ and $\mathbf{X}_v$ induced by inverting these vector-valued functions is actually linear.

The strongest of these assumptions is the spanning assumption (assumption A5 in Altonji and Mansfield, 2018) which states that the coefficient vectors $\mathbf{\Theta}^U$ need to be linear combinations of $\mathbf{\Theta}$ and/or elements of $\mathbf{X}_i^U$ that are correlated with $\mathbf{X}_i$. One of the two sufficient conditions for this spanning assumption to hold is that $\mathbf{f}$ is invertible. A necessary condition for invertibility is that the dimension of $\mathbf{A}^{\mathbf{X}}$, the subset of amenities that affect the distribution of community averages, is less than the number of elements in $\mathbf{X}_v$. This would occur if $\mathbb{V}(\mathbf{X}_v)$ is rank deficient.

In our empirical implementation, we use a vector of 38 variables constructed from unit-level 2010 census data for $\mathbf{X}_v$. These variables include the community's average age, years of schooling, household size, the percentage of the community that is female, the percent who self-identify with different religions and with ethnicities, the share with different types of employment status and marital status, and the share who speak Indonesian at home. Appendix Table A.1 reports a principal components analysis of these 38 $\mathbf{X}_v$ variables. In our urban *Susenas* sample (column 2), only 27 factors explain 95 percent of the total variation in $\mathbf{X}_v$, 32 factors explain 99 percent of the total variation in $\mathbf{X}_v$, and 37 factors explain 100 percent of the total variation in $\mathbf{X}_v$. This suggests that for the urban *Susenas* sample, $\mathbf{X}_v$ is rank deficient.

Appendix Table A.2 also formally tests hypotheses about the rank of the $\mathbf{X}_v$ covariance matrix, using the test proposed by Kleibergen and Paap (2006). We find that for the full *Susenas* sample, we cannot reject the null hypothesis that the rank of the variance-covariance matrix of $\mathbf{X}_v$ is 34 against the alternative that it is 35 or greater. For the urban sample, we cannot reject the null hypothesis that the rank of the variance-covariance matrix of $\mathbf{X}_v$ is 28 against the alternative that it is 29 or greater. The results from both Appendix Table A.1 and Appendix Table A.2 suggest that because $\mathbf{X}_v$ is rank deficient, $\mathbf{f}$ is likely invertible, so that it can be used as a control function for sorting on unobservables.

### 5.2 Production of Social Capital

After households choose locations, we assume that the social capital outcome for household $i$ living in community $v$, denoted by $y_{vi}$, is produced according to the following linear, additively separable function:

$$y_{vi} = \mathbf{X}_i\beta + x_i^U + \theta \log \text{density}_v + \mathbf{W}_v\mathbf{\Gamma} + w_v^U + \eta_{vi} + \xi_{vi}\,. \tag{2}$$

Because many outcomes recorded in the 2012 *Susenas* data are either binary or take on discrete values (often 4 point scales), $y_{vi}$ is the continuous latent variable that determines these values. Equation (2) is composed of three sets of terms: (1) an individual component; (2) a community-level component; and (3) an idiosyncratic component. We describe each of these components in detail.

The individual component, $\mathbf{X}_i\beta + x_i^U$, includes a row vector, $\mathbf{X}_i$, collecting individual $i$'s observed attributes that affect average willingness to contribute to the social capital outcome. The parameter $\beta$ measures how those observed attributes increase or decrease $y_{vi}$. The second part of the individual component consists of a scalar, $x_i^U \equiv \mathbf{X}_i^U\beta^{\mathbf{U}}$, which summarizes the contribution of unobserved individual characteristics ($\mathbf{X}_i^U$) to social capital outcomes.

The community-level component, $\theta \log \text{density}_v + \mathbf{W}_v\mathbf{\Gamma} + w_v^U$, contains three terms. The first is a measure of log population density at the community-level, and the key object of interest, $\theta$, is the parameter that measures the semi-elasticity of social capital outcomes with respect to density. The second component is a row vector, $\mathbf{W}_v$, capturing the influence of other observed community-level characteristics on social capital outcomes. Finally, the third term, $w_v^U \equiv \mathbf{W}_v^U\mathbf{\Gamma}^U$, represents a scalar that summarizes the contribution of unobserved neighborhood characteristics to the social capital outcome.

The idiosyncratic component, $\eta_{vi} + \xi_{vi}$, contains $\eta_{vi}$ which captures deviations in community contributions to social capital across individuals living in that community. Some factors determining $\eta_{vi}$ may be captured by observed and unobserved community-level variables (e.g. $\log \text{density}_v$, $\mathbf{W}_v$, and $w_v^U$). This component also contains $\xi_{vi}$ which captures other influences to $i$'s social capital outcome that are determined after household $i$ arrives in community $v$, but are unpredictable given $\mathbf{X}_i$, $x_i^U$, $\log \text{density}_v$, $\mathbf{W}_v$, $w_v^U$, and $\eta_{vi}$. Such influences could include shocks to local public goods influencing certain individuals and communities, or local labor market shocks that make it harder or easier to participate in the community.

We partition the remaining group-level variables (excluding log density), $\mathbf{W}_v$, into $\mathbf{W}_v = [\mathbf{X}_v, \mathbf{W}_{2v}]$, and we partition their coefficients analogously, so that $\mathbf{\Gamma} = [\mathbf{\Gamma}_1, \mathbf{\Gamma}_2]$. The term $\mathbf{X}_v$ includes community averages of individual-level observables, while the term $\mathbf{W}_{2v}$ includes community-level characteristics that are not mechanically related to community composition. In our baseline specifications, these include pre-determined, exogenous natural amenities, such as elevation or ruggedness, which may make it easier or harder to sustain a social capital outcome. This notation lets us we rewrite equation (2) as follows:

$$y_{vi} = \mathbf{X}_i\beta + x_i^U + \theta \log \text{density}_v + \mathbf{X}_v\mathbf{\Gamma}_1 + \mathbf{W}_{2v}\mathbf{\Gamma}_2 + w_v^U + \eta_{vi} + \xi_{vi}\,.$$

### 5.3 An IV Estimator for $\theta$

Let $\widetilde{\mathbf{X}}_{iv} \equiv [\mathbf{X}_i, \mathbf{X}_v, \mathbf{W}_{2v}]$ collect the observed variables that do not include log density, and let $\widetilde{\beta} = [\beta, \mathbf{\Gamma}_1, \mathbf{\Gamma}_2]$ collect their parameters. Also let $u_{iv} = x_i^U + w_v^U + \eta_{vi} + \xi_{vi}$ collect the unobserved components. Using this notation, we can simplify (2) even further:

$$y_{vi} = \theta \log \text{density}_v + \widetilde{\mathbf{X}}_{iv}\widetilde{\beta} + u_{iv}\,.$$

Let $\mathbf{Z}$ denote a vector of instruments for density and let $\widetilde{\mathbf{X}}_{iv}$ act as instruments for themselves. An IV estimator for $\theta$ can be written as:

$$\widehat{\theta}_{IV} = \left(\mathbf{Z}'\mathbf{M}_{\widetilde{\mathbf{X}}} \text{log density}\right)^{-1} \mathbf{Z}'\mathbf{M}_{\widetilde{\mathbf{X}}}\mathbf{y}\,, \tag{3}$$

where $\mathbf{M}_{\widetilde{\mathbf{X}}}$ is an orthogonal projection matrix for $\widetilde{\mathbf{X}}$.[26] We show in Appendix B that $\widehat{\theta}_{IV}$ is an unbiased estimator of $\theta$ if it satisfies the following moment condition:

$$\mathbb{E}\left[ w_v^U \;\middle|\; \mathbf{Z}, \widetilde{\mathbf{X}}, \text{log density} \right] = 0\,.$$

Crucially, our density shifters, $\mathbf{Z}$, need to be uncorrelated with community-level unobservables that influence overall social capital in the community. We next describe two different sets of instruments for density and discuss the plausibility of their exclusion restrictions.

**Soil Quality.** Stable, fertile soils historically attracted greater numbers of people to settle in specific areas. To measure soil attributes, we use data from SoilGrids to capture various soil characteristics predominant in Indonesian communities, including (1) bulk density; (2) water content; (3) sand content; (4) clay content; (5) texture; and (6) soil taxonomy information. Because soil mineralogy and the parent materials of soils were determined millions of years ago but are correlated with population density today, they should have a strong first stage relationship with population density.[27] Similar geologic instruments have been used in prior work (e.g Hoxby, 2000; Black et al., 2002; Rosenthal and Strange, 2008; Combes et al., 2010).

There are two key concerns with using soil characteristics as an instrument for density. The first is the exclusion restriction: soil attributes need to only affect social capital outcomes today through their effect on density. As long as fertile land and stable soils are no longer relevant drivers of local wealth, because local employment in agriculture is no longer sizable, the exclusion restriction should be satisfied. Because we focus on cities where agricultural employment is not important, this seems sensible. As discussed in Section 3, we also only use soil attributes measured at a depth of 60 cm or more, ensuring that they are unaffected by human activity, and we exclude certain measures that are easily changed by human activity, such as organic carbon content and soil pH. The second concern is that we have a large number of soil attributes to choose from, measured at different depths, and many of these are correlated. We use post-double-selection lasso techniques to select the appropriate instruments in the analysis, following Belloni et al. (2012).[28]

**GHSL 1975.** Using long lags of population density to instrument for the size of the current local population has been a standard identification strategy since the pioneering work of Ciccone and Hall (1996). We work with a proxy of historical population data derived from satellite imagery, namely measures of the built up extent of communities in 1975. These data measure the spatial distribution of the population

[26]This matrix is given by: $\mathbf{M}_{\widetilde{\mathbf{X}}} = \mathbf{I} - \widetilde{\mathbf{X}}\left(\widetilde{\mathbf{X}}'\widetilde{\mathbf{X}}\right)^{-1}\widetilde{\mathbf{X}}'$.

[27]Dell and Olken (2019) emphasize that Dutch colonial production activities are correlated with the suitability of the local environment, but they also emphasize that a suitable environment is not sufficient for attracting density. For example, there were plenty of suitable areas that could have been chosen as locations for sugar factors, but they were not.

[28]Note also that in the empirical analysis, we use soil quality measure conditional on metropolitan area fixed effects. Much of the soil quality variation is across metropolitan areas, not within areas, and this reduces the identifying variation.

and economic activity when Indonesia was a much poorer country, and before much industrialization and structural transformation had occurred.[29]

In order for the 1975 measure to be a suitable instrument, the first stage relationship relies upon some persistence in the spatial distribution of the population. The exclusion restriction requires that the local drivers of social capital today are different from those before Indonesia's industrialization and structural transformation. One concern is that some permanent location characteristics are driving both past population locations and contemporaneous social capital outcomes. A leading candidate is favorable geography, such as low elevation and less rugged terrain. We control for these attributes in our baseline specifications.

### 5.4 Mean Effect Analysis

When estimating the impact of population density on a number of closely related outcomes, we create summary impact measures using a mean effect analysis, following Kling et al. (2007). To estimate mean effects, we first form groups of related outcomes, where a single outcome for individual $i$ in community $v$ is given by $y_{iv}(k)$, and $k = 1, ..., K$ indexes outcomes. We first modify the signs of each variable in the group so that increases denote greater social capital (e.g. improved trust, increased community participation, or greater intergroup tolerance). Next, we simultaneously estimate (2) for all $K$ outcomes, using a SUR system and a stacked vector of the standardized $y(k)$'s as the dependent variable. The mean effect size we report is simply an estimate of the weighted average effect of density on this group of outcomes, where each effect is weighted by the outcome's standard deviation. Formally, this is given by:

$$\tau = \frac{1}{K} \sum_k \frac{\theta_k}{\sigma_k}\,, \tag{4}$$

where $K$ is the total number of outcomes in the grouping, $\theta_k$ is the effect of density on outcome $k$, and $\sigma_k$ is the standard deviation of outcome $k$.[30]

## 6 Results

**First Stage.** In Table 2, we assess the first stage relationship between log density in 2010 and two different sets of instrumental variables: (1) soil characteristics; and (2) measures of the built up area in 1975. We report parameter estimates from the following regression equation:

$$\text{log density}_{c,v} = \alpha_c + \mathbf{z}'_{c,v}\beta + \varepsilon_{c,v}\,, \tag{5}$$

[29] An ideal measure of historical population information would come from the 1930 Census, administered by the Dutch colonists, as this was the first village-level population census of the country (Dell and Olken, 2019). However, such data would need to be hand-matched to current village names, a painstaking exercise.

[30] To calculate the mean effect size $\tau$ and compute standard errors, we follow the supplementary appendix of Kling et al. (2007) and use a seemingly unrelated regressions (SUR) system to estimate the effect of population density on individual outcomes. Standard errors are obtained from the variance-covariance matrix of the SUR system. This approach allows us to estimate a single mean effect across all individuals in the 2012 *Susenas*, even when missing values are reported for certain individuals' responses to different outcomes. More details can be found in Appendix B.3.

where $v$ indexes communities, $c$ indexes urban areas, $\alpha_c$ denotes a city-specific intercept, $\mathbf{z}_{c,v}$ denotes a vector of instruments, and $\varepsilon_{c,v}$ is an error term.

Column 1 of Table 2 reports coefficients of the relationship between log density and various soil characteristics, all measured at a depth of 60 cm or below. Because we have a large vector of soil attributes which are all plausibly exogenous and may potentially impact density, we use lasso regression select the appropriate variables in this regression, following Belloni et al. (2014). We find that within urban areas, population density in 2010 was positively related to the density of the parent material and negatively related to the parent material's sand and water content. Density was also lower in communities whose parent material had a sandy clay texture. In addition, 13 different indicators for soil classification were also significant (coefficients not shown). The overall $F$-statistic for the regression is fairly large (176.4), and within urban areas, the regression explains roughly 33 percent of the variation in density.

Column 2 reports estimates of the elasticity of density in 2010 with respect to the log share of built up areas measured in 1975. Note that the sample size in this regression falls substantially, because of missing GHS-BUILT 1975 data for most of Sumatra. The elasticity of density today with respect to built up areas in 1975 is nearly 0.4 and highly significant, and the first stage $F$-stat is substantial (2334.2). Within urban areas, this single measure explains roughly 58 percent of the variation in density. Overall, the results from Table 2 suggest that our two instrumental variable sets both have a strong first stage relationship with population density, the key dependent variable in our analysis.

**Baseline Results.** To estimate the impact of density on social capital outcomes, we run linear instrumental variable regressions of the following form:

$$y_{vi} = \mathbf{X}_i\beta + \theta \log \text{density}_v + \mathbf{X}_v\mathbf{\Gamma}_1 + \mathbf{W}_{2v}\mathbf{\Gamma}_2 + \varepsilon_{vi}, \tag{6}$$

where $\mathbf{X}_i$ is a vector of individual-level observables, $\mathbf{X}_v$ is a vector of group averages of individual characteristics of people living in community $v$ (constructed from 2010 census microdata), $\mathbf{W}_{2v}$ are community characteristic controls that are not mechanically related to sorting, and $\varepsilon_{vi}$ is an error term. To illustrate our empirical strategy, Table 3 shows the results for a single outcome variable, namely trust in neighbors. For ease of interpretation, we have coded $y_{vi}$ as a binary variable (coarsening the 4-point index), so that the regression is a linear probability model. However, we use the full indices for all variables in the mean effect analysis below and we employ limited dependent variable models as robustness checks. Standard errors are clustered at the sub-district level.

In Panel A of Table 3, we report estimates of $\theta$ in (6) from separate regression specifications, where we set $\mathbf{\Gamma}_1 = 0$ as a baseline. These estimates measure the unconditional impact of density on trust in neighbors, omitting controls for sorting. In column 1, our OLS specification finds that increasing log density by 1 (or increasing density by 2.72 people per km) reduces the probability of trust in neighbors index by 2 percent. Although highly significant, this is a moderate effect size, equivalent to roughly 5 percent of a standard deviation in the index.

One way of interpreting this effect size is to consider how trust in neighbors changes when moving from an average neighborhood in the suburbs to an average neighborhood near the CBD. On average, log density near the CBD for cities in our sample is approximately 8.8, while around 20 km away, log density declines to 6.7. So, we can multiply $\widehat{\theta}$ by 2.1 to find that moving from an average suburban neighborhood to one near the CBD reduces trust in neighbors by 4.1 percent, roughly 10 percent of a standard deviation in the index.

Columns 2 and 3 report the relationship between density and trust in neighbors estimated from instrumental variables specifications. Column 2 applies a post-double-selection lasso estimator to select the best soil characteristic instruments, following Belloni et al. (2012), while Column 3 uses 2SLS/GMM. Overall, the estimate of $\theta$ remains highly significant and has a similar effect size, increasing the coefficient magnitude to -0.03 to -0.04 in the IV specifications.[31] In both IV columns, the Kleibergen-Papp Wald Rank $F$-Stat, a generalization of the first-stage $F$-statistic for multiple instrumental variables, is large. The Kleibergen and Paap (2006) LM test rejects the null of weak instruments of the endogenous density variable. Overall, the results in Table 3 point to a well-specified IV model.

In Panel B, we report results of the full model, where we include individual-specific variables, $\mathbf{X}_i$, community-specific characteristics, $\mathbf{W}_{2v}$, and averages of 38 different individual-level variables at the community level, $\mathbf{X}_v$, to control for sorting. In columns 2 and 3, the estimates of the effect of density on trust in neighbors increase slightly and remain significant at conventional significance levels. Although the Kleibergen-Papp Wald Rank $F$-Stat falls in the Panel C specifications, the Kleibergen and Paap (2006) LM tests still reject the null of weak instruments of the endogenous density variable, suggesting that the IV model is still well specified, even after adding controls for sorting.

At the bottom of the table, we report p-values of $F$-tests for the significance of $\mathbf{\Gamma}_1$ and $\mathbf{\Gamma}_2$. These tests typically reject the null that they are jointly equal to zero, which suggests that controls for sorting and controls for community-level covariates matter for predicting outcomes. We also run an $F$-test that compares $\theta_A$, the estimate of $\theta$ from Panel A to $\theta_B$, the estimate of $\theta$ from Panel B. In the soil IV specification, we reject the hypothesis that these two estimates are equal, but in the GHSL 1975 IV specification, we cannot. Overall, the results from Table 3 suggests that across IV specifications, greater density moderately reduces trust in neighbors, and that this effect is causal and robust to controls for sorting on observables and unobservables.[32]

**Mean Effect Analysis.** In Table 4, we report estimates of $\tau$ from (4), the mean effect size of log density on different types of social capital outcomes. Separate panels are reserved for the three different groupings of outcomes (as described in Table 1) and as in Table 3, different columns report results from different estimation strategies while different rows indicate the presence of different controls. In Panel A, we see that greater density reduces trust in neighbors. This effect is robust to different IV strategies and to controls for sorting (row 2). Based on an $F$-test, we can reject the joint hypothesis that the coefficients on the $\mathbf{X}_v$ controls are equal to zero for all outcomes, so these controls clearly matter for predicting outcomes. However, for both IV specifications, we cannot reject the hypothesis that estimates of $\tau$ from row 1 are different from row 2. This suggests that the relationship between density and trust in neighbors is causal and robust to both controls for sorting and simultaneity.

To interpret the mean effect size, consider increasing density by moving from an average suburban neighborhood (20 km away from the CBD) to a neighborhood by the CBD (i.e. increasing log density

[31] Although estimates of $\beta$ and $\mathbf{\Gamma}_2$ are supposed from Panel A, Table 3, Appendix Table A.3 reports these coefficients. Trust in neighbors falls with education and has an inverse U relationship with age.

[32] In Appendix Table A.4, we report the full set of estimates of $\mathbf{\Gamma}_1$ from the specification in Panel C, Table 3 (supressing estimates of $\beta$ and $\mathbf{\Gamma}_2$). A greater share of recent migrants reduces trust in neighbors, while an increased share of "ever migrants" increases trust in neighbors. The sizes of shares of certain ethnicities are also related to trust in neighbors.

by 2.1). This increase in density reduces average trust in neighbors by between 0.10 and 0.12 standard deviations ($\sigma$), depending on the choice of IV. This moderate effect size is much larger than, for example, the impact of an additional year of schooling on average trust in neighbors (-0.002 $\sigma$).

In Panel B, we find that greater density is associated with reduced community participation. This effect is robust to controls for $\mathbf{X}_v$, suggesting that sorting and simultaneity do not confound the relationship. Increasing density by moving 20 km from a suburban community to a community by the CBD causes a 0.13-0.15 $\sigma$ reduction in community participation, a moderate effect size. This effect size is substantially larger than the impact of an additional year of schooling on community participation (0.008 $\sigma$). This effect could have important policy implications, and efforts to increase participation in higher density communities, perhaps through greater outreach or community organizing, may reverse these trends. The findings of Panels A and B echo those of Brueckner and Largey (2008) on the negative effects of density on social interactions in U.S. cities.

However, in Panel C, we find that greater density is associated with increased intergroup tolerance. This can be interpreted either as a causal impact of density, an outcome of sorting (i.e., individuals who dislike other ethnic groups may sort into less dense and more homogeneous areas), or a combination of both. Our findings do not strongly support a single hypothesis. We find that the estimates of the impact of density on intergroup tolerance differ across the IV specifications and are not always robust to sorting controls, except in column 3 (GHSL 1975 IV). This suggests such estimates may partly reflect sorting.[33]

**Specification Checks.** We conduct a number of specification checks to ensure the robustness of our main results. In Appendix Tables A.8, A.9, and A.10, we report the individual-outcome results from a binary linear probability model, instead of the linear-index specifications used as the basis for Table 4. Before estimating these models, we coarsen the dependent variable into binary variables, where a 1 indicates positive social capital outcomes and a 0 does not. Although the magnitudes of the estimated effects differ, the general conclusions of Table 4 are robust to this specification.

Next, we take two approaches for addressing the limited nature of the dependent variables in our analysis. First, in Appendix Tables A.11, A.12, and A.13, we again coarsen multiple responses into binary variables. We then estimate the impact of density on individual outcomes using a binary probit model with instrumental variables. Second, in Appendix Tables A.14, A.15, and A.16, we estimate effects using ordered probit models with instruments, adopting the control function procedure proposed by Chesher and Rosen (2019). Our results on the impact of density on outcomes remain robust to both limited dependent variable specifications.

**Excluding Agricultural Communities.** One concern with our urban sample is that communities in the periphery may contain a significant number of households employed in agriculture. For such households, soil characteristics may still directly affect social capital outcomes today, violating the exclusion restriction. To address this concern, we first use the 2010 census data to define an agricultural household as one where all of its employed members report working in agriculture. In Appendix Table A.17, we re-run our analysis after dropping communities where 75 percent or more households are classified as

[33] The individual linear-index outcome results for trust and community participation, upon which estimates of $\tau$ in Table 4, Panel A and Panel B are based, can be found in Appendix Tables A.5 and A.6. For intergroup tolerance, the individual outcome results can be found in Appendix Table A.7. Note that in the GHSL 1975 IV specification, only the interethnic tolerance outcome is significant at the 10 percent level.

agricultural. This exercise reduces our sample by approximately 3,200 individuals (14% of the total). Nevertheless, the results on trust, community participation, and interethnic tolerance are very similar compared to Table 4, in terms of both effect sizes and also precision. This suggests that rural agricultural areas in the periphery of our sample are not driving our main results.

**Additional Community-Level Controls.** We also explore whether our estimated effects are really due to density, or owe instead to other amenities that are influenced by density. To do so, we use data from Indonesia's Village Potential Survey (*Potensi Desa* or *Podes*) in 2011 to add additional community-level variables to the $\mathbf{W}_{2v}$ vector.[34] We construct several proxies for local amenities that may influence social interactions, including the community's distance to formal markets, if any restaurants exist, distance to schools, if there are any mobile phone or TV signals, the type of main water sources, if there are local community empowerment programs, the number of houses of worships, distance to medical facilities, and distance to maternal health facilities. Comparing rows 2 and 3 across the panels of Appendix Table A.18, we find that these additional controls do not affect our main estimates from Table 4.

**IFLS Results.** Next, we estimate the impact of density on social capital using a different dataset: the Indonesia Family Life Survey (IFLS). The IFLS provides a useful check against our main *Susenas* results for several reasons. First, the IFLS contains different social capital measures and a completely different sampling strategy from the *Susenas*, so it would be reassuring if we find similar effects in the cross-section. Second, we can exploit individual-level panel data from the IFLS to address sorting in a completely different way from what we do with the cross-sectional *Susenas* results.

We begin working with the IFLS by grouping variables from the social capital module into the three categories used in Table 4. For the most recent IFLS wave (IFLS 5, fielded in 2014/2015), variable names, the groups to which variables were assigned, and summary statistics can be found in Appendix Table A.19.[35] Next, using restricted access data, we linked IFLS communities to communities from the 2010 census, so that we could obtain density measures and controls for sorting. Finally, we estimated the mean effects of density on social capital outcomes, analogous to Table 4.

Table 5 reports the IFLS results on the single cross-section. In Panel A, we find somewhat larger estimates of the effect of density on trust in neighbors than in Table 4. In Panel B, the estimate of $\tau$ from the soil IV specification is insignificant, while the GHSL 1975 IV estimate is negative and larger than our main *Susenas* results. In Panel C, we estimate the impact of density on intergroup tolerance, and we find positive and marginally significant estimates of $\tau$, although these estimates are somewhat smaller than those presented in Table 4. Overall, we view these results from IFLS 5 as broadly consistent with the qualitative patterns found in our main *Susenas* results.[36]

Next, we use the longitudinal nature of the IFLS data to address sorting in a different way from our cross-sectional results, following the two-step estimation approach described by Combes et al. (2008). In

[34] The *Podes* is a census of Indonesian villages conducted approximately every three years by Indonesia's statistical agency, BPS Indonesia. It collects detailed information from community informants about community characteristics, such as demographics, geography, as well as social and economic infrastructure.

[35] A similar table for IFLS 4 can be found in Appendix Table A.20. Note that the social capital questions were asked in exactly the same way between the two waves. Although the IFLS has 5 waves to date (the first was fielded in 1993), questions on trust and intergroup tolerance were only asked in waves 4 and 5. While community participation questions were also asked in wave 3, we only consider waves 4 and 5 in this section to make the analysis consistent across outcomes.

[36] Appendix Table A.21 presents cross-sectional mean effects results for IFLS 4, using density in 2010 as the dependent variable. Although these results have similar magnitudes, they are somewhat less robust to controls for sorting.

the first step, we estimate local, time-varying effects of social capital after conditioning out the impact of individual-specific effects and the effect of time-varying individual-level observables. This step effectively purges the social capital outcomes of any bias from sorting. We then average the residuals from this regression, and estimate a cross-sectional regression of the average social capital measures (averaged over community years) on our density measure in 2010.[37]

For a single outcome, the first step involves estimating the following regression equation:

$$y_{ivt} = \mathbf{x}'_{it}\beta + \alpha_i + \alpha_{vt} + \varepsilon_{it} \,, \tag{7}$$

where $y_{ivt}$ is the social capital outcome for individual $i$ in community $v$, $\mathbf{x}_{it}$ is a vector of time-varying controls for individual $i$ (capturing age, changes in education, and changes in marital status), $\alpha_i$ is an individual-level fixed effect, $\alpha_{vt}$ is a community-year intercept, and $\varepsilon_{it}$ is an error term. The object of interest in this regression is $\alpha_{vt}$, which is the social capital index for each community and year, after conditioning out individual fixed effects and time-varying individual-level observables. Because we work with a large number of related outcomes, we use a mean effects approach and estimate equation (7) with a stacked SUR system, where we impose the restriction that the $\alpha_{vt}$ terms are common across equations.

In the second step, we form a community-level average of the $\alpha_{vt}$'s across years, $\alpha_v \equiv \frac{1}{T}\sum_{t=1}^{T} \alpha_{vt}$, and we use this as the dependent variable in a cross-sectional regression:

$$\alpha_v = \mathbf{W}_{2v}\beta_2 + \theta \log \text{density}_v + \Delta\varepsilon_i \,, \tag{8}$$

where we instrument log $\text{density}_v$ with our two sets of instruments, and $\mathbf{W}_{2v}$ is the same as above. We restrict the sample to contain only the original 182 IFLS communities in urban areas in Indonesia.[38]

Table 6 reports our two-step estimates of $\theta$ from the IFLS panel data. Although our estimates are generally not significant, they have similar signs and magnitudes as those reported in Tables 4 and Table 5. A major difference between these two specifications is that the IFLS panel results are based on a much smaller sample size, increasing confidence intervals and reducing the power of the instruments. Nevertheless, we take the evidence in Table 6 as broadly consistent with the main findings of the paper.[39]

**Heterogeneity and Mechanisms.** Although we do not find that greater sprawl leads to worsening trust in neighbors or community trust and participation, the basic logic of Putnam (2000) could still be playing an important role. Glaeser and Gottlieb (2006) argue that when people have higher opportunity costs, this reduces their ability to spend time on civic and community participation. In Table 7, we explore the extent to which opportunity costs mediate the relationship between density and social capital by allowing the effect of density to differ across different types of individuals.

[37] See Appendix B.4 for more details on precisely how this approach was implemented.

[38] Although there were 2,330 communities observed in IFLS 3 and 3,343 communities observed in IFLS 4, many of these communities correspond to only a handful of observations, as those communities are where individuals from the original IFLS communities moved and formed new households. Working with those communities makes it difficult to reliably estimate $\alpha_{vt}$ separately from individual-level fixed effects. There are a total of 312 original communities in the IFLS but only 182 were located in our urban area sample.

[39] In the first stage of Table 6, we use a SUR approach, but we also try a single-index approach in the first step, forming a single average of the dependent variables in each group as the regressor. Estimates of $\theta$ from the second step using this single-index approach can be found in Appendix Table A.22. These results are broadly similar to those presented in Table 6.

We estimate a stacked, SUR system of equations like (6), but we include levels of individual indicators, as well as interaction terms between those indicators and log density.[40] In Table 7, column 1, we report our baseline estimates of the mean effect of density on trust in neighbors (Panel A), community trust and participation (Panel B), and intergroup tolerance (Panel C), after controlling for sorting and simultaneity. These estimates use the GHSL 1975 instrument and can also be found in the Table 4, Column 2 (row 3 of each panel).

In column 2, we find that for trust in neighbors and community participation, the effects of density seem to be driven by younger and middle-aged individuals (age 30 and below is the reference group). These patterns are similar to those found by Brueckner and Largey (2008), who study the relationship between density and social interactions in U.S. cities. However, for inter-ethnic tolerance, the effect of density increases with age.

In column 3, we find that the effects of density on trust in neighbors, community participation, and interethnic tolerance are largest in married households. If married households have greater opportunity costs for participating in their communities because of larger family and child-raising responsibilities, we would have expected to see weaker community participation in lower density areas for those households (and a positive sign on the interaction term in Panels A and B). Instead, we find the opposite result, suggesting that opportunity costs are not playing as much of a role in these findings.

We find similar results when we use education and income as proxies for opportunity costs. Columns 4 and 5 show that the effect of density increases with education and income. More educated and higher income households have greater opportunity costs for participating in their communities, so we would have again expected that in low density communities far from the CBD, such households would be even more unwilling to participate in their communities (leading to a positive-signed interaction term). However, we find the opposite effect providing further evidence against the opportunity costs hypothesis.

Finally, in column 6, we examine how the effects of density differ by people who use different modes of transport to get to work. We find that the effects of density on trust in neighbors, community participation, and interethnic tolerance are amplified for people who take private transport modes (cars and motorcycles), relative to the reference group of public transport and non-motorized transit. If private transportation is reducing social capital, we would expect that in low density areas far from the CBD, trust and community participation would be even lower, leading to a positive interaction term, but we do not find this result. This suggests again that opportunity costs are not driving the relationship between density and social capital that we observe.[41]

Given that individual-level opportunity costs do not seem to explain the relationship between density and social capital, we next explore whether city-level factors may play an important role. In Table 8, we conduct a similar heterogeneity analysis as Table 7, but this time we examine how the relationship between density and social capital differs across different types of cities. Column 1 again reports our baseline GHSL 1975 IV estimates of the mean effect of density on trust in neighbors (Panel A), community trust and participation (Panel B), and intergroup tolerance (Panel C), after controlling for sorting

[40] The set of instruments we use is augmented by interactions between our instruments and those indicators. See Appendix B.5 for more details.

[41] Appendix Table A.23 shows similar results to Table 7, but instead of using the GHSL 1975 instrument, it uses the soil IVs. The big differences in these tables owe to the results on intergroup tolerance (Panel C). Recall from Table 4 that for the GHSL 1975 instrument, the effect of density on intergroup tolerance is positive and significant, while it is insignificant when instrumenting for density with the soil IVs.

and simultaneity.

In column 2, we report estimates of the interaction between density and an indicator for cities having a large (above median) urban core, a proxy for larger commuting costs. We find more negative effects of density on trust in neighbors and community participation, while we find more positibve effects of density on interethnic tolerance in cities with a larger spatial extent. If longer commuting times increase the opportunity costs of community participation, we would expect weaker community participation in less dense areas of lager cities, so that the interaction term should be positive. Instead, we find the opposite result, which suggests again that the opportunity cost story of Putnam (2000) may not be playing a role. Similarly, in column 3, we also find that density increases trust in neighbors and community participation more in cities that have experienced more rapid sprawl in recent years (column 3).

In column 4, we find that for both trust and community participation, the effects of density are amplified in more diverse cities, where greater diversity is measured by above median city-level ethnolinguistic fractionalization. Low density communities in more diverse cities have both greater levels of trust and community participation and also lower levels of inter-ethnic cooperation than low density communities in less diverse cities, although the latter result is insignificant.

In columns 5 and 6, we examine the role of crime in mediating the results on density and social capital outcomes. We use the 2011 *Podes* data to construct measures of the probability of encountering violent and property crimes in each city.[42] We then interact density with indicators for whether or not a city has above median property crime exposure (column 5) and above median violent crime exposure (column 6). We find that for all three outcome groupings, the effects of density are amplified in high crime cities. Exposure to crime in such cities may induce people to sort into enclaves in lower density areas, where they invest more heavily in their communities and have lower tolerance for other ethnic and religious groups.[43]

## 7 How Density Weakens Trust

Our empirical results suggest that density reduces trust in neighbors, an important component of local social capital and one of the main focuses of our analysis. Urban sociologists have long argued that greater density in urban life increases anonymity and reduces the quality of social interactions among neighbors (see, e.g., Simmel, 1903; Wirth, 1938).[44] This increase in anonymity counteracts the beneficial effects of density on the number of opportunities for social interactions along the line of Jacobs (1961) and Putnam (2000). Following Manapat et al. (2013), we study the impact of this anonymity on community trust using an agent-based model of individuals who play trust games with other members of their community. We extend Manapat et al. (2013)'s model by introducing multiple groups in the community.

[42] We construct these measures by calculating the number of communities where these crimes exist in each city, and then aggregating these existence variables by population.

[43] Appendix Table A.24 shows similar results to Table 8, but instead of using the GHSL 1975 instrument, it uses the soil IVs.

[44] Wirth (1938, p.11), for example, argues that "[large] numbers involve . . . a greater range of individual variation" and that such variations imply that the "bonds of kinship, of neighborliness, and the sentiments arising out of living together for generations under a common folk tradition are likely to be absent or, at best, relatively weak in an aggregate the members of which have such diverse origins and backgrounds." Greater density increasing the probability of anonymous interactions is also consistent with the concept of Dunbar's number in anthropology. Dunbar (1992) argues that there is "an upper limit on the size of groups which any given species can maintain as cohesive social units through time" (p. 469), and this number is around 150, which is directly related to the size of the neocortex in human brains.

Consider a community with $N$ residents comprised of two different groups, $A$ and $B$. Let $\alpha \equiv N_A/N$ denote the share of residents belonging to group $A$, so that $(1-\alpha) \equiv N_B/N$ is the share of residents belonging to group $B$. We assume that amenities, commuting costs, and housing prices will vary across communities in such a way to rationalize any observed $N$, $\alpha$, and population density in a given community (Brueckner et al., 1999). Therefore, conditional on $\alpha$, $N$, and density, we study the overall level of trust that emerges.

In the community, each group is split into an equal number of *investors* and *trustees*. In each period of the model, community members play a round-robin tournament of trust games, where each investor plays a trust game with each trustee in the community, and payoffs are realized. After the current period's tournament ends, players' strategies change through a within-group evolutionary process, with higher payoff strategies in the group becoming more common and lower payoff strategies eventually dying out.

In a single trust game, an investor decides whether or not to transfer one unit of social capital, $S = 1$, to the trustee with whom she is matched. If the transfer is made, the transferred stake is multiplied by an amount $\theta_0$ ($\theta_1$) if the trustee belongs to the different (same) group as $i$. We assume that $1 < \theta_0 \leq \theta_1$, so that both types of transfers are beneficial, but own-group transfers are weakly more beneficial than cross-group transfers. After receiving the transfer, the trustee decides how much to send back to the investor. In a one-shot anonymous trust game, there is no reason for a rational trustee to return anything, so no transfers occur in a Nash equilibrium. However, there is a large experimental literature showing that investors make the transfer with a large probability and trustees return significant amounts (e.g. Berg et al., 1995; Glaeser et al., 2000; Fehr, 2009). Using Manapat et al. (2013), we demonstrate how better prior information about opponents' strategies, associated with lower-density communities, increases trust and equilibrium payoffs.

Suppose player $i$ is an investor, and player $j$ is a trustee. If $i$ and $j$ belong to different groups, they play a "cross-group" trust game, while if $i$ and $j$ belong to the same group, they play an "own-group" trust game. Let $r_{0j}$ ($r_{1j}$) denote trustee $j$'s return fraction in a cross-group (own-group) trust game. The degree of anonymity of interactions in the community is regulated by the parameter $Q$, the probability that in each round, investor $i$ is randomly paired with a trustee $j$ whose return fraction she can observe. We assume that $Q$ falls, and the propensity for anonymous interactions increases, as the community's population density increases.

Consider the case when the transaction is not anonymous and investor $i$ knows trustee $j$'s return fraction $r_j$. To simplify the exposition, we will focus on the cross-group case, but similar expressions can also be derived for the own-group case. Investor $i$ will make the transfer if $\theta_0 r_{0j} \geq 1$, and she will never transfer if $\theta_0 r_{0j} < 1$. Let $p^*_{0j} \equiv p^*(r_{0j}, \theta_0)$ denote the probability that investor $i$ makes a cross-group transfer to trustee $j$ when the interaction is non-anonymous:

$$p^*_{0j} = \begin{cases} 0 & \text{if } r_{0j} < \frac{1}{\theta_{0j}} \\ 1 & \text{if } r_{0j} \geq \frac{1}{\theta_{0j}} \end{cases}. \tag{9}$$

Using this, we can write investor $i$ and trustee $j$'s payoffs for cross-group transfers as follows:

$$\Pi_{0,ij}^{\text{Inv}*} = \left(1 - p_{0j}^*\right) + \theta_0 r_{0j} p_{0j}^* \qquad \Pi_{0,ij}^{\text{Tru}*} = \theta_{0j} p_{0j}^* \left(1 - r_{0j}\right),$$

where the Inv and Tru superscripts denote investors and trustees respectively.[45]

Next, consider the case where investor $i$ does not know trustee $j$'s strategy and the interaction is anonymous. In this case, suppose the investor makes a cross-group transfer to player $j$ with probability $p_{0i}$. The resulting payoffs for investors and trustees from cross-group transfers are given by:

$$\Pi_{0,ij}^{\text{Inv}} = \left(1 - p_{0i}\right) + \theta_0 r_{0j} p_{0i} \qquad \Pi_{0,ij}^{\text{Tru}} = \theta_{0j} p_{0i} \left(1 - r_{0j}\right).$$

We can derive the expression for the average payoffs of players that belong to group $A$. Recall that $\alpha$ is the share of group $A$'s population in the community and $Q$ denotes the probability that an interaction with $j$ is non-anonymous. The average payoffs across both game states and across own and cross-group interactions for investors are given by:

$$\overline{\Pi}^{\text{Inv}} = \alpha \left[Q\Pi_1^{\text{Inv}*} + (1-Q)\,\Pi_1^{\text{Inv}}\right] + (1-\alpha)\left[Q\Pi_0^{\text{Inv}*} + (1-Q)\,\Pi_0^{\text{Inv}}\right]$$

Similar expressions can be obtained to construct the average payoffs for Group A trustees, and for Group B investors and trustees by swapping population weights.

At the beginning of the evolutionary game, each investor $i$ and trustee $j$ draws a set of random strategies, $(p_{0i}, p_{1i})$ and $(r_{0j}, r_{1j})$ respectively, from $[0,1]$ uniform distributions. After each period's round robin tournament is over, players' strategies evolve following a "pairwise comparison process" (Traulsen et al., 2007). For each group, two investors and two trustees compare their payoffs, and the payoff-dominated player adopts the payoff-dominating player's strategy in the next round, with the revision probability defined as follows. Let $\overline{\Pi}_1$ denote the average payoff of Player 1 across all round-robin games played that period, and $\overline{\Pi}_2$ denote the same object for Player 2. The revision probability is defined by $\rho$:

$$\rho = \frac{1}{1 + \exp\left\{-\beta\left(\overline{\Pi}_1 - \overline{\Pi}_2\right)\right\}} \tag{10}$$

so that the "pairwise comparison process" is defined as follows:

$$\text{Player 2 is replaced with} \begin{cases} \text{Player 1} & \text{with probability } \rho\,(1-\mu) \\ \text{a random mutant} & \text{with probability } \mu \\ \text{no one} & \text{with probability } \ (1-\mu)\,(1-\rho)\,, \end{cases} \tag{11}$$

where $\beta$ governs the intensity of selection and $\mu$ is a genetic mutation rate (Manapat et al., 2013). As $\beta$ grows, it becomes more likely that a player will imitate someone doing something better. As $\mu$ gets larger, it becomes more likely that a player mutates and selects a strategy chosen uniformly at random from $[0,1]$. After strategies evolve in this way, a new round begins.

[45] Symmetric definitions apply for own-group transfers, by simply replacing subscript 0 with 1.

### 7.1 Simulating the Impact of Density on Trust

To investigate how density impacts trust and payoffs for investors and trustees from different groups, we used agent-based simulations to study the game's stochastic evolutionary dynamics in finite populations where communities vary by ethnic composition. In each simulation, investors start out with draws of $p_0, p_1 \sim U[0,1]$ and trustees start out with draws $r_0, r_1 \sim U[0,1]$. Trustees always play $r_0$ and $r_1$ and do not know if investors have information about them. We also set $\theta_0 = 3$ and $\theta_1 = 4$.[46]

The outcome of interest corresponding to our empirical results is the *realized* trust (proxied by investors' transfers) in the population conditional on the information set. When $Q$ is low, most interactions will be anonymous and realized trust would put more weight on investor strategies under anonymous transactions, i.e., $p_0$ ($p_1$) in the own-group (cross-group) games. As $Q$ increases, investor strategies under non-anonymous transactions $p_0^*$ and $p_1^*$ play a more prominent role in the community's level of the realized trust. We therefore define the realized trust outcome in own-group games, $\widetilde{p_1}$, and the realized trust for cross-group games, $\widetilde{p_0}$, as follows:

$$\widetilde{p_1} = Qp_1^* + (1-Q)p_1 \,, \qquad\qquad \widetilde{p_0} = Qp_0^* + (1-Q)p_0 \,.$$

Figure 6 shows the impact of $Q$ on investor and trustee profits (Panel A), realized trust and return probabilities for own-group games (Panel B), and realized trust and return probabilities for cross-group games (Panel C). To construct this figure, we simulated how $p_1$, $p_0$, $r_1$, and $r_0$ evolve after 50,000 rounds of the game for different communities that vary by $\alpha$ and $Q$. We focus on two different ethnic mixes: (1) an evenly divided community, with $\alpha = 0.5$ (depicted with purple lines); and (2) a majority group $A$ community, with $\alpha = 0.8$ (depicted with yellow lines).

Panel A shows that investor payoffs are roughly constant and do not change very much as density decreases. However, in high density communities with very low values of $Q$, trustee payoffs are very low, suggesting that investors simply keep their capital and do not send any portion of $S$ to the trustee. This is confirmed by inspecting Panels B and C, which show that in very dense communities with low values of $Q$, $\widetilde{p_0}$ and $\widetilde{p_1}$ are close to 0. As density falls and interactions become less anonymous ($Q$ increases), investors increase their trust, as reflected by $\widetilde{p_0}$ and $\widetilde{p_1}$ both increasing rapidly and the increasing trustee payoffs. Average payoffs for the less diverse community are higher because own-group games— whose payoff is higher than that of cross-group games—are more likely.

Note that when density is sufficiently low and $Q$ grows to $Q \geq 1/\theta$, trustees always choose $r = 1/\theta + \varepsilon$. Investor's $p_0$ and $p_1$ begin to fall with very large values of $Q$, because as interactions become less anonymous, the selection pressure on these terms becomes weaker, and they become less relevant to payoffs. This is why we focus on results on realized trust, $\widetilde{p_1}$ and $\widetilde{p_0}$. More details on the game, including the Nash Equilibrium behavior and how strategies differ by group, can be found in Appendix C. Nevertheless, the model clearly demonstrates that regardless of ethnic composition, the increased $Q$ levels in low density communities lead to greater trust outcomes and higher payoffs.[47]

[46] Following Manapat et al. (2013), we also set $\beta = 20$ and $\mu = 0.05$.

[47] It is important to note that realized cross-group trust, $\widetilde{p_0}$, is conceptually distinct from the intergroup tolerance/trust variables in our empirical analysis. Tolerance does not necessarily imply trust: tolerant individuals may still mistrust non-coethnics due to, e.g., statistical discrimination. Meanwhile, our empirical intergroup trust variables (such as those in IFLS 5) measure *relative* trust of non-coethnic (v. co-ethnic) whereas $\widetilde{p_0}$ measures the *level* of trust of a non-coethnic.

### 7.2 Robustness to Sorting on Unobservables

We modify the model to simulate the impact of density on trust while controlling for the potential for individuals in the community to have unobservable (ethnic) group intolerance, which may have a separate, independent impact on community-level trust. We run a new set of agent based simulations, where we introduce a set of intolerant agents. When paired with agents from a different group, intolerant agents do not trust (i.e. have low values of $p_0$) and are not trustworthy (i.e. have low values of $r_0$). Moreover, their strategy evolves only through pairwise comparisons with similarly intolerant individuals, with mutations that reflect these parameter restrictions. In these simulations, we vary the share of intolerant individuals in the majority group.

More precisely, let $R$ be the share of majority group $A$'s agents that is not tolerant of group $B$. Using $R$, we conduct a number of community-level simulations, where we choose 5 different values of $\alpha$ ($\alpha \in [0.5, ..., 0.9]$), 21 different values of $Q$ ($Q \in [0, 0.05, 0.1, ..., 0.9, 0.95, 1]$), and 4 different values of $R$ ($R \in [0, 0.1, 0.2, 0.3]$). With $NS = 20$ different draws of initial parameter values for each choice of $\alpha$, $Q$, and $R$, we obtain a simulation dataset of 8,400 different simulated communities, each with equilibrium values of $p_0, p_1, r_0, r_1$, and average profits for investors ($\overline{\Pi}^{\text{Inv}}$) and trustees ($\overline{\Pi}^{\text{Tru}}$).

Let $v$ denote a simulation village with initial parameter draw $d$, and let $y_{v,d}$ denote one of six community-level average trust outcomes (e.g. investor profits, trustee profits, realized trust for own-group games, realized trust for cross-group games, and return strategies for own and cross-group games). To explore the extent to which the share of ethnically intolerant individuals may influence community-level trust outcomes, we run the following regressions:

$$y_{i,d} = \alpha_d + \beta_1 R_i + f(Q_i) + \beta_3 \alpha_i + \varepsilon_i \,. \tag{12}$$

where $\alpha_d$ is a draw fixed effect, $R_i$ measures community $i$'s intolerant share, $Q_i$ measures information (or the inverse of density), and $\alpha_i$ measures group composition. This regression equation is similar to (6), in that we effectively control for sorting on observables (i.e. the group share, $\alpha$), and unobservables (i.e. the intolerant share, $R_i$), but we do so using known model parameter values. We estimate the semiparametric model in (12) following Robinson (1988). The results in Figure 7 show that as $Q$ increases and density falls, trust outcomes improve, echoing our empirical findings.[48]

# 8 Conclusion

This paper presents causal estimates of the effect of urban sprawl on different aspects of social capital in Indonesian cities. Researchers who estimate these relationships must address two fundamental identification problems: (1) simultaneity, whereby omitted place-specific variables drive both density and social capital, and (2) sorting, where individuals with particular tastes for contributing to social capital systematically sort into places with different levels of density. Using high quality, spatially disaggregated data, we confront the first identification challenge using historical instruments for density, and we address the second challenge using controls for sorting on observables and unobservables, extending an approach by Altonji and Mansfield (2018).

[48] Linear and quadratic specifications for $f(\cdot)$ are shown in Appendix Table A.25.

Our major finding is that in Indonesian cities, increases in density lead to lower levels of trust in neighbors and reduced community participation, echoing the results of Brueckner and Largey (2008). These results are robust to controls for sorting, different sets of instruments, different datasets, and two different approaches to addressing sorting. In some specifications, we find that increased density leads to greater levels of intergroup tolerance, but these effects are not robust to our different instruments for density. Using a heterogeneity analysis, we find that instead of differential opportunity costs driving these findings, density weakens trust and community participation more in more ethnically diverse cities and in cities with higher crime rates.

Using an evolutionary trust game following Manapat et al. (2013), we provide support for an information theory that may explain why less dense communities have greater levels of trust. In the model, individuals from different groups interact repeatedly by playing trust games with different members of their community, and the payoffs from cross-group and own-group interactions vary. Interactions are anonymous in denser communities, and players are less likely to have information about what strategies their opponents will play. This reduces the overall level of trust in equilibrium. We confirm that the model's findings are robust to differences in ethnic composition and sorting.

As emphasized by Brueckner and Largey (2008), social planners may want to use growth controls to curb sprawl if it leads to undesirable social externalities. If sprawl were to weaken interethnic tolerance, this could provide a mechanism through which such negative social externalities may occur. However, lower density also has positive social externalities because it increases trust in neighbors and community participation. Because we understand very little about the tradeoffs between improving within-community cohesion at the expense of fostering intergroup relationships, policymakers should proceed with caution. Such effects also need to be compared to the costs of other aspects of urban sprawl, especially energy use and the carbon intensity of living. This is an important endeavor that we plan to undertake in future research.

More research is needed to understand whether these patterns of sprawl and social capital are common to LMICs. Indonesia's unique history and relatively weak interethnic conflict make it an interesting case study, but the impact of sprawl on social capital could be very different in countries with a legacy of violent ethnic conflict, greater religious tensions, or a recent experience of civil war. Other aspects of urban sprawl, particularly energy use and the carbon intensity of living, are also first order in trying to quantify the costs and benefits of sprawl in LMIC cities.

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**Table 1:** Summary Statistics: Social Capital Outcomes

| **Panel A: Trust in Neighbors** | **Description** | **Mean (sd)** | ***N*** |
|---|---|---|---|
| trust neighbor to watch house | Do you trust your neighbors to watch your house if you are away? | 2.91 (0.51) | 23,766 |
| trust neighbor to tend children | Do you trust your neighbors to watch your child if there was no adult at home in your house? | 2.65 (0.63) | 23,766 |
| ready to help neighbor | Are you ready to help others who are helpless (need help) in the neighborhood? | 2.98 (0.51) | 23,766 |
| contribute to assist unfortunate neigbhors | Do you usually help people who are experiencing disasters (such as death, illness, etc.)? | 2.81 (0.70) | 23,766 |
| easily access to neighbors' help | Is it easy for you to get help from neighbors when you are experiencing financial problems? | 2.65 (0.71) | 23,766 |
| **Panel B: Community Trust and Participation** | **Description** | **Mean (sd)** | ***N*** |
| join community group(s) | Do you usually participate in community activities in the neighborhood (e.g. social gathering, sports, art, etc.)? | 2.36 (0.90) | 22,196 |
| join religious activities | Do you usually participate in religious activities in the neighborhood (e.g., recitation, religious celebration, etc.)? | 2.68 (0.78) | 23,352 |
| join religious activities recently | Have you participated in any religious activities in the last 3 months? | 0.62 (0.48) | 71,894 |
| voluntary public good provision | Do you usually volunteer for your neighborhood (e.g. building public facilities, community service, etc.)? | 2.50 (0.81) | 22,925 |
| join community activities recently | Have you participated in any community social activities in the last 3 months (e.g. sports, arts, skills dev., funerals, etc.)? | 0.71 (0.46) | 71,882 |
| trust religious leader | In general, do you believe that religious leaders in the neighborhood can act as moral role models? | 3.05 (0.40) | 23,726 |
| trust community leader | In general, do you believe that community leaders can play a role in helping people to solve problems? | 2.98 (0.38) | 23,766 |
| trust village leader | In general, do you believe that the village leader carries out his/her duties well? | 2.95 (0.43) | 23,766 |
| **Panel C: Intergroup Tolerance** | **Description** | **Mean (sd)** | ***N*** |
| pleased with non-coreligions | How happy are you with activities in the neighborhood by another religion? | 2.74 (0.58) | 21,041 |
| pleased with non-coethnics | How happy are you with activities in the neighborhood by another ethnic group? | 2.83 (0.51) | 21,195 |

*Notes:* This table reports short titles, longer descriptions, and summary statistics for the social capital outcomes we analyze from the 2012 SUSENAS. Most of these questions were asked to household head respondents in the social capital module of the SUSENAS, but some were asked in the core module. Summary statistics were computed using data only from the sample of communities comprising metropolitan areas. The groupings of variables listed here correspond to the groupings used in the mean effects analysis (e.g. Table 4).

**Table 2:** First Stage: Log Density vs. Soil Characteristics, Built Up Area in 1975, and 2000 Subdistrict Density

| | **Soil IV** | **GHSL 1975** |
|---|---|---|
| | **(1)** | **(2)** |
| Soil bulk density at 60 cm depth (kg / m3) | 0.027*** | |
| | (0.002) | |
| Sand content at 60 cm depth (% (kg / kg)) | -0.051*** | |
| | (0.004) | |
| Soil water content at 33kPa (field capacity) at 60 cm depth | -0.044*** | |
| | (0.004) | |
| Sandy clay (SaCl), 60 cm depth | -0.088 | |
| | (0.059) | |
| Sandy clay (SaCl), 100 cm depth | -0.123** | |
| | (0.054) | |
| Log Builtup Density (1975) | | 0.399*** |
| | | (0.008) |
| $N$ | 20,571 | 14,938 |
| $N$ Clusters | 2,059 | 1,426 |
| Adj. $R^2$ | 0.484 | 0.666 |
| Adj. $R^2$ (Within) | 0.326 | 0.580 |
| Regression $F$-Stat | 176.4 | 2334.2 |
| Soil Taxonomy Indicators | Yes | . |
| City FE | Yes | Yes |

*Notes:* This table reports estimates of equation (5), the first stage relationship between log population density in 2010 (the dependent variable) and three different sets of instrumental variables. Column 1 reports selected coefficients of various soil characteristics, all measured at a depth of 60 cm or below. We use lasso regression to select the appropriate soil characteristics variables in this regression, following Belloni et al. (2014). The specification in Column 1 also includes 13 different indicators for soil classification (at the great group level) that were also significant (coefficients not shown). Columns 2 are least squares estimates of equation (5) with the single coefficient on the regressor reported. All regressions are limited to the sample of villages within urban areas and include city-fixed effects. The sample size falls substantially in Column 2 because of missing GHSL 1975 data for Sumatra. Robust standard errors, clustered at the subdistrict-level, are reported in parentheses. */**/*** denotes significant at the 10% / 5% / 1% levels.

**Table 3:** The Effect of Density on Trust in Neighbors

| | | Soil IV | GHSL 1975 |
|---|---|---|---|
| **Panel A: Only $\mathbf{X}_i$ and $\mathbf{W}_{2v}$ Controls** | **OLS (1)** | **IV-LASSO (2)** | **2SLS (3)** |
| Log Density (2010) | -0.020*** | -0.038*** | -0.034*** |
| | (0.004) | (0.009) | (0.006) |
| $N$ | 23,280 | 23,280 | 14,774 |
| $N$ Clusters | 1,290 | 1,290 | 867 |
| Adjusted $R^2$ | 0.036 | 0.037 | 0.039 |
| Adjusted $R^2$ (within) | 0.011 | 0.012 | 0.013 |
| Kleibergen-Paap Wald Rank $F$ Stat | | 73.517 | 883.644 |
| Under Id. Test (KP Rank LM Stat) | | 178.104 | 229.871 |
| p-Value | | 0.000 | 0.000 |
| AR Wald Test (Weak IV Robust Inf.) | | 6.818 | 30.764 |
| p-Value | | 0.000 | 0.000 |
| Hansen J Stat | | 18.699 | 0.000 |
| p-Value | | 0.002 | |
| **Panel B: Adding $\mathbf{X}_v$ Controls** | **(1)** | **(2)** | **(3)** |
| Log Density (2010) | -0.007 | -0.053*** | -0.043*** |
| | (0.006) | (0.019) | (0.014) |
| $N$ | 23,280 | 23,280 | 14,774 |
| $N$ Clusters | 1,290 | 1,290 | 867 |
| Adjusted $R^2$ | 0.044 | 0.046 | 0.045 |
| Adjusted $R^2$ (within) | 0.020 | 0.022 | 0.019 |
| Kleibergen-Paap Wald Rank $F$ Stat | | 19.599 | 224.076 |
| Under Id. Test (KP Rank LM Stat) | | 77.864 | 126.261 |
| p-Value | | 0.000 | 0.000 |
| AR Wald Test (Weak IV Robust Inf.) | | 4.003 | 9.474 |
| p-Value | | 0.001 | 0.002 |
| Hansen J Stat | | 13.855 | 0.000 |
| p-Value | | 0.017 | |
| $H_o : \mathbf{\Gamma}_1 = 0$ (p-value) | 0.000 | 0.000 | 0.054 |
| $H_o : \theta_A = \theta_B$ (p-value) | 0.012 | 0.042 | 0.252 |
| City FE | Yes | Yes | Yes |

*Notes:* Each cell reports the coefficient on log population density in 2010 from a separate linear probability model of (6) where the dependent variable is a binary coarsening of trust in neighbors. In the sample, the average of the dependent variable, $y$, is 0.841, and the standard deviation is 0.366. Column 1 reports OLS estimates, while Column 2 applies a post-double-selection lasso estimator to select the best soil characteristics instruments, following Belloni et al. (2012). Columns 3 use 2SLS with the GHSL 1975 instruments. In Panel A, we only control for $\mathbf{X}_i$ and $\mathbf{W}_{2v}$, setting $\mathbf{\Gamma}_1 = 0$. Panel B reports the full, unrestricted model. The specific variables we include in $\mathbf{X}_i$, $\mathbf{W}_{2v}$, and $\mathbf{X}_v$, as well as their coefficients, are reported in Appendix Table A.3 and Appendix Table A.4. All regressions are limited to the sample of villages within urban areas and include city-fixed effects. The sample size falls substantially in Column 3 because of missing GHSL 1975 data for Sumatra. Robust standard errors, clustered at the subdistrict-level, are reported in parentheses. */**/*** denotes significant at the 10% / 5% / 1% levels.

**Table 4:** The Effect of Density on Social Capital: Mean Effects

| | | Soil IV | GHSL 1975 |
|---|---|---|---|
| | **OLS** | **IV-LASSO** | **2SLS** |
| **Panel A: Trust in Neighbors** | **(1)** | **(2)** | **(3)** |
| 1. Only $\mathbf{X}_i$ and $\mathbf{W}_{2v}$ Controls | -0.041*** | -0.064*** | -0.064*** |
| | (0.005) | (0.011) | (0.008) |
| 2. Adding $\mathbf{X}_v$ Controls | -0.002 | -0.058** | -0.048*** |
| | (0.008) | (0.024) | (0.018) |
| $H_o : \mathbf{\Gamma}_1 = 0$ (p-value) | 0.000 | 0.000 | 0.000 |
| $H_o : \tau_1 = \tau_2$ (p-value) | 0.000 | 0.988 | 0.384 |
| $N$ Outcomes | 5 | 5 | 5 |
| N | 116,400 | 116,400 | 73,870 |
| N individuals | 23,280 | 23,280 | 14,774 |
| **Panel B: Community Participation** | **(1)** | **(2)** | **(3)** |
| 1. Only $\mathbf{X}_i$ and $\mathbf{W}_{2v}$ Controls | -0.022*** | -0.047*** | -0.035*** |
| | (0.004) | (0.009) | (0.007) |
| 2. Adding $\mathbf{X}_v$ Controls | -0.019*** | -0.075*** | -0.063*** |
| | (0.006) | (0.019) | (0.015) |
| $H_o : \mathbf{\Gamma}_1 = 0$ (p-value) | 0.000 | 0.000 | 0.000 |
| $H_o : \tau_1 = \tau_2$ (p-value) | 0.423 | 0.050 | 0.013 |
| $N$ Outcomes | 9 | 9 | 9 |
| N | 159,672 | 159,672 | 101,595 |
| N individuals | 21,767 | 21,767 | 13,970 |
| **Panel C: Intergroup Tolerance** | **(1)** | **(2)** | **(3)** |
| 1. Only $\mathbf{X}_i$ and $\mathbf{W}_{2v}$ Controls | 0.054*** | 0.030 | 0.118*** |
| | (0.010) | (0.021) | (0.020) |
| 2. Adding $\mathbf{X}_v$ Controls | 0.046*** | -0.031 | 0.100** |
| | (0.016) | (0.046) | (0.045) |
| $H_o : \mathbf{\Gamma}_1 = 0$ (p-value) | 0.000 | 0.000 | 0.000 |
| $H_o : \tau_1 = \tau_2$ (p-value) | 0.377 | 0.029 | 0.687 |
| $N$ Outcomes | 5 | 5 | 5 |
| N | 41,320 | 41,320 | 25,409 |
| N individuals | 20,578 | 20,578 | 12,648 |
| City FE | Yes | Yes | Yes |

*Notes:* Each cell reports the mean effect estimate, $\tau$, of log population density in 2010 on groups of related outcomes, from equation (4), following the approach described in Section 5.4. Outcome groupings, and the outcomes themselves, are repoted in Table 1. Column 1 reports OLS estimates, while Column 2 applies a post-double-selection lasso estimator to select the best soil characteristics instruments, following Belloni et al. (2012). Columns 3 use 2SLS with the GHSL 1975 instruments. In each panel, in Row 1, we only control for $\mathbf{X}_i$ and $\mathbf{W}_{2v}$, setting $\mathbf{\Gamma}_1 = 0$. Row 3 reports the full, unrestricted model. All regressions are limited to the sample of villages within urban areas and include city-fixed effects. The sample size falls substantially in Column 3 because of missing GHSL 1975 data for Sumatra. Robust standard errors, clustered at the subdistrict-level, are reported in parentheses. */**/*** denotes significant at the 10% / 5% / 1% levels.

**Table 5:** The Effect of Density on Social Capital: Mean Effects (IFLS 5)

| | | Soil IV | GHSL 1975 |
|---|---|---|---|
| | **OLS** | **IV-LASSO** | **2SLS** |
| **Panel A: Trust in Neighbors** | **(1)** | **(2)** | **(3)** |
| 1. Only $\mathbf{X}_i$ and $\mathbf{W}_{2v}$ Controls | -0.040*** | -0.089*** | -0.109*** |
| | (0.006) | (0.012) | (0.014) |
| 2. Adding $\mathbf{X}_v$ Controls | -0.001 | -0.138*** | -0.144*** |
| | (0.007) | (0.040) | (0.046) |
| N | 60,533 | 60,505 | 34,603 |
| N individuals | 16,384 | 16,376 | 9,415 |
| $N$ Outcomes | 4 | 4 | 4 |
| $H_o : \mathbf{\Gamma}_1 = 0$ (p-value) | 0.000 | 0.000 | 0.000 |
| $H_o : \tau_1 = \tau_2$ (p-value) | 0.000 | 0.083 | 0.206 |
| **Panel B: Community Participation** | **(1)** | **(2)** | **(3)** |
| 1. Only $\mathbf{X}_i$ and $\mathbf{W}_{2v}$ Controls | -0.030*** | -0.038*** | -0.089*** |
| | (0.005) | (0.011) | (0.016) |
| 2. Adding $\mathbf{X}_v$ Controls | -0.027*** | 0.004 | -0.160*** |
| | (0.006) | (0.029) | (0.043) |
| N | 97,668 | 97,620 | 56,166 |
| N individuals | 16,278 | 16,270 | 9,361 |
| $N$ Outcomes | 6 | 6 | 6 |
| $H_o : \mathbf{\Gamma}_1 = 0$ (p-value) | 0.000 | 0.000 | 0.000 |
| $H_o : \tau_1 = \tau_2$ (p-value) | 0.062 | 0.009 | 0.239 |
| **Panel C: Intergroup Tolerance** | **(1)** | **(2)** | **(3)** |
| 1. Only $\mathbf{X}_i$ and $\mathbf{W}_{2v}$ Controls | 0.077*** | 0.133*** | 0.095*** |
| | (0.006) | (0.011) | (0.012) |
| 2. Adding $\mathbf{X}_v$ Controls | 0.009 | 0.056* | 0.063* |
| | (0.006) | (0.029) | (0.032) |
| N | 114,686 | 114,630 | 65,903 |
| N individuals | 16,384 | 16,376 | 9,415 |
| $N$ Outcomes | 7 | 7 | 7 |
| $H_o : \mathbf{\Gamma}_1 = 0$ (p-value) | 0.000 | 0.000 | 0.000 |
| $H_o : \tau_1 = \tau_2$ (p-value) | 0.000 | 0.012 | 0.566 |
| City FE | Yes | Yes | Yes |

*Notes:* Each cell reports the mean effect estimate, $\tau$, of log population density in 2010 on groups of related outcomes, from equation (4), following the approach described in Section 5.4, but using the IFLS 5 data for outcomes. Outcome groupings, and the outcomes themselves, are repoted in Appendix Table A.19. Column 1 reports OLS estimates, while Column 2 applies a post-double-selection lasso estimator to select the best soil characteristics instruments, following Belloni et al. (2012). Columns 3 use 2SLS with the GHSL 1975 instruments. In each panel, in Row 1, we only control for $\mathbf{X}_i$ and $\mathbf{W}_{2v}$, setting $\mathbf{\Gamma}_1 = 0$. Row 3 reports the full, unrestricted model. All regressions are limited to the sample of villages within urban areas and include city-fixed effects. The sample size falls substantially in Column 3 because of missing GHSL 1975 data for Sumatra. Robust standard errors, clustered at the subdistrict-level, are reported in parentheses. */**/*** denotes significant at the 10% / 5% / 1% levels.

**Table 6:** The Effect of Density on Social Capital: IFLS Panel Regressions

| | | Soil IV | GHSL 1975 |
|---|---|---|---|
| | **OLS** | **IV-LASSO** | **2SLS** |
| | **(1)** | **(2)** | **(3)** |
| Trust in neighbors | -0.098*** | -0.117* | -0.005 |
| | (0.030) | (0.065) | (0.078) |
| $N$ | 169 | 169 | 89 |
| Adjusted $R^2$ | 0.056 | 0.028 | -0.045 |
| Kleibergen-Paap Wald Rank $F$ Stat | | 29.983 | 25.181 |
| Under Id. Test (KP Rank LM Stat) | | 25.776 | 23.429 |
| p-Value | | 0.000 | 0.000 |
| AR Wald Test (Weak IV Robust Inf.) | | 3.031 | 0.003 |
| p-Value | | 0.051 | 0.953 |
| Community participation | -0.011 | 0.021 | -0.015 |
| | (0.015) | (0.025) | (0.034) |
| $N$ | 169 | 169 | 89 |
| Adjusted $R^2$ | -0.006 | -0.035 | -0.043 |
| Kleibergen-Paap Wald Rank $F$ Stat | | 28.063 | 25.181 |
| Under Id. Test (KP Rank LM Stat) | | 22.170 | 23.429 |
| p-Value | | 0.000 | 0.000 |
| AR Wald Test (Weak IV Robust Inf.) | | 0.441 | 0.188 |
| p-Value | | 0.644 | 0.666 |
| Intergroup tolerance | 0.063** | 0.048 | 0.024 |
| | (0.031) | (0.056) | (0.052) |
| $N$ | 169 | 169 | 89 |
| Adjusted $R^2$ | 0.044 | -0.002 | -0.047 |
| Kleibergen-Paap Wald Rank $F$ Stat | | 29.983 | 25.181 |
| Under Id. Test (KP Rank LM Stat) | | 25.776 | 23.429 |
| p-Value | | 0.000 | 0.000 |
| AR Wald Test (Weak IV Robust Inf.) | | 0.349 | 0.208 |
| p-Value | | 0.706 | 0.649 |

*Notes:* This table reports mean effect estimates of the impact of density on trust in neighbors, community participation, and social capital, using IFLS panel data and a two-step estimation procedure described by Combes et al. (2008) and Combes et al. (2010). In the first step, we use the panel data to estimate local, time-varying effects of social capital after conditioning out the impact of individual-specific effects and the effect of time-varying individual-level observables. We then average the residuals from this regression, and estimate a cross-sectional regression of the average social capital measures (averaged over village years), instrumenting for our density measure in 2010 with the instruments listed in the column headers. See the text for further discussion. Robust standard errors are reported in parentheses. */**/*** denotes significant at the 10% / 5% / 1% levels.

**Table 7:** Heterogeneous Effects of Density on Social Capital: Individual-Level Interactions

| **Panel A: Trust in Neighbors** | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** |
|---|---|---|---|---|---|---|
| Log density | -0.048*** | -0.060*** | -0.035* | -0.041** | -0.036 | -0.051*** |
| | (0.018) | (0.019) | (0.019) | (0.019) | (0.023) | (0.019) |
| ... × Age: 41-65 | | -0.045** | | | | |
| | | (0.019) | | | | |
| ... × Age: +65 | | -0.032 | | | | |
| | | (0.022) | | | | |
| ... × Married | | | -0.051*** | | | |
| | | | (0.019) | | | |
| ... × Education: High | | | | -0.065*** | | |
| | | | | (0.019) | | |
| ... × Income: Middle | | | | | -0.062*** | |
| | | | | | (0.019) | |
| ... × Income: High | | | | | -0.066*** | |
| | | | | | (0.019) | |
| ... × Private | | | | | | -0.065*** |
| | | | | | | (0.019) |
| **Panel B: Community Trust and Participation** | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** |
| Log density | -0.063*** | -0.094*** | -0.036** | -0.061*** | -0.052*** | -0.063*** |
| | (0.015) | (0.016) | (0.016) | (0.016) | (0.020) | (0.017) |
| ... × Age: 41-65 | | -0.055*** | | | | |
| | | (0.015) | | | | |
| ... × Age: +65 | | -0.016 | | | | |
| | | (0.018) | | | | |
| ... × Married | | | -0.070*** | | | |
| | | | (0.016) | | | |
| ... × Education: High | | | | -0.069*** | | |
| | | | | (0.015) | | |
| ... × Income: Middle | | | | | -0.077*** | |
| | | | | | (0.017) | |
| ... × Income: High | | | | | -0.066*** | |
| | | | | | (0.016) | |
| ... × Private | | | | | | -0.080*** |
| | | | | | | (0.016) |
| **Panel C: Intergroup Tolerance** | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** |
| Log density | 0.100** | 0.093** | 0.104** | 0.099** | 0.071 | 0.116** |
| | (0.045) | (0.044) | (0.045) | (0.048) | (0.055) | (0.050) |
| ... × Age: 41-65 | | 0.103** | | | | |
| | | (0.046) | | | | |
| ... × Age: +65 | | 0.103** | | | | |
| | | (0.051) | | | | |
| ... × Married | | | 0.099** | | | |
| | | | (0.046) | | | |
| ... × Education: High | | | | 0.102** | | |
| | | | | (0.042) | | |
| ... × Income: Middle | | | | | 0.097** | |
| | | | | | (0.048) | |
| ... × Income: High | | | | | 0.094** | |
| | | | | | (0.043) | |
| ... × Private | | | | | | 0.092** |
| | | | | | | (0.045) |

*Notes:* This table reports mean effects and mean interaction terms for the impact of density on social capital, using GHSL 1975 built up area and their interactions as instruments and including both the $\mathbf{W}_{2v}$ and $\mathbf{X}_v$ controls. For each panel, Column 1 replicates estimates from Table 4, Column 3, Row 3. See Appendix B.5 for more details on the estimation methodology and variables used for Columns 2-6. Robust standard errors, clustered at the subdistrict-level, are reported in parentheses. */**/*** denotes significant at the 10% / 5% / 1% levels.

**Table 8:** Heterogeneous Effects of Density on Social Capital: City-Level Interactions

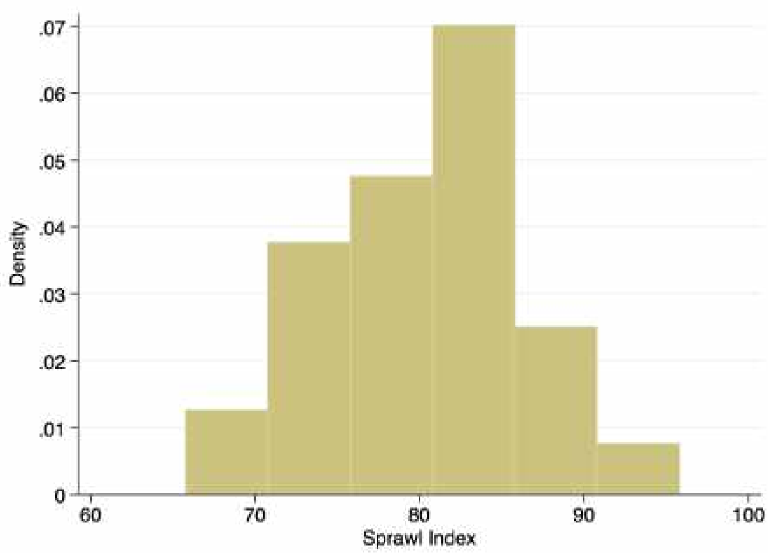
| **Panel A: Trust in Neighbors** | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** |
|---|---|---|---|---|---|---|
| Log density | -0.048*** | -0.049** | -0.044** | -0.054** | -0.055*** | -0.080*** |
| | (0.018) | (0.021) | (0.020) | (0.022) | (0.020) | (0.024) |
| … × Urban core: Large | | -0.048** | | | | |
| | | (0.020) | | | | |
| … × Sprawl (2000-2014): High | | | -0.052*** | | | |
| | | | (0.019) | | | |
| … × Ethinic Frac: High | | | | -0.043** | | |
| | | | | (0.018) | | |
| … × Property Crime: High | | | | | -0.038* | |
| | | | | | (0.019) | |
| … × Violent Crime: High | | | | | | -0.038** |
| | | | | | | (0.018) |
| **Panel B: Community Trust and Participation** | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** |
| Log density | -0.063*** | -0.059*** | -0.071*** | -0.063*** | -0.068*** | -0.066*** |
| | (0.015) | (0.017) | (0.017) | (0.019) | (0.017) | (0.019) |
| … × Urban core: Large | | -0.066*** | | | | |
| | | (0.016) | | | | |
| … × Sprawl (2000-2014): High | | | -0.058** | | | |
| | | | (0.016) | | | |
| … × Ethinic Frac: High | | | | -0.063*** | | |
| | | | | (0.015) | | |
| … × Property Crime: High | | | | | -0.056*** | |
| | | | | | (0.016) | |
| … × Violent Crime: High | | | | | | -0.063*** |
| | | | | | | (0.015) |
| **Panel C: Intergroup Tolerance** | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** |
| Log density | 0.100** | 0.038 | 0.122** | 0.146** | 0.093* | 0.073 |
| | (0.045) | (0.047) | (0.048) | (0.060) | (0.048) | (0.061) |
| … × Urban core: Large | | 0.135*** | | | | |
| | | (0.049) | | | | |
| … × Sprawl (2000-2014): High | | | 0.081* | | | |
| | | | (0.048) | | | |
| … × Ethinic Frac: High | | | | 0.059 | | |
| | | | | (0.037) | | |
| … × Property Crime: High | | | | | 0.112** | |
| | | | | | (0.048) | |
| … × Violent Crime: High | | | | | | 0.109** |
| | | | | | | (0.043) |

*Notes:* This table reports mean effects and mean interaction terms for the impact of density on social capital, using GHSL 1975 built up area and their interactions as instruments and including both the $\mathbf{W}_{2v}$ and $\mathbf{X}_v$ controls. For each panel, Column 1 replicates estimates from Table 4, Column 3, Row 3. See Appendix B.5 for more details on the estimation methodology and variables used for Columns 2-6. Robust standard errors, clustered at the subdistrict-level, are reported in parentheses. */**/*** denotes significant at the 10% / 5% / 1% levels.

**Figure 1:** Indonesia's Urban Areas

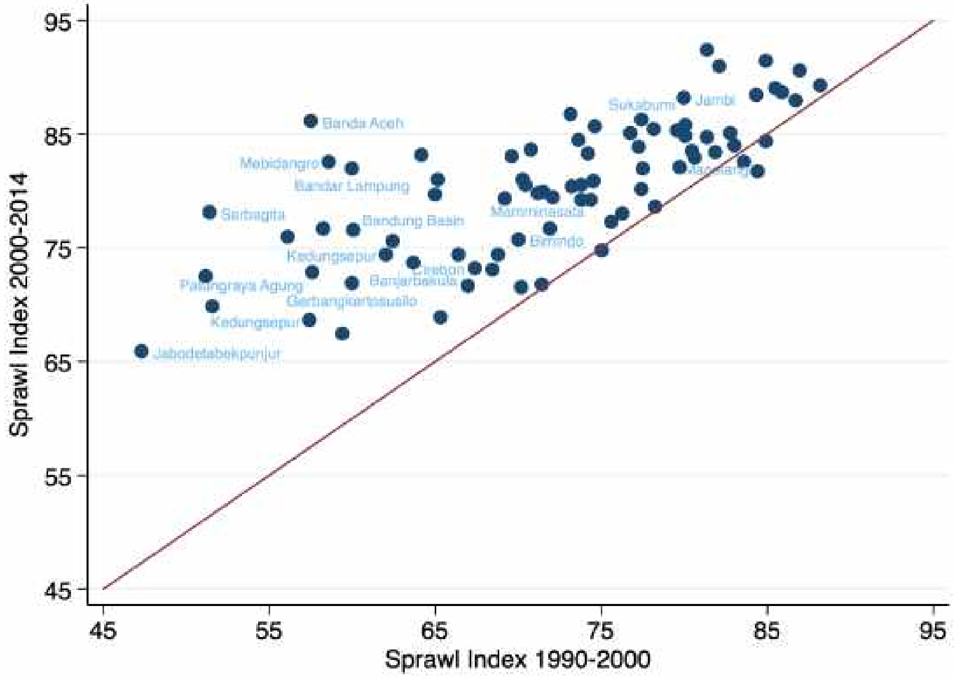
*Notes*: This figure presents a map of urban areas in Indonesia, where our approach for delineating metro areas, which follows Burchfield et al. (2006), is described in Section 4. We delineated 80 urban metropolitan areas in Indonesia out of the 83 metropolitan areas initially listed by the EAP-UE project. The remaining 3 areas were dropped because they either lacked a well-identified core or did not exhibit sufficiently strong urban expansion in 2014.

**Figure 2:** Distribution of Urban Sprawl across Indonesian Cities



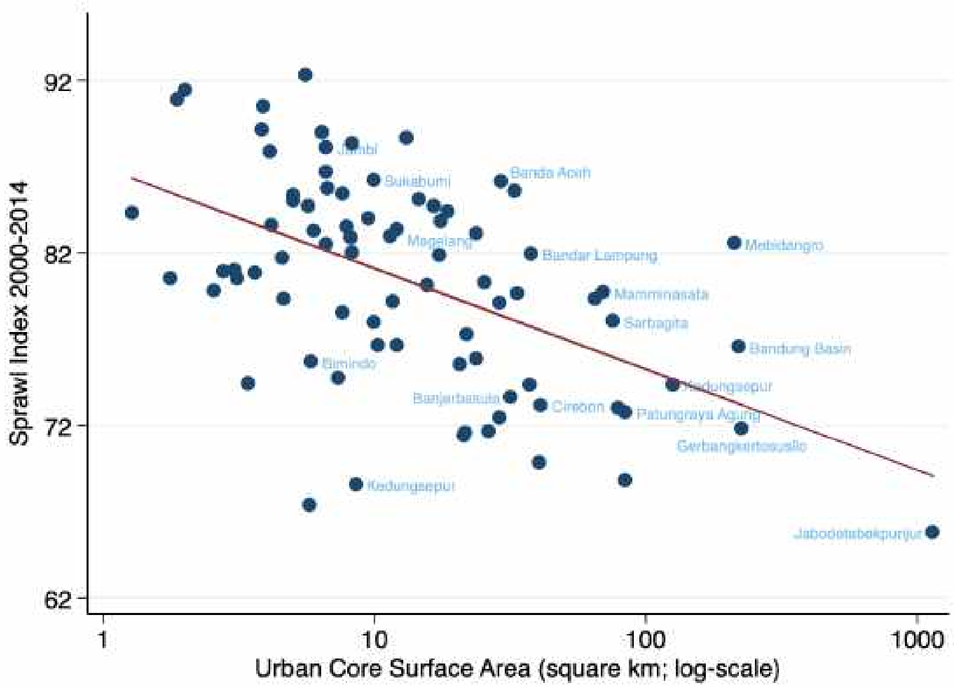

*Notes*: This is a histogram of the sprawl indices across Indonesian cities, where the sprawl measure is described in Section 4.1. The sprawl index ranges from a minimum of 65.8 to a maximum of 92.3, with mean of 80.3 and standard deviation equal to 6.1.

**Figure 3:** Evolution of the Urban Sprawl Indexes over Time




*Notes*: This figure presents a scatterplot of the relationship between urban sprawl from 2000-2014 against urban sprawl from 1990-2000. Each point in the scatterplot represents a different city.

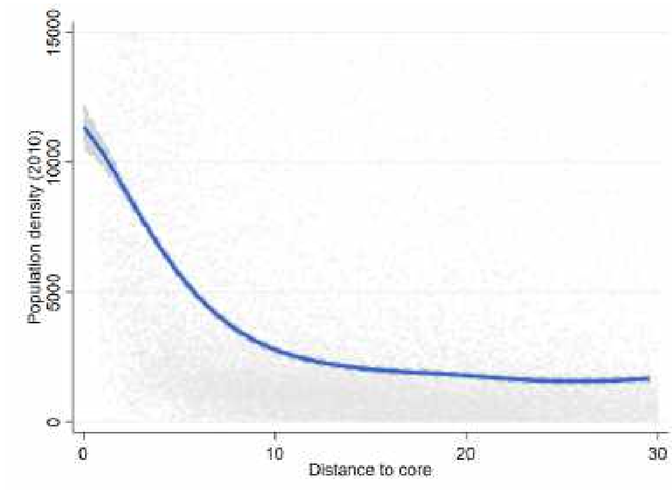
**Figure 4:** Relation between Urban Sprawl and Size of the Urban Core Area



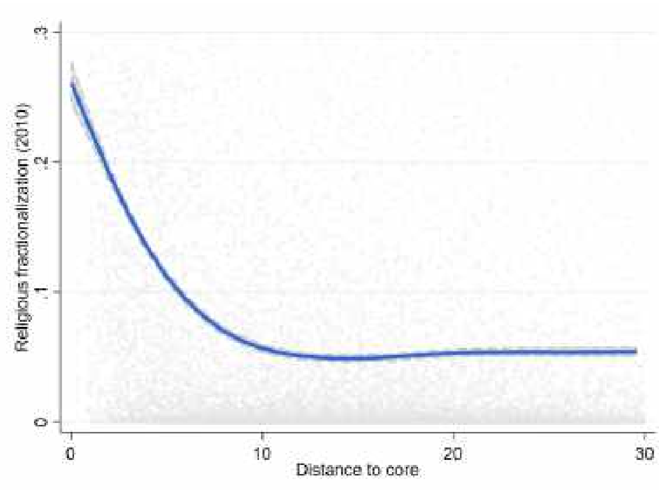

*Notes*: This figure presents a scatterplot of the relationship between urban sprawl from 2000-2014 against the size of the urban core area in 2000. The estimated semi-elasticity of the linear regression line is $-2.54$ (p-value .00). Each point in the scatterplot represents a different city. The horizontal axis is expressed in log-scale.

**Figure 5:** Population Density, Ethnic Composition, and Distance to the CBD

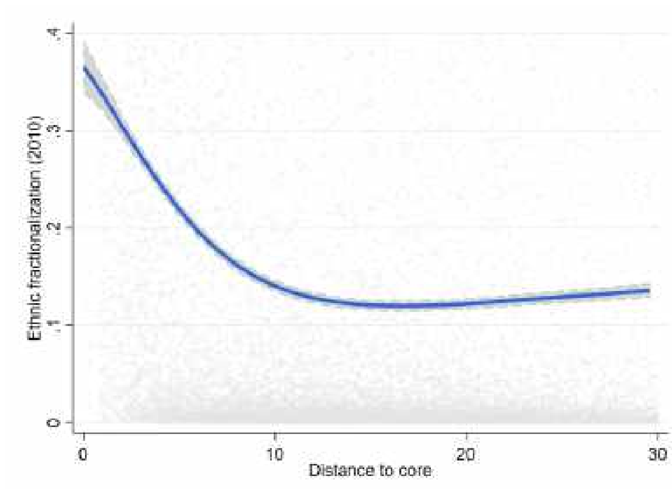
**(A)** DENSITY



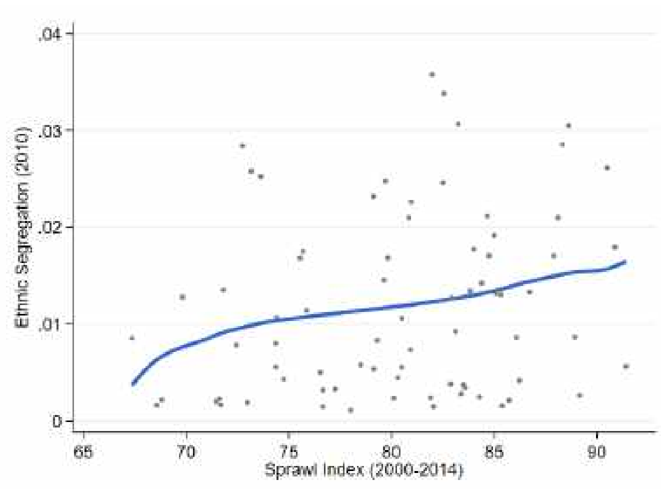

**(C)** RELIGIOUS FRACTIONALIZATION




**(B)** ETHNIC FRACTIONALIZATION



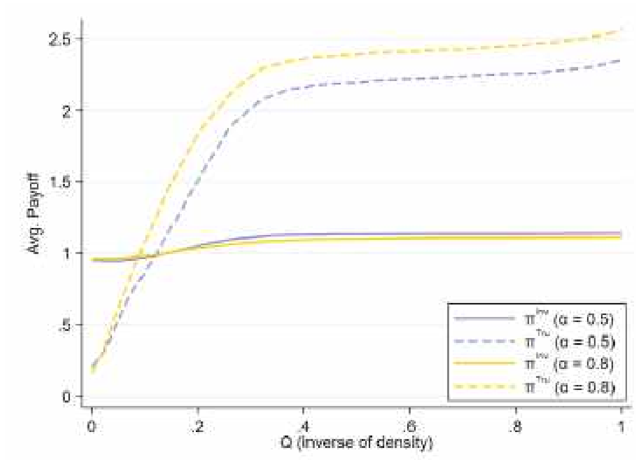

**(D)** ETHNIC SEGREGATION



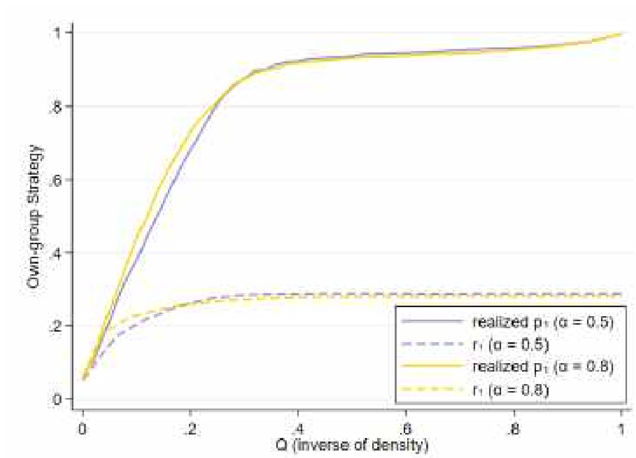

*Notes*: These figures plot local polynomial smooth of census trends on distance to CBD. The smooth uses an Epanechnikov kernel, rule-of-thumb bandwidth and local cubic function. Panel D (Segregation) plots the Alesina and Zhuravskaya (2011) across cities in Indonesia, using villages as the small unit. We omit two cities (Greater Jakarta and Pulang Pisau) from this figure because they are outliers in the relationship.

**Figure 6:** How Lower Density Increases Trust

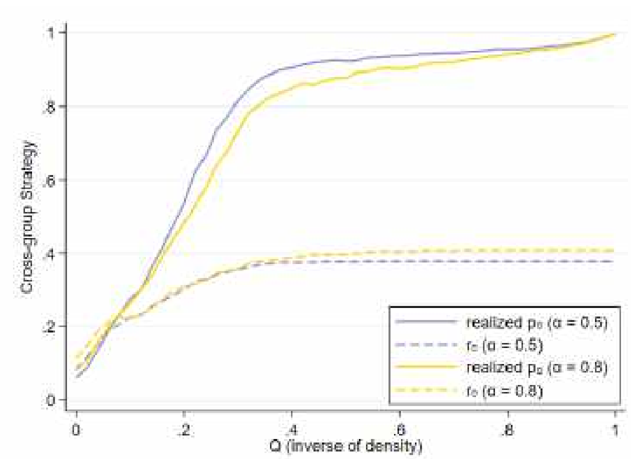
**(A)** PROFITS




**(B)** $\widetilde{p}_1$ (REALIZED $p_1$) AND $r_1$

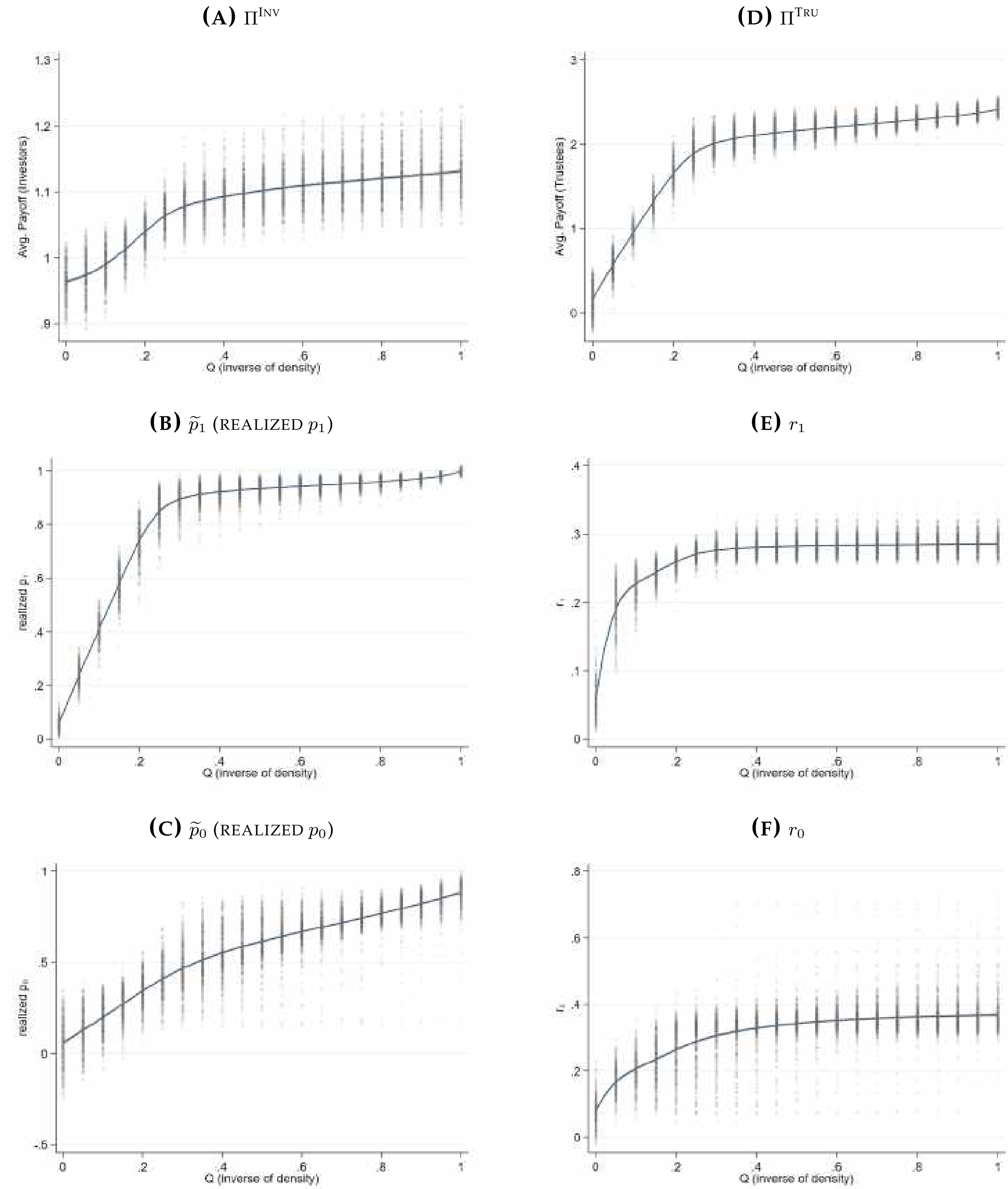



**(C)** $\widetilde{p}_0$ (REALIZED $p_0$) AND $r_0$




*Notes*: For each simulation, we use the following parameters: the total population size $N = 100$, the mutation rate $\mu = 0.01$, and the selection intensity $\beta = 20$. Results are averaged over the last 80 percent of 50 simulation runs, where each run consists of 50,000 rounds.

**Figure 7:** The Effect of Density on Trust: Controlling for Sorting with Simulations




**(A)** $\Pi^{\text{INV}}$

**(D)** $\Pi^{\text{TRU}}$

**(B)** $\widetilde{p}_1$ (REALIZED $p_1$)

**(E)** $r_1$

**(C)** $\widetilde{p}_0$ (REALIZED $p_0$)

**(F)** $r_0$

*Notes*: This figure shows the relationship between $Q$ and trust game outcomes from a partially linear regression of (12), where we control for $R$, the unobserved share of intolerant individuals in the community. The data are 8,400 different simulated communities that vary by initial parameter draws, $\alpha$, $R$, and $Q$. Outcomes shown include investor payoffs (Panel A), trustee payoffs (Panel B), realized investor trust in own-group games (Panel C), realized investor trust in cross-group games (Panel D), own-return probabilities (Panel E), and cross-group return probabilities (Panel F) For each simulation, we use the following parameters: the total population size $N = 100$, the mutation rate $\mu = 0.01$, and the selection intensity $\beta = 20$. Results are averaged over the last 80 percent of 50 simulation runs, where each run consists of 50,000 rounds.

# A Appendix Tables and Figures

**Table A.1:** Principal Components Analysis of $\mathbf{X}_v$

| | **Full SUSENAS** | **Urban SUSENAS** |
|---|---|---|
| | **(1)** | **(2)** |
| # of Variables in $\mathbf{X}_v$ | 38 | 38 |
| # of factors needed to explain: | | |
| ... 75% of total $\mathbf{X}_v$ variation | 18 | 16 |
| ... 90% of total $\mathbf{X}_v$ variation | 25 | 23 |
| ... 95% of total $\mathbf{X}_v$ variation | 28 | 27 |
| ... 99% of total $\mathbf{X}_v$ variation | 33 | 32 |
| ... 100% of total $\mathbf{X}_v$ variation | 38 | 37 |

*Notes:* This table reports a principal components analysis of the 38 $\mathbf{X}_v$ variables, both for the full SUSENAS sample (column 1) and for our urban SUSENAS sample described in Section 4 (column 2). The first row lists the number of variables in $\mathbf{X}_v$. The next set of rows report the number of factors needed to explain 75%, 90%, 95%, 99% and 100% of the total variation in $\mathbf{X}_v$.

**Table A.2:** Kleibergen and Paap (2006) Cluster-Robust Tests of the Rank of the $\mathbf{X}_v$ Covariance Matrix

| # Fact. | | Full SUSENAS | Urban SUSENAS |
|---|---|---|---|
| | | P-Value | P-Value |
| $H_0$ | $H_A$ | (1) | (2) |
| 0 | 1+ | 0.000 | . |
| 1 | 2+ | 0.000 | . |
| 2 | 3+ | 0.000 | . |
| 3 | 4+ | 0.000 | . |
| 4 | 5+ | 0.000 | . |
| 5 | 6+ | 0.000 | . |
| 6 | 7+ | 0.000 | . |
| 7 | 8+ | 0.000 | . |
| 8 | 9+ | 0.000 | . |
| 9 | 10+ | 0.000 | . |
| 10 | 11+ | 0.000 | 0.210 |
| 11 | 12+ | 0.000 | 0.043 |
| 12 | 13+ | 0.000 | 0.006 |
| 13 | 14+ | 0.000 | 0.002 |
| 14 | 15+ | 0.000 | 0.000 |
| 15 | 16+ | 0.000 | 0.000 |
| 16 | 17+ | 0.000 | 0.000 |
| 17 | 18+ | 0.000 | 0.000 |
| 18 | 19+ | 0.000 | 0.000 |
| 19 | 20+ | 0.000 | 0.000 |
| 20 | 21+ | 0.000 | 0.000 |
| 21 | 22+ | 0.000 | 0.000 |
| 22 | 23+ | 0.000 | 0.000 |
| 23 | 24+ | 0.000 | 0.000 |
| 24 | 25+ | 0.000 | 0.000 |
| 25 | 26+ | 0.000 | 0.007 |
| 26 | 27+ | 0.000 | 0.077 |
| 27 | 28+ | 0.000 | 0.047 |
| 28 | 29+ | 0.000 | 0.138 |
| 29 | 30+ | 0.000 | 0.388 |
| 30 | 31+ | 0.000 | 0.408 |
| 31 | 32+ | 0.000 | 0.679 |
| 32 | 33+ | 0.003 | 0.883 |
| 33 | 34+ | 0.000 | 0.997 |
| 34 | 35+ | 0.144 | 1.000 |
| 35 | 36+ | 0.340 | 1.000 |
| 36 | 37+ | 0.857 | 0.999 |

*Notes:* Each element of this table reports a $p$-value from a test based on Kleibergen and Paap (2006) of the null hypothesis that the rank of the covariance matrix of $\mathbf{X}_v$ is equal to the value associated with the row label, against the alternative that the rank exceeds this value. These $p$-values are robust and account for clustering at the sub-district level. The entry "." corresponds to a case in which the rank test returned an error due to a non-positive definite covariance matrix. Column 1 performs this test on the full SUSENAS sample, while column 2 performs it just for our urban SUSENAS sample, described in Section 4.

**Table A.3:** The Effect of Density on Trust in Neighbors: Individual Controls

| | | Soil IV | GHSL 1975 |
|---|---|---|---|
| | **OLS** | **IV-LASSO** | **2SLS** |
| | **(1)** | **(2)** | **(3)** |
| Log Density (2010) | -0.020*** | -0.038*** | -0.034*** |
| | (0.004) | (0.009) | (0.006) |
| Age | 0.004*** | 0.004*** | 0.004*** |
| | (0.001) | (0.001) | (0.001) |
| Age$^2$ | -0.000*** | -0.000*** | -0.000** |
| | (0.000) | (0.000) | (0.000) |
| Female (0 1) | -0.011 | -0.010 | 0.003 |
| | (0.011) | (0.011) | (0.014) |
| Some High School (0 1) | 0.003 | 0.010 | -0.001 |
| | (0.011) | (0.012) | (0.012) |
| Only Completed High School (0 1) | -0.030** | -0.016 | -0.025* |
| | (0.014) | (0.015) | (0.015) |
| Any Higher Education (0 1) | -0.054*** | -0.040** | -0.051*** |
| | (0.016) | (0.017) | (0.018) |
| Married (0 1) | -0.018 | -0.026 | -0.015 |
| | (0.017) | (0.017) | (0.021) |
| Divorced (0 1) | -0.010 | -0.018 | -0.022 |
| | (0.022) | (0.022) | (0.026) |
| Widowed (0 1) | -0.006 | -0.013 | -0.016 |
| | (0.019) | (0.019) | (0.022) |
| Working in Agriculture (0 1) | 0.011 | -0.003 | -0.012 |
| | (0.008) | (0.010) | (0.009) |
| Non-employed (0 1) | -0.008 | -0.008 | -0.009 |
| | (0.010) | (0.010) | (0.011) |
| Self-employed (0 1) | -0.007 | -0.005 | 0.003 |
| | (0.007) | (0.007) | (0.009) |
| Employer (0 1) | -0.022*** | -0.022*** | -0.011 |
| | (0.008) | (0.008) | (0.009) |
| Household Size | -0.003 | -0.002 | -0.004* |
| | (0.002) | (0.002) | (0.002) |
| Ever Migrant (0 1) | -0.012 | -0.006 | -0.014 |
| | (0.008) | (0.008) | (0.010) |
| Recent Migrant (0 1) | 0.007 | 0.006 | -0.028 |
| | (0.016) | (0.016) | (0.020) |
| Elevation | -0.000 | -0.000** | -0.000* |
| | (0.000) | (0.000) | (0.000) |
| Ruggedness | -0.037 | -0.049 | -0.034 |
| | (0.030) | (0.030) | (0.038) |
| $N$ | 23,280 | 23,280 | 14,774 |
| $N$ Clusters | 1,290 | 1,290 | 867 |
| Adjusted $R^2$ | 0.036 | 0.037 | 0.039 |
| Adjusted $R^2$ (within) | 0.011 | 0.012 | 0.013 |
| Kleibergen-Paap Wald Rank $F$ Stat | | 73.517 | 883.644 |
| Under Id. Test (KP Rank LM Stat) | | 178.104 | 229.871 |
| p-Value | | 0.000 | 0.000 |
| AR Wald Test (Weak IV Robust Inf.) | | 6.818 | 30.764 |
| p-Value | | 0.000 | 0.000 |
| Hansen J Stat | | 18.699 | 0.000 |
| p-Value | | 0.002 | |
| City FE | Yes | Yes | Yes |

*Notes:* This table reports estimates of $\theta$ and $\beta$ from equation (6), where we set $\mathbf{\Gamma}_1 = 0$. This specification is identical to Table 3, Panel A, but we report estimates of $\beta$ here instead of supressing them as we do in the main table. Robust standard errors, clustered at the subdistrict-level, are reported in parentheses. */**/*** denotes significant at the 10% / 5% / 1% levels.

**Table A.4:** The Effect of Density on Trust in Neighbors: Adding $\mathbf{X}_v$

| | | Soil IV | GHSL 1975 |
|---|---|---|---|
| | OLS | IV-LASSO | 2SLS |
| | (1) | (2) | (3) |
| Log Density (2010) | -0.007 | -0.053*** | -0.043*** |
| | (0.006) | (0.019) | (0.014) |
| Avg. Age | -0.003 | -0.005 | -0.006 |
| | (0.005) | (0.006) | (0.007) |
| Percent Female | 0.076 | -0.073 | -0.186 |
| | (0.376) | (0.381) | (0.406) |
| Percent Working in Agriculture | 0.054 | -0.074 | -0.048 |
| | (0.039) | (0.062) | (0.054) |
| Avg. Household Size | -0.000 | -0.000 | -0.000 |
| | (0.000) | (0.000) | (0.000) |
| Avg. Years of Schooling | -0.013 | 0.002 | 0.002 |
| | (0.008) | (0.010) | (0.010) |
| Percent Single | -0.447 | -0.767 | -1.172 |
| | (0.740) | (0.757) | (0.917) |
| Percent Married | -0.239 | -0.603 | -1.038 |
| | (0.674) | (0.697) | (0.809) |
| Percent Divorced | 0.134 | 0.276 | 0.318 |
| | (1.476) | (1.491) | (1.596) |
| Percent Unemployed | -0.050 | -0.051 | -0.088 |
| | (0.086) | (0.086) | (0.114) |
| Percent Self-employed | -0.198 | -0.149 | -0.345** |
| | (0.124) | (0.127) | (0.147) |
| Percent Employer | -0.238* | -0.152 | -0.226 |
| | (0.141) | (0.148) | (0.163) |
| Percent Ever Migrants | 0.123** | 0.156*** | 0.121 |
| | (0.057) | (0.059) | (0.085) |
| Percent Recent Migrants | -0.159 | -0.290** | -0.453** |
| | (0.120) | (0.127) | (0.178) |
| Percent Speak Indonesian | 0.056 | -0.020 | -0.108 |
| | (0.123) | (0.125) | (0.140) |
| Percent Religion: Islam | -0.463 | 0.006 | -1.107 |
| | (1.172) | (1.261) | (1.058) |
| Percent Religion: Christian | -0.523 | -0.054 | -1.089 |
| | (1.177) | (1.266) | (1.065) |
| Percent Religion: Catholic | -0.674 | -0.379 | -0.983 |
| | (1.198) | (1.270) | (1.081) |
| Percent Religion: Hindu | -1.009 | -0.545 | -1.584 |
| | (1.200) | (1.292) | (1.095) |
| Percent Religion: Buddhist | -0.333 | 0.087 | -1.569 |
| | (1.187) | (1.268) | (1.090) |
| Percent Religion: Confucian | -0.537 | -0.576 | -0.903 |
| | (1.229) | (1.301) | (1.708) |
| Percent Jawa | -0.043 | -0.038 | -0.000 |
| | (0.056) | (0.055) | (0.081) |
| Percent Sunda | 0.012 | -0.000 | 0.001 |
| | (0.052) | (0.050) | (0.063) |
| Percent Batak | 0.023 | 0.072 | 0.136 |
| | (0.099) | (0.103) | (1.609) |
| Percent Ethnicities from Nusa Tenggara | -0.446 | -0.447 | 0.779 |
| | (0.273) | (0.284) | (0.610) |
| Percent Madura | -0.164 | -0.127 | -0.087 |
| | (0.103) | (0.102) | (0.109) |
| Percent Betawi | -0.090 | -0.078 | 0.292** |
| | (0.096) | (0.094) | (0.144) |
| Percent Aceh | -0.856 | -0.975* | -17.356 |
| | (0.554) | (0.582) | (19.384) |
| Percent Minangkabau | 0.182 | 0.411 | 4.817** |
| | (0.228) | (0.265) | (2.114) |
| Percent Bugis | -0.255 | -0.212 | -0.228 |
| | (0.191) | (0.220) | (0.228) |
| Percent Malay | -0.217 | -0.143 | -0.880** |
| | (0.142) | (0.146) | (0.421) |
| Percent Ethnicities from South Sumatra | -0.221** | -0.161 | -1.211 |
| | (0.111) | (0.114) | (4.784) |
| Percent Ethnicities from Banten | -0.580*** | -0.604*** | -3.470 |
| | (0.205) | (0.198) | (2.241) |
| Percent Banjar | -0.002 | 0.091 | 0.023 |
| | (0.147) | (0.159) | (0.166) |
| Percent Dayak | -0.280 | -0.249 | -0.490* |
| | (0.243) | (0.266) | (0.276) |
| Percent Chinese | -0.436** | -0.260 | -0.159 |
| | (0.215) | (0.224) | (0.293) |
| Percent Ethnicities from Central Sulawesi | 0.115 | 0.087 | 0.031 |
| | (0.159) | (0.171) | (0.166) |
| Percent Ethnicities from Papua | -2.064 | -1.571 | -7.951* |
| | (3.404) | (3.454) | (4.077) |
| Percent Makassar | -0.201 | -0.165 | -0.188 |
| | (0.185) | (0.207) | (0.213) |
| $N$ | 23,280 | 23,280 | 14,774 |
| $N$ Clusters | 1,290 | 1,290 | 867 |
| Adjusted $R^2$ | 0.044 | 0.046 | 0.045 |
| Adjusted $R^2$ (within) | 0.020 | 0.022 | 0.019 |
| Kleibergen-Paap Wald Rank $F$ Stat | | 19.599 | 224.076 |
| Under Id. Test (KP Rank LM Stat) | | 77.864 | 126.261 |
| p-Value | | 0.000 | 0.000 |
| AR Wald Test (Weak IV Robust Inf.) | | 4.003 | 9.474 |
| p-Value | | 0.001 | 0.002 |
| Hansen J Stat | | 13.855 | 0.000 |
| p-Value | | 0.017 | |
| $\mathbf{X}_i$ Controls | Yes | Yes | Yes |
| $\mathbf{W}_{2v}$ Controls | Yes | Yes | Yes |
| City FE | Yes | Yes | Yes |

*Notes:* This table reports estimates of $\theta$ and $\mathbf{\Gamma}$ from equation (6). This specification is identical to Table 3, Panel B, but we report estimates of $\mathbf{\Gamma}$ here instead of supressing them as we do in the main table. Estimates of $\beta$ are supressed. Robust standard errors, clustered at the subdistrict-level, are reported in parentheses. */**/*** denotes significant at the 10% / 5% / 1% levels.

**Table A.5:** The Effect of Density on Trust in Neighbors (Linear Index)

| | OLS | Soil IV<br>IV-LASSO | GHSL 1975<br>2SLS | Dep.Var<br>Mean (SE) | N |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | | |
| 1. trust neighbor to watch house | -0.028*** | -0.056*** | -0.048*** | 2.916*** | 23280.000 |
| | (0.005) | (0.012) | (0.009) | (0.003) | (.) |
| ... adding $\mathbf{X}_v$ controls | -0.006 | -0.059** | -0.056*** | | |
| | (0.009) | (0.025) | (0.020) | | |
| 2. trust neighbor to tend children | -0.053*** | -0.078*** | -0.057*** | 2.649*** | 23280.000 |
| | (0.007) | (0.016) | (0.013) | (0.004) | (.) |
| ... adding $\mathbf{X}_v$ controls | -0.024** | -0.062* | -0.064** | | |
| | (0.011) | (0.033) | (0.026) | | |
| 3. ready to help neighbor | -0.000 | 0.010 | -0.018** | 2.978*** | 23280.000 |
| | (0.005) | (0.012) | (0.009) | (0.003) | (.) |
| ... adding $\mathbf{X}_v$ controls | 0.013 | 0.011 | -0.030* | | |
| | (0.008) | (0.024) | (0.018) | | |
| 4. contribute to assist unfortunate neigbhors | -0.022*** | -0.021 | -0.045*** | 2.808*** | 23280.000 |
| | (0.008) | (0.016) | (0.012) | (0.005) | (.) |
| ... adding $\mathbf{X}_v$ controls | -0.003 | 0.002 | -0.043* | | |
| | (0.011) | (0.033) | (0.025) | | |
| 5. easily access to neighbors' help | -0.026*** | -0.034* | -0.029** | 2.649*** | 23280.000 |
| | (0.008) | (0.017) | (0.014) | (0.005) | (.) |
| ... adding $\mathbf{X}_v$ controls | 0.018 | -0.001 | 0.051* | | |
| | (0.012) | (0.036) | (0.030) | | |
| City FE | Yes | Yes | Yes | | |

*Notes:* Each cell reports the coefficient on log population density in 2010 from a separate linear regression of (6) where the dependent variable is the outcome listed in the row header. Column 1 reports OLS estimates, while Column 2 applies a post-double-selection lasso estimator to select the best soil characteristics instruments, following Belloni et al. (2012). Columns 3 use 2SLS with the GHSL 1975 instruments. In the first row of each panel, we only control for $\mathbf{X}_i$ and $\mathbf{W}_{2v}$, setting $\mathbf{\Gamma}_1 = 0$. The second row of each panel reports the full, unrestricted model. All regressions are limited to the sample of villages within urban areas and include city-fixed effects. The sample size falls substantially in Column 3 because of missing GHSL 1975 data for Sumatra. Robust standard errors, clustered at the subdistrict-level, are reported in parentheses. */**/*** denotes significant at the 10% / 5% / 1% levels.

**Table A.6:** The Effect of Density on Community Trust and Participation (Linear Index)

| | | Soil IV | GHSL 1975 | | |
|---|---|---|---|---|---|
| | OLS (1) | IV-LASSO (2) | 2SLS (3) | Dep.Var Mean (SE) | N |
| 6. join community group(s) | 0.014 | -0.011 | 0.015 | 2.364*** | 21767.000 |
| | (0.009) | (0.019) | (0.016) | (0.006) | (.) |
| ... adding $\mathbf{X}_v$ controls | -0.007 | -0.077* | -0.097*** | | |
| | (0.013) | (0.041) | (0.030) | | |
| 7. join religious activities | -0.035*** | -0.044*** | -0.045*** | 2.683*** | 22899.000 |
| | (0.008) | (0.015) | (0.012) | (0.005) | (.) |
| ... adding $\mathbf{X}_v$ controls | -0.025** | -0.035 | -0.060** | | |
| | (0.011) | (0.033) | (0.027) | | |
| 8. join religious activities recently | -0.017*** | -0.035*** | -0.025*** | 0.725*** | 23006.000 |
| | (0.004) | (0.010) | (0.008) | (0.003) | (.) |
| ... adding $\mathbf{X}_v$ controls | -0.016** | -0.044** | -0.036** | | |
| | (0.007) | (0.021) | (0.018) | | |
| 9. voluntary public good provision | -0.024*** | -0.036* | -0.038*** | 2.503*** | 22487.000 |
| | (0.008) | (0.018) | (0.014) | (0.005) | (.) |
| ... adding $\mathbf{X}_v$ controls | -0.009 | -0.046 | -0.069** | | |
| | (0.013) | (0.040) | (0.029) | | |
| 10. join community activities recently | -0.008* | -0.015* | -0.010 | 0.796*** | 22993.000 |
| | (0.005) | (0.009) | (0.008) | (0.003) | (.) |
| ... adding $\mathbf{X}_v$ controls | -0.009 | -0.030 | -0.017 | | |
| | (0.007) | (0.019) | (0.016) | | |
| 11. trust religious leader | -0.006 | -0.012 | -0.018** | 3.051*** | 23240.000 |
| | (0.004) | (0.009) | (0.008) | (0.003) | (.) |
| ... adding $\mathbf{X}_v$ controls | 0.002 | -0.005 | -0.020 | | |
| | (0.007) | (0.020) | (0.017) | | |
| 12. trust communtiy leader | -0.009** | -0.016** | -0.011 | 2.978*** | 23280.000 |
| | (0.004) | (0.008) | (0.007) | (0.003) | (.) |
| ... adding $\mathbf{X}_v$ controls | -0.003 | -0.018 | -0.011 | | |
| | (0.006) | (0.017) | (0.015) | | |
| City FE | Yes | Yes | Yes | | |

*Notes:* Each cell reports the coefficient on log population density in 2010 from a separate linear regression of (6) where the dependent variable is the outcome listed in the row header. Column 1 reports OLS estimates, while Column 2 applies a post-double-selection lasso estimator to select the best soil characteristics instruments, following Belloni et al. (2012). Columns 3 use 2SLS with the GHSL 1975 instruments. In the first row of each panel, we only control for $\mathbf{X}_i$ and $\mathbf{W}_{2v}$, setting $\mathbf{\Gamma}_1 = 0$. The second row of each panel reports the full, unrestricted model. All regressions are limited to the sample of villages within urban areas and include city-fixed effects. The sample size falls substantially in Column 3 because of missing GHSL 1975 data for Sumatra. Robust standard errors, clustered at the subdistrict-level, are reported in parentheses. */**/*** denotes significant at the 10% / 5% / 1% levels.

**Table A.7:** The Effect of Density on Intergroup Tolerance (Linear Index)

| | OLS | Soil IV<br>IV-LASSO | GHSL 1975<br>2SLS | Dep.Var<br>Mean (SE) | N |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | | |
| 13. pleased with non-coreligions | 0.046*** | 0.038** | 0.083*** | 2.733*** | 20578.000 |
| | (0.009) | (0.019) | (0.017) | (0.004) | (.) |
| ... adding $\mathbf{X}_v$ controls | 0.040*** | 0.012 | 0.059 | | |
| | (0.013) | (0.038) | (0.037) | | |
| 14. pleased with non-coethnics | 0.015** | -0.007 | 0.048*** | 2.823*** | 20742.000 |
| | (0.007) | (0.015) | (0.014) | (0.004) | (.) |
| ... adding $\mathbf{X}_v$ controls | 0.015 | -0.050 | 0.053* | | |
| | (0.011) | (0.032) | (0.031) | | |
| City FE | Yes | Yes | Yes | | |

*Notes:* Each cell reports the coefficient on log population density in 2010 from a separate linear regression of (6) where the dependent variable is the outcome listed in the row header. Column 1 reports OLS estimates, while Column 2 applies a post-double-selection lasso estimator to select the best soil characteristics instruments, following Belloni et al. (2012). Columns 3 use 2SLS with the GHSL 1975 instruments. In the first row of each panel, we only control for $\mathbf{X}_i$ and $\mathbf{W}_{2v}$, setting $\mathbf{\Gamma}_1 = 0$. The second row of each panel reports the full, unrestricted model. All regressions are limited to the sample of villages within urban areas and include city-fixed effects. The sample size falls substantially in Column 3 because of missing GHSL 1975 data for Sumatra. Robust standard errors, clustered at the subdistrict-level, are reported in parentheses. */**/*** denotes significant at the 10% / 5% / 1% levels.

**Table A.8:** The Effect of Density on Trust in Neighbors (Linear Prob)

| | | Soil IV | GHSL 1975 | | |
|---|---|---|---|---|---|
| | **OLS** | **IV-LASSO** | **2SLS** | **Dep.Var** | |
| | **(1)** | **(2)** | **(3)** | **Mean (SE)** | **N** |
| 1. trust neighbor to watch house | -0.020*** | -0.038*** | -0.034*** | 0.843*** | 23280.000 |
| | (0.004) | (0.009) | (0.006) | (0.002) | (.) |
| ... adding $\mathbf{X}_v$ controls | -0.007 | -0.053*** | -0.043*** | | |
| | (0.006) | (0.019) | (0.014) | | |
| 2. trust neighbor to tend children | -0.040*** | -0.057*** | -0.036*** | 0.641*** | 23280.000 |
| | (0.006) | (0.012) | (0.010) | (0.003) | (.) |
| ... adding $\mathbf{X}_v$ controls | -0.023*** | -0.059** | -0.026 | | |
| | (0.009) | (0.027) | (0.021) | | |
| 3. ready to help neighbor | -0.001 | 0.007 | -0.008 | 0.880*** | 23280.000 |
| | (0.004) | (0.008) | (0.005) | (0.002) | (.) |
| ... adding $\mathbf{X}_v$ controls | 0.006 | 0.016 | -0.002 | | |
| | (0.005) | (0.017) | (0.012) | | |
| 4. contribute to assist unfortunate neigbhors | -0.018*** | -0.017 | -0.030*** | 0.704*** | 23280.000 |
| | (0.005) | (0.011) | (0.008) | (0.003) | (.) |
| ... adding $\mathbf{X}_v$ controls | -0.010 | -0.008 | -0.031* | | |
| | (0.008) | (0.023) | (0.017) | | |
| 5. easily access to neighbors' help | -0.019*** | -0.022* | -0.026*** | 0.623*** | 23280.000 |
| | (0.006) | (0.012) | (0.010) | (0.003) | (.) |
| ... adding $\mathbf{X}_v$ controls | 0.006 | -0.010 | 0.023 | | |
| | (0.008) | (0.026) | (0.021) | | |
| City FE | Yes | Yes | Yes | | |

*Notes:* Each cell reports the coefficient on log population density in 2010 from a separate linear probability model of (6) where the dependent variable is a binary coarsening of the outcome listed in the row header. Column 1 reports OLS estimates, while Column 2 applies a post-double-selection lasso estimator to select the best soil characteristics instruments, following Belloni et al. (2012). Columns 3 use 2SLS with the GHSL 1975 instruments. In the first row of each panel, we only control for $\mathbf{X}_i$ and $\mathbf{W}_{2v}$, setting $\mathbf{\Gamma}_1 = 0$. The second row of each panel reports the full, unrestricted model. All regressions are limited to the sample of villages within urban areas and include city-fixed effects. The sample size falls substantially in Column 3 because of missing GHSL 1975 data for Sumatra. Robust standard errors, clustered at the subdistrict-level, are reported in parentheses. */**/*** denotes significant at the 10% / 5% / 1% levels.

**Table A.9:** The Effect of Density on Community Trust and Participation (Linear Prob)

| | OLS (1) | Soil IV<br>IV-LASSO (2) | GHSL 1975<br>2SLS (3) | Dep.Var Mean (SE) | N |
|---|---|---|---|---|---|
| 6. join community group(s) | 0.006 | -0.012 | 0.009 | 0.474*** | 21767.000 |
| | (0.005) | (0.010) | (0.009) | (0.003) | (.) |
| ... adding $\mathbf{X}_v$ controls | -0.006 | -0.056** | -0.039** | | |
| | (0.007) | (0.024) | (0.018) | | |
| 7. join religious activities | -0.021*** | -0.022** | -0.028*** | 0.639*** | 22899.000 |
| | (0.005) | (0.010) | (0.008) | (0.003) | (.) |
| ... adding $\mathbf{X}_v$ controls | -0.021*** | -0.022 | -0.034* | | |
| | (0.007) | (0.022) | (0.018) | | |
| 8. join religious activities recently | -0.017*** | -0.035*** | -0.025*** | 0.725*** | 23006.000 |
| | (0.004) | (0.010) | (0.008) | (0.003) | (.) |
| ... adding $\mathbf{X}_v$ controls | -0.018*** | -0.046** | -0.036* | | |
| | (0.007) | (0.022) | (0.018) | | |
| 9. voluntary public good provision | -0.019*** | -0.024** | -0.027*** | 0.520*** | 22487.000 |
| | (0.005) | (0.011) | (0.009) | (0.003) | (.) |
| ... adding $\mathbf{X}_v$ controls | -0.020** | -0.039 | -0.049** | | |
| | (0.009) | (0.026) | (0.020) | | |
| 10. join community activities recently | -0.008* | -0.015* | -0.010 | 0.796*** | 22993.000 |
| | (0.005) | (0.009) | (0.008) | (0.003) | (.) |
| ... adding $\mathbf{X}_v$ controls | -0.012* | -0.035* | -0.018 | | |
| | (0.007) | (0.021) | (0.018) | | |
| 11. trust religious leader | -0.003 | -0.009** | -0.006* | 0.952*** | 23240.000 |
| | (0.002) | (0.004) | (0.003) | (0.001) | (.) |
| ... adding $\mathbf{X}_v$ controls | -0.000 | -0.020** | -0.006 | | |
| | (0.003) | (0.009) | (0.007) | | |
| 12. trust communtiy leader | -0.008*** | -0.013** | -0.006 | 0.921*** | 23280.000 |
| | (0.003) | (0.005) | (0.004) | (0.002) | (.) |
| ... adding $\mathbf{X}_v$ controls | -0.006 | -0.024** | -0.002 | | |
| | (0.004) | (0.011) | (0.010) | | |
| City FE | Yes | Yes | Yes | | |

*Notes:* Each cell reports the coefficient on log population density in 2010 from a separate linear probability model of (6) where the dependent variable is a binary coarsening of the outcome listed in the row header. Column 1 reports OLS estimates, while Column 2 applies a post-double-selection lasso estimator to select the best soil characteristics instruments, following Belloni et al. (2012). Columns 3 use 2SLS with the GHSL 1975 instruments. In the first row of each panel, we only control for $\mathbf{X}_i$ and $\mathbf{W}_{2v}$, setting $\mathbf{\Gamma}_1 = 0$. The second row of each panel reports the full, unrestricted model. All regressions are limited to the sample of villages within urban areas and include city-fixed effects. The sample size falls substantially in Column 3 because of missing GHSL 1975 data for Sumatra. Robust standard errors, clustered at the subdistrict-level, are reported in parentheses. */**/*** denotes significant at the 10% / 5% / 1% levels.

**Table A.10:** The Effect of Density on Intergroup Tolerance (Linear Prob)

| | | Soil IV | GHSL 1975 | | |
|---|---|---|---|---|---|
| | **OLS** | **IV-LASSO** | **2SLS** | **Dep.Var** | |
| | **(1)** | **(2)** | **(3)** | **Mean (SE)** | **N** |
| 13. pleased with non-coreligions | 0.034*** | 0.032** | 0.059*** | 0.759*** | 20578.000 |
| | (0.007) | (0.014) | (0.012) | (0.003) | (.) |
| ... adding $\mathbf{X}_v$ controls | 0.028*** | 0.004 | 0.038 | | |
| | (0.010) | (0.029) | (0.027) | | |
| 14. pleased with non-coethnics | 0.011** | -0.002 | 0.036*** | 0.827*** | 20742.000 |
| | (0.005) | (0.012) | (0.011) | (0.003) | (.) |
| ... adding $\mathbf{X}_v$ controls | 0.010 | -0.043* | 0.044* | | |
| | (0.009) | (0.026) | (0.024) | | |
| City FE | Yes | Yes | Yes | | |

*Notes:* Each cell reports the coefficient on log population density in 2010 from a separate linear probability model of (6) where the dependent variable is a binary coarsening of the outcome listed in the row header. Column 1 reports OLS estimates, while Column 2 applies a post-double-selection lasso estimator to select the best soil characteristics instruments, following Belloni et al. (2012). Columns 3 use 2SLS with the GHSL 1975 instruments. In the first row of each panel, we only control for $\mathbf{X}_i$ and $\mathbf{W}_{2v}$, setting $\mathbf{\Gamma}_1 = 0$. The second row of each panel reports the full, unrestricted model. All regressions are limited to the sample of villages within urban areas and include city-fixed effects. The sample size falls substantially in Column 3 because of missing GHSL 1975 data for Sumatra. Robust standard errors, clustered at the subdistrict-level, are reported in parentheses. */**/*** denotes significant at the 10% / 5% / 1% levels.

**Table A.11:** The Effect of Density on Trust in Neighbors (Binary Probit)

| | | Soil IV | GHSL 1975 | | |
|---|---|---|---|---|---|
| | **ML** | **ML** | **ML** | **Dep.Var** | |
| | **(1)** | **(2)** | **(3)** | **Mean (SE)** | **N** |
| 1. trust neighbor to watch house | -0.086*** | -0.162*** | -0.159*** | 0.843*** | 23280.000 |
| | (0.017) | (0.040) | (0.029) | (0.002) | (.) |
| ... adding $\mathbf{X}_{\text{-}v}$ controls | -0.026 | -0.237*** | -0.212*** | | |
| | (0.027) | (0.092) | (0.065) | | |
| 2. trust neighbor to tend children | -0.114*** | -0.171*** | -0.105*** | 0.641*** | 23280.000 |
| | (0.016) | (0.037) | (0.029) | (0.003) | (.) |
| ... adding $\mathbf{X}_{\text{-}v}$ controls | -0.063** | -0.201** | -0.077 | | |
| | (0.025) | (0.086) | (0.062) | | |
| 3. ready to help neighbor | -0.005 | 0.012 | -0.048 | 0.880*** | 23280.000 |
| | (0.018) | (0.041) | (0.029) | (0.002) | (.) |
| ... adding $\mathbf{X}_{\text{-}v}$ controls | 0.027 | 0.031 | -0.012 | | |
| | (0.025) | (0.090) | (0.068) | | |
| 4. contribute to assist unfortunate neigbhors | -0.055*** | -0.055 | -0.095*** | 0.704*** | 23280.000 |
| | (0.015) | (0.034) | (0.025) | (0.003) | (.) |
| ... adding $\mathbf{X}_{\text{-}v}$ controls | -0.031 | -0.033 | -0.101* | | |
| | (0.023) | (0.072) | (0.057) | | |
| 5. easily access to neighbors' help | -0.052*** | -0.060* | -0.069*** | 0.623*** | 23280.000 |
| | (0.015) | (0.036) | (0.026) | (0.003) | (.) |
| ... adding $\mathbf{X}_{\text{-}v}$ controls | 0.019 | -0.039 | 0.069 | | |
| | (0.022) | (0.078) | (0.059) | | |
| City FE | Yes | Yes | Yes | | |

*Notes:* Each cell reports the coefficient on log population density in 2010 from a separate binary probit model of (6). All columns report maximum likelihood estimates; column 1 reports them without using instruments, while columns 2 use the instruments listed in the column headers. In column 2, we follow Belloni et al. (2012) and use a lasso procedure to select the best soil characteristics instruments before implementing the ML estimator. In the first row of each panel, we only control for $\mathbf{X}_i$ and $\mathbf{W}_{2v}$, setting $\mathbf{\Gamma}_1 = 0$. The second row of each panel reports the full, unrestricted model. All regressions are limited to the sample of villages within urban areas and include city-fixed effects. The sample size falls substantially in Column 2 because of missing GHSL 1975 data for Sumatra. Robust standard errors, clustered at the subdistrict-level, are reported in parentheses. */**/*** denotes significant at the 10% / 5% / 1% levels.

**Table A.12:** The Effect of Density on Community Trust and Participation (Binary Probit)

| | | Soil IV | GHSL 1975 | | |
|---|---|---|---|---|---|
| | ML (1) | ML (2) | ML (3) | Dep.Var Mean (SE) | N |
| 6. join community group(s) | 0.017 | -0.054* | 0.025 | 0.474*** | 21767.000 |
| | (0.013) | (0.031) | (0.025) | (0.003) | (.) |
| ... adding $\mathbf{X}_{-v}$ controls | -0.016 | -0.187*** | -0.114** | | |
| | (0.020) | (0.072) | (0.052) | | |
| 7. join religious activities | -0.060*** | -0.063** | -0.080*** | 0.639*** | 22899.000 |
| | (0.013) | (0.030) | (0.023) | (0.003) | (.) |
| ... adding $\mathbf{X}_{-v}$ controls | -0.062*** | -0.071 | -0.100* | | |
| | (0.020) | (0.068) | (0.054) | | |
| 8. join religious activities recently | -0.055*** | -0.093*** | -0.080*** | 0.725*** | 23006.000 |
| | (0.014) | (0.034) | (0.026) | (0.003) | (.) |
| ... adding $\mathbf{X}_{-v}$ controls | -0.058*** | -0.110 | -0.114* | | |
| | (0.022) | (0.077) | (0.062) | | |
| 9. voluntary public good provision | -0.052*** | -0.061* | -0.074*** | 0.520*** | 22487.000 |
| | (0.014) | (0.033) | (0.024) | (0.003) | (.) |
| ... adding $\mathbf{X}_{-v}$ controls | -0.052** | -0.104 | -0.133** | | |
| | (0.024) | (0.076) | (0.055) | | |
| 10. join community activities recently | -0.032* | -0.058 | -0.038 | 0.796*** | 22993.000 |
| | (0.017) | (0.037) | (0.031) | (0.003) | (.) |
| ... adding $\mathbf{X}_{-v}$ controls | -0.046* | -0.133 | -0.069 | | |
| | (0.026) | (0.085) | (0.071) | | |
| 11. trust religious leader | -0.026 | -0.105** | -0.075* | 0.952*** | 23240.000 |
| | (0.021) | (0.043) | (0.040) | (0.001) | (.) |
| ... adding $\mathbf{X}_{-v}$ controls | -0.003 | -0.255*** | -0.089 | | |
| | (0.031) | (0.099) | (0.086) | | |
| 12. trust communtiy leader | -0.049*** | -0.087** | -0.047 | 0.921*** | 23280.000 |
| | (0.017) | (0.037) | (0.033) | (0.002) | (.) |
| ... adding $\mathbf{X}_{-v}$ controls | -0.035 | -0.176** | -0.015 | | |
| | (0.027) | (0.083) | (0.076) | | |
| City FE | Yes | Yes | Yes | | |

*Notes:* Each cell reports the coefficient on log population density in 2010 from a separate binary probit model of (6). All columns report maximum likelihood estimates; column 1 reports them without using instruments, while columns 2 use the instruments listed in the column headers. In column 2, we follow Belloni et al. (2012) and use a lasso procedure to select the best soil characteristics instruments before implementing the ML estimator. In the first row of each panel, we only control for $\mathbf{X}_i$ and $\mathbf{W}_{2v}$, setting $\mathbf{\Gamma}_1 = 0$. The second row of each panel reports the full, unrestricted model. All regressions are limited to the sample of villages within urban areas and include city-fixed effects. The sample size falls substantially in Column 2 because of missing GHSL 1975 data for Sumatra. Robust standard errors, clustered at the subdistrict-level, are reported in parentheses. */**/*** denotes significant at the 10% / 5% / 1% levels.

**Table A.13:** The Effect of Density on Intergroup Tolerance (Binary Probit)

| | | Soil IV | GHSL 1975 | | |
|---|---|---|---|---|---|
| | **ML** **(1)** | **ML** **(2)** | **ML** **(3)** | **Dep.Var Mean (SE)** | **N** |
| 13. pleased with non-coreligions | 0.122*** | 0.112** | 0.196*** | 0.759*** | 20578.000 |
| | (0.023) | (0.052) | (0.041) | (0.003) | (.) |
| ... adding $\mathbf{X}_{\text{-}v}$ controls | 0.102*** | 0.009 | 0.126 | | |
| | (0.036) | (0.116) | (0.092) | | |
| 14. pleased with non-coethnics | 0.051** | -0.004 | 0.145*** | 0.827*** | 20742.000 |
| | (0.022) | (0.054) | (0.040) | (0.003) | (.) |
| ... adding $\mathbf{X}_{\text{-}v}$ controls | 0.045 | -0.160 | 0.186** | | |
| | (0.037) | (0.129) | (0.093) | | |
| City FE | Yes | Yes | Yes | | |

*Notes:* Each cell reports the coefficient on log population density in 2010 from a separate binary probit model of (6). All columns report maximum likelihood estimates; column 1 reports them without using instruments, while columns 2 use the instruments listed in the column headers. In column 2, we follow Belloni et al. (2012) and use a lasso procedure to select the best soil characteristics instruments before implementing the ML estimator. In the first row of each panel, we only control for $\mathbf{X}_i$ and $\mathbf{W}_{2v}$, setting $\mathbf{\Gamma}_1 = 0$. The second row of each panel reports the full, unrestricted model. All regressions are limited to the sample of villages within urban areas and include city-fixed effects. The sample size falls substantially in Column 2 because of missing GHSL 1975 data for Sumatra. Robust standard errors, clustered at the subdistrict-level, are reported in parentheses. */**/*** denotes significant at the 10% / 5% / 1% levels.

**Table A.14:** The Effect of Density on Trust in Neighbors (Ordered Probit Using Control Function)

| | | Soil IV | GHSL 1975 | | |
|---|---|---|---|---|---|
| | ML<br>(1) | CF<br>(2) | CF<br>(3) | Dep.Var<br>Mean (SE) | N |
| 1. trust neighbor to watch house | -0.066***<br>(0.013) | -0.143***<br>(0.031) | -0.116***<br>(0.022) | 2.916***<br>(0.003) | 23280.000<br>(.) |
| ... adding $\mathbf{X}_{-}v$ controls | -0.014<br>(0.021) | -0.187***<br>(0.065) | -0.138***<br>(0.050) | | |
| 2. trust neighbor to tend children | -0.099***<br>(0.014) | -0.156***<br>(0.032) | -0.109***<br>(0.024) | 2.649***<br>(0.004) | 23280.000<br>(.) |
| ... adding $\mathbf{X}_{-}v$ controls | -0.043**<br>(0.021) | -0.154**<br>(0.069) | -0.101*<br>(0.054) | | |
| 3. ready to help neighbor | -0.001<br>(0.013) | 0.014<br>(0.031) | -0.049**<br>(0.023) | 2.978***<br>(0.003) | 23280.000<br>(.) |
| ... adding $\mathbf{X}_{-}v$ controls | 0.033<br>(0.021) | 0.027<br>(0.067) | -0.063<br>(0.049) | | |
| 4. contribute to assist unfortunate neigbhors | -0.036***<br>(0.012) | -0.038<br>(0.028) | -0.073***<br>(0.020) | 2.808***<br>(0.005) | 23280.000<br>(.) |
| ... adding $\mathbf{X}_{-}v$ controls | -0.010<br>(0.019) | -0.005<br>(0.060) | -0.064<br>(0.042) | | |
| 5. easily access to neighbors' help | -0.041***<br>(0.013) | -0.054*<br>(0.030) | -0.044*<br>(0.022) | 2.649***<br>(0.005) | 23280.000<br>(.) |
| ... adding $\mathbf{X}_{-}v$ controls | 0.027<br>(0.019) | -0.025<br>(0.064) | 0.065<br>(0.051) | | |
| City FE | Yes | Yes | Yes | | |

*Notes:* Each cell reports the coefficient on log population density in 2010 from a separate ordered probit model of (6). Column 1 reports maximum likelihood (ML) estimates, while columns 2-4 adopt the control function (CF) procedure described by Chesher and Rosen (2019), together with the instruments listed in the column headers. In column 2, we follow Belloni et al. (2012) and use a lasso procedure to select the best soil characteristics instruments before implementing the control function estimator. In the first row of each panel, we only control for $\mathbf{X}_i$ and $\mathbf{W}_{2v}$, setting $\mathbf{\Gamma}_1 = 0$. The second row of each panel reports the full, unrestricted model. All regressions are limited to the sample of villages within urban areas and include city-fixed effects. The sample size falls substantially in Column 3 because of missing GHSL 1975 data for Sumatra. Robust standard errors, clustered at the subdistrict-level, are reported in parentheses. */**/*** denotes significant at the 10% / 5% / 1% levels.

**Table A.15:** The Effect of Density on Community Trust and Participation (Ordered Probit Using Control Function)

| | ML | Soil IV<br>CF | GHSL 1975<br>CF | Dep.Var | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | Mean (SE) | N |
| 6. join community group(s) | 0.018 | -0.027 | 0.020 | 2.364*** | 21767.000 |
| | (0.011) | (0.026) | (0.020) | (0.006) | (.) |
| ... adding $\mathbf{X}_{-}v$ controls | -0.010 | -0.113* | -0.116*** | | |
| | (0.017) | (0.059) | (0.041) | | |
| 7. join religious activities | -0.050*** | -0.064*** | -0.065*** | 2.683*** | 22899.000 |
| | (0.011) | (0.024) | (0.018) | (0.005) | (.) |
| ... adding $\mathbf{X}_{-}v$ controls | -0.044** | -0.060 | -0.093** | | |
| | (0.017) | (0.054) | (0.042) | | |
| 9. voluntary public good provision | -0.033*** | -0.047* | -0.053*** | 2.503*** | 22487.000 |
| | (0.012) | (0.028) | (0.020) | (0.005) | (.) |
| ... adding $\mathbf{X}_{-}v$ controls | -0.019 | -0.060 | -0.085* | | |
| | (0.019) | (0.063) | (0.044) | | |
| 11. trust religious leader | -0.021 | -0.058* | -0.060** | 3.051*** | 23240.000 |
| | (0.015) | (0.033) | (0.026) | (0.003) | (.) |
| ... adding $\mathbf{X}_{-}v$ controls | 0.010 | -0.071 | -0.064 | | |
| | (0.024) | (0.074) | (0.058) | | |
| 12. trust communtiy leader | -0.030** | -0.065** | -0.040 | 2.978*** | 23280.000 |
| | (0.014) | (0.030) | (0.025) | (0.003) | (.) |
| ... adding $\mathbf{X}_{-}v$ controls | -0.005 | -0.081 | -0.023 | | |
| | (0.022) | (0.067) | (0.058) | | |
| City FE | Yes | Yes | Yes | | |

*Notes:* Each cell reports the coefficient on log population density in 2010 from a separate ordered probit model of (6). Column 1 reports maximum likelihood (ML) estimates, while columns 2-4 adopt the control function (CF) procedure described by Chesher and Rosen (2019), together with the instruments listed in the column headers. In column 2, we follow Belloni et al. (2012) and use a lasso procedure to select the best soil characteristics instruments before implementing the control function estimator. In the first row of each panel, we only control for $\mathbf{X}_i$ and $\mathbf{W}_{2v}$, setting $\mathbf{\Gamma}_1 = 0$. The second row of each panel reports the full, unrestricted model. All regressions are limited to the sample of villages within urban areas and include city-fixed effects. The sample size falls substantially in Column 3 because of missing GHSL 1975 data for Sumatra. Robust standard errors, clustered at the subdistrict-level, are reported in parentheses. */**/*** denotes significant at the 10% / 5% / 1% levels.

**Table A.16:** The Effect of Density on Intergroup Tolerance (Ordered Probit Using Control Function)

| | | Soil IV | GHSL 1975 | | |
|---|---|---|---|---|---|
| | **ML** | **CF** | **CF** | **Dep.Var** | |
| | **(1)** | **(2)** | **(3)** | **Mean (SE)** | **N** |
| 13. pleased with non-coreligions | 0.100*** | 0.082** | 0.164*** | 2.733*** | 20578.000 |
| | (0.019) | (0.042) | (0.034) | (0.004) | (.) |
| ... adding $\mathbf{X}_{-v}$ controls | 0.090*** | 0.015 | 0.095 | | |
| | (0.030) | (0.087) | (0.077) | | |
| 14. pleased with non-coethnics | 0.038** | -0.021 | 0.118*** | 2.823*** | 20742.000 |
| | (0.019) | (0.040) | (0.032) | (0.004) | (.) |
| ... adding $\mathbf{X}_{-v}$ controls | 0.038 | -0.142 | 0.132* | | |
| | (0.030) | (0.089) | (0.074) | | |
| City FE | Yes | Yes | Yes | | |

*Notes:* Each cell reports the coefficient on log population density in 2010 from a separate ordered probit model of (6). Column 1 reports maximum likelihood (ML) estimates, while columns 2-4 adopt the control function (CF) procedure described by Chesher and Rosen (2019), together with the instruments listed in the column headers. In column 2, we follow Belloni et al. (2012) and use a lasso procedure to select the best soil characteristics instruments before implementing the control function estimator. In the first row of each panel, we only control for $\mathbf{X}_i$ and $\mathbf{W}_{2v}$, setting $\mathbf{\Gamma}_1 = 0$. The second row of each panel reports the full, unrestricted model. All regressions are limited to the sample of villages within urban areas and include city-fixed effects. The sample size falls substantially in Column 3 because of missing GHSL 1975 data for Sumatra. Robust standard errors, clustered at the subdistrict-level, are reported in parentheses. */**/*** denotes significant at the 10% / 5% / 1% levels.

**Table A.17:** The Effect of Density on Social Capital: Dropping Agricultural Communities

| | | Soil IV | GHSL 1975 |
|---|---|---|---|
| **Panel A: Trust in Neighbors** | **OLS (1)** | **IV-LASSO (2)** | **GMM (3)** |
| 1. Only $\mathbf{X}_i$ and $\mathbf{W}_{2v}$ Controls | -0.038*** | -0.065*** | -0.062*** |
| | (0.006) | (0.014) | (0.009) |
| 2. Adding $\mathbf{X}_v$ Controls | 0.000 | -0.052* | -0.043** |
| | (0.008) | (0.030) | (0.020) |
| $H_o : \tau_1 = \tau_2$ (p-value) | 0.000 | 0.655 | 0.322 |
| $N$ Outcomes | 5 | 5 | 5 |
| N | 100,180 | 100,180 | 65,630 |
| N individuals | 20,036 | 20,036 | 13,126 |
| **Panel B: Community Participation** | **(1)** | **(2)** | **(3)** |
| 1. Only $\mathbf{X}_i$ and $\mathbf{W}_{2v}$ Controls | -0.018*** | -0.045*** | -0.034*** |
| | (0.005) | (0.010) | (0.007) |
| 2. Adding $\mathbf{X}_v$ Controls | -0.010 | -0.069*** | -0.046*** |
| | (0.007) | (0.023) | (0.016) |
| $H_o : \tau_1 = \tau_2$ (p-value) | 0.113 | 0.189 | 0.394 |
| $N$ Outcomes | 9 | 9 | 9 |
| N | 137,605 | 137,605 | 90,309 |
| N individuals | 18,873 | 18,873 | 12,472 |
| **Panel C: Intergroup Tolerance** | **(1)** | **(2)** | **(3)** |
| 1. Only $\mathbf{X}_i$ and $\mathbf{W}_{2v}$ Controls | 0.077*** | 0.050* | 0.135*** |
| | (0.012) | (0.027) | (0.022) |
| 2. Adding $\mathbf{X}_v$ Controls | 0.072*** | 0.011 | 0.144*** |
| | (0.018) | (0.054) | (0.046) |
| $H_o : \tau_1 = \tau_2$ (p-value) | 0.581 | 0.145 | 0.607 |
| $N$ Outcomes | 5 | 5 | 5 |
| N | 36,133 | 36,133 | 23,017 |
| N individuals | 18,012 | 18,012 | 11,472 |
| City FE | Yes | Yes | Yes |

*Notes:* This table shows the results restricted to communities where agricultural households constitute less than 25% of the population. An agricultural household is defined if all employed household members report working in agricultural sectors, based on 2010 census data. Each cell reports the mean effect estimate, $\tau$, of log population density in 2010 on groups of related outcomes, from equation (4), following the approach described in Section 5.4. Outcome groupings, and the outcomes themselves, are repoted in Table 1. Column 1 reports OLS estimates, while Column 2 applies a post-double-selection lasso estimator to select the best soil characteristics instruments, following Belloni et al. (2012). Columns 3 use 2SLS/GMM with the instruments listed in the column header. In each panel, in Row 1, we only control for $\mathbf{X}_i$ and $\mathbf{W}_{2v}$, setting $\mathbf{\Gamma} = 0$. Row 3 reports the full, unrestricted model. All regressions are limited to the sample of villages within urban areas and include city-fixed effects. The sample size falls substantially in Column 3 because of missing GHSL 1975 data for Sumatra. Robust standard errors, clustered at the subdistrict-level, are reported in parentheses. */**/*** denotes significant at the 10% / 5% / 1% levels.

**Table A.18:** The Effect of Density on Social Capital: Mean Effects, Adding More Controls

| | | Soil IV | GHSL 1975 |
|---|---|---|---|
| | OLS | IV-LASSO | 2SLS |
| **Panel A: Trust in Neighbors** | **(1)** | **(2)** | **(3)** |
| 1. Only $\mathbf{X}_i$ and $\mathbf{W}_{2v}$ Controls | -0.041*** | -0.064*** | -0.064*** |
| | (0.005) | (0.011) | (0.008) |
| 2. Adding $\mathbf{X}_v$ Controls | -0.002 | -0.058** | -0.048*** |
| | (0.008) | (0.024) | (0.018) |
| 3. Adding More $\mathbf{W}_{2v}$ Controls | -0.002 | -0.063** | -0.036* |
| | (0.008) | (0.025) | (0.020) |
| **Panel B: Community Participation** | **(1)** | **(2)** | **(3)** |
| 1. Only $\mathbf{X}_i$ and $\mathbf{W}_{2v}$ Controls | -0.022*** | -0.047*** | -0.035*** |
| | (0.004) | (0.009) | (0.007) |
| 2. Adding $\mathbf{X}_v$ Controls | -0.019*** | -0.075*** | -0.063*** |
| | (0.006) | (0.019) | (0.015) |
| 3. Adding More $\mathbf{W}_{2v}$ Controls | -0.017*** | -0.076*** | -0.057*** |
| | (0.006) | (0.020) | (0.016) |
| **Panel C: Intergroup Tolerance** | **(1)** | **(2)** | **(3)** |
| 1. Only $\mathbf{X}_i$ and $\mathbf{W}_{2v}$ Controls | 0.054*** | 0.030 | 0.118*** |
| | (0.010) | (0.021) | (0.020) |
| 2. Adding $\mathbf{X}_v$ Controls | 0.046*** | -0.031 | 0.100** |
| | (0.016) | (0.046) | (0.045) |
| 3. Adding More $\mathbf{W}_{2v}$ Controls | 0.046*** | -0.047 | 0.122** |
| | (0.017) | (0.048) | (0.048) |
| City FE | Yes | Yes | Yes |

*Notes:* Each cell reports the mean effect estimate, $\tau$, of log population density in 2010 on groups of related outcomes, from equation (4), following the approach described in Section 5.4. Outcome groupings, and the outcomes themselves, are repoted in Table 1. Column 1 reports OLS estimates, while Column 2 applies a post-double-selection lasso estimator to select the best soil characteristics instruments, following Belloni et al. (2012). Columns 3 use 2SLS with the GHSL 1975 instruments. In each panel, in Row 1, we only control for $\mathbf{X}_i$ and $\mathbf{W}_{2v}$, setting $\mathbf{\Gamma}_1 = 0$. Row 2 reports the full, unrestricted model. All regressions are limited to the sample of villages within urban areas and include city-fixed effects. The sample size falls substantially in Column 3 because of missing GHSL 1975 data for Sumatra. Robust standard errors, clustered at the subdistrict-level, are reported in parentheses. */**/*** denotes significant at the 10% / 5% / 1% levels. The additional $\mathbf{W}_{2v}$ include the community's distance to formal markets, if any restaurants exist, distance to schools, if there are any mobile phone or TV signals, the type of main water sources, if there are local community empowerment programs, the number of houses of worships, distance to medical facilities, and distance to maternal health facilities.

**Table A.19:** Summary Statistics: Social Capital Outcomes (IFLS 5)

| **Panel A: Trust in Neighbors** | **Description** | **Code** | **Mean (sd)** | ***N*** |
|---|---|---|---|---|
| Trust neighbors to return wallet | Would you trust your neighbors to return your wallet if it was lost? | TR08 | 2.87 (1.05) | 15,964 |
| Trust neighbor to watch house | I would ask my neighbors to watch my house if I leave for a few days. | TR05 | 2.81 (0.57) | 16,326 |
| Trust neighbor to tend to children | I would leave children w/ neighbors for a few hours if I can't bring them along. | TR04 | 2.56 (0.64) | 11,656 |
| Willing to help villagers in need | I am willing to help people in this village if they need it. | TR01 | 3.24 (0.46) | 16,326 |
| **Panel B: Community Trust and Participation** | **Description** | **Code** | **Mean (sd)** | ***N*** |
| Participate in village meetings? | In the last 12 months, did you participate in any village meetings? | PM16A | 0.21 (0.41) | 16,219 |
| Participate in cooperatives? | In the last 12 months, did you participate in any cooperative? | PM16B | 0.04 (0.19) | 16,219 |
| Participate in voluntary labor? | In the last 12 months, did you participate in any voluntary labor? | PM16C | 0.27 (0.44) | 16,219 |
| Participate in program to improve the neighborhood? | In the last 12 months, did you participate in any program to improve the neighborhood? | PM16D | 0.20 (0.40) | 16,219 |
| Participate in youth group activities? | In the last 12 months, did you participate in any youth group activities (Karang Taruna)? | PM16E | 0.08 (0.27) | 16,219 |
| Participate in religious activities? | In the last 12 months, did you participate in any religious activities (Prayer groups, etc.)? | PM16F | 0.52 (0.50) | 16,219 |
| **Panel C: Intergroup Tolerance** | **Description** | **Code** | **Mean (sd)** | ***N*** |
| Trust own ethnic group more | Do you trust people with the same ethnicity as mine more than others | TR03 | 2.30 (0.66) | 16,326 |
| Trust own religious group more | Do you trust people with the same relgion as mine more than others | TR23 | 2.04 (0.67) | 16,325 |
| Tolerate diff. faith living in the same village | What if someone with a different faith lives in your village? | TR24 | 2.82 (0.59) | 16,326 |
| Tolerate diff. faith living in the same neighborhood | What if someone with a different faith lives in your neighborhood? | TR25 | 2.81 (0.58) | 16,326 |
| Tolerate diff. faith renting a room | What if someone with a different faith rents a room from you? | TR26 | 2.46 (0.71) | 16,326 |
| Tolerate diff. faith marrying relatives | What if someone with a different faith marries a close relative or child? | TR27 | 1.78 (0.72) | 16,325 |
| Tolerate diff. faith building house of worship nearby | What if people with a different faith build a house of worship in your community? | TR28 | 2.27 (0.77) | 16,326 |

*Notes:* This table reports short titles, longer descriptions, and summary statistics for the social capital outcomes we analyze from the IFLS 5 data (2014-2015). Summary statistics were computed using data only from the sample of communities comprising metropolitan areas. The groupings of variables listed here correspond to the groupings used in the IFLS 5 mean effects analysis (e.g. Table 5).

**Table A.20:** Summary Statistics: Social Capital Outcomes (IFLS 4)

| **Panel A: Trust in Neighbors** | **Description** | **Code** | **Mean (sd)** | ***N*** |
|---|---|---|---|---|
| Trust neighbors to return wallet | Would you trust your neighbors to return your wallet if it was lost? | TR08 | 2.99 (0.94) | 13,784 |
| Trust neighbor to watch house | I would ask my neighbors to watch my house if I leave for a few days. | TR05 | 2.84 (0.47) | 14,092 |
| Trust neighbor to tend to children | I would leave children w/ neighbors for a few hours if I can't bring them along. | TR04 | 2.61 (0.58) | 10,459 |
| Willing to help villagers in need | I am willing to help people in this village if they need it. | TR01 | 3.14 (0.37) | 14,094 |
| **Panel B: Community Trust and Participation** | **Description** | **Code** | **Mean (sd)** | ***N*** |
| Participate in village meetings? | In the last 12 months, did you participate in any village meetings? | PM16A | 0.21 (0.41) | 14,085 |
| Participate in cooperatives? | In the last 12 months, did you participate in any cooperative? | PM16B | 0.03 (0.16) | 14,085 |
| Participate in voluntary labor? | In the last 12 months, did you participate in any voluntary labor? | PM16C | 0.26 (0.44) | 14,085 |
| Participate in program to improve the neighborhood? | In the last 12 months, did you participate in any program to improve the neighborhood? | PM16D | 0.18 (0.38) | 14,085 |
| Participate in youth group activities? | In the last 12 months, did you participate in any youth group activities (Karang Taruna)? | PM16E | 0.06 (0.23) | 14,085 |
| Participate in religious activities? | In the last 12 months, did you participate in any religious activities (Prayer groups, etc.)? | PM16F | 0.50 (0.50) | 14,085 |
| **Panel C: Intergroup Tolerance** | **Description** | **Code** | **Mean (sd)** | ***N*** |
| Trust own ethnic group more | Do you trust people with the same ethnicity as mine more than others | TR03 | 2.41 (0.58) | 14,093 |
| Trust own religious group more | Do you trust people with the same relgion as mine more than others | TR23 | 2.26 (0.58) | 14,094 |
| Tolerate diff. faith living in the same village | What if someone with a different faith lives in your village? | TR24 | 2.86 (0.48) | 14,094 |
| Tolerate diff. faith living in the same neighborhood | What if someone with a different faith lives in your neighborhood? | TR25 | 2.83 (0.51) | 14,094 |
| Tolerate diff. faith renting a room | What if someone with a different faith rents a room from you? | TR26 | 2.50 (0.68) | 14,093 |
| Tolerate diff. faith marrying relatives | What if someone with a different faith marries a close relative or child? | TR27 | 1.75 (0.79) | 14,093 |
| Tolerate diff. faith building house of worship nearby | What if people with a different faith build a house of worship in your community? | TR28 | 2.33 (0.78) | 14,094 |

*Notes:* This table reports short titles, longer descriptions, and summary statistics for the social capital outcomes we analyze from the IFLS 4 data (2007). Summary statistics were computed using data only from the sample of communities comprising metropolitan areas. The groupings of variables listed here correspond to the groupings used in the IFLS 4 mean effects analysis (e.g. Appendix Table A.21).

**Table A.21:** The Effect of Density on Social Capital: Mean Effects (IFLS 4)

| | | Soil IV | GHSL 1975 |
|---|---|---|---|
| | **OLS** | **IV-LASSO** | **2SLS** |
| **Panel A: Trust in Neighbors** | **(1)** | **(2)** | **(3)** |
| 1. Only $\mathbf{X}_i$ and $\mathbf{W}_{2v}$ Controls | -0.043*** | -0.067*** | -0.081*** |
| | (0.007) | (0.014) | (0.015) |
| 2. Adding $\mathbf{X}_v$ Controls | -0.014 | -0.099** | -0.079 |
| | (0.009) | (0.042) | (0.059) |
| N | 53,917 | 53,898 | 31,305 |
| N individuals | 14,474 | 14,469 | 8,366 |
| $N$ Outcomes | 4 | 4 | 4 |
| $H_o : \mathbf{\Gamma} = 0$ (p-value) | 0.000 | 0.000 | 0.000 |
| $H_o : \tau_1 = \tau_2$ (p-value) | 0.000 | 0.674 | 0.998 |
| **Panel B: Community Participation** | **(1)** | **(2)** | **(3)** |
| 1. Only $\mathbf{X}_i$ and $\mathbf{W}_{2v}$ Controls | -0.029*** | -0.014 | -0.055*** |
| | (0.006) | (0.012) | (0.014) |
| 2. Adding $\mathbf{X}_v$ Controls | -0.018** | 0.049 | -0.042 |
| | (0.007) | (0.031) | (0.052) |
| N | 86,802 | 86,772 | 50,214 |
| N individuals | 14,467 | 14,462 | 8,369 |
| $N$ Outcomes | 6 | 6 | 6 |
| $H_o : \mathbf{\Gamma} = 0$ (p-value) | 0.000 | 0.000 | 0.000 |
| $H_o : \tau_1 = \tau_2$ (p-value) | 0.020 | 0.002 | 0.583 |
| **Panel C: Intergroup Tolerance** | **(1)** | **(2)** | **(3)** |
| 1. Only $\mathbf{X}_i$ and $\mathbf{W}_{2v}$ Controls | 0.088*** | 0.120*** | 0.082*** |
| | (0.007) | (0.013) | (0.012) |
| 2. Adding $\mathbf{X}_v$ Controls | 0.043*** | 0.170*** | 0.070 |
| | (0.008) | (0.035) | (0.044) |
| N | 101,316 | 101,281 | 58,560 |
| N individuals | 14,474 | 14,469 | 8,366 |
| $N$ Outcomes | 7 | 7 | 7 |
| $H_o : \mathbf{\Gamma} = 0$ (p-value) | 0.000 | 0.000 | 0.000 |
| $H_o : \tau_1 = \tau_2$ (p-value) | 0.000 | 0.196 | 0.931 |
| City FE | Yes | Yes | Yes |

*Notes:* Each cell reports the mean effect estimate, $\tau$, of log population density in 2010 on groups of related outcomes, from equation (4), following the approach described in Section 5.4, but using the IFLS 4 data for outcomes. Outcome groupings, and the outcomes themselves, are repoted in Appendix Table A.20. Column 1 reports OLS estimates, while Column 2 applies a post-double-selection lasso estimator to select the best soil characteristics instruments, following Belloni et al. (2012). Columns 3 use 2SLS with the GHSL 1975 instruments. In each panel, in Row 1, we only control for $\mathbf{X}_i$ and $\mathbf{W}_{2v}$, setting $\mathbf{\Gamma}_1 = 0$. Row 2 reports the full, unrestricted model. All regressions are limited to the sample of villages within urban areas and include city-fixed effects. The sample size falls substantially in Column 3 because of missing GHSL 1975 data for Sumatra. Robust standard errors, clustered at the subdistrict-level, are reported in parentheses. */**/*** denotes significant at the 10% / 5% / 1% levels.

**Table A.22:** Mean Effects, IFLS Panel Regressions (Single Index First Step)

| | OLS (1) | Soil IV IV-LASSO (2) | GHSL 1975 2SLS (3) |
|---|---|---|---|
| Trust in neighbors | -0.096** | -0.201*** | 0.023 |
| | (0.045) | (0.073) | (0.129) |
| $N$ | 174 | 173 | 91 |
| Adjusted $R^2$ | 0.016 | -0.016 | -0.016 |
| Kleibergen-Paap Wald Rank $F$ Stat | | 36.885 | 28.097 |
| Under Id. Test (KP Rank LM Stat) | | 42.291 | 24.556 |
| p-Value | | 0.000 | 0.000 |
| AR Wald Test (Weak IV Robust Inf.) | | 3.266 | 0.031 |
| p-Value | | 0.013 | 0.860 |
| Community participation | -0.038 | -0.045 | -0.024 |
| | (0.038) | (0.064) | (0.085) |
| $N$ | 174 | 173 | 91 |
| Adjusted $R^2$ | -0.001 | -0.009 | -0.009 |
| Kleibergen-Paap Wald Rank $F$ Stat | | 36.885 | 28.097 |
| Under Id. Test (KP Rank LM Stat) | | 42.291 | 24.556 |
| p-Value | | 0.000 | 0.000 |
| AR Wald Test (Weak IV Robust Inf.) | | 1.599 | 0.080 |
| p-Value | | 0.177 | 0.778 |
| Intergroup tolerance | 0.091** | 0.129* | 0.023 |
| | (0.041) | (0.074) | (0.061) |
| $N$ | 174 | 173 | 91 |
| Adjusted $R^2$ | 0.024 | 0.020 | -0.015 |
| Kleibergen-Paap Wald Rank $F$ Stat | | 36.885 | 28.097 |
| Under Id. Test (KP Rank LM Stat) | | 42.291 | 24.556 |
| p-Value | | 0.000 | 0.000 |
| AR Wald Test (Weak IV Robust Inf.) | | 1.496 | 0.141 |
| p-Value | | 0.206 | 0.708 |

*Notes:* This table reports panel regression results using IFLS 4/5 data. A single index is created by taking average over all related outcome variables seperately for each group. Then the 3 constructed single-index outcomes variables, namely trust in neighbors, community participation and Intergroup tolerance are regressed on log density. Column 1 reports OLS estimates, while Column 2 applies a post-double-selection lasso estimator to select the best soil characteristics instruments, following Belloni et al. (2012). Columns 3 use 2SLS with the GHSL 1975 instruments. In each panel, in Row 1, we only control for $\mathbf{X}_i$ and $\mathbf{W}_{2v}$, setting $\mathbf{\Gamma}_1 = 0$. Row 2 reports the full, unrestricted model. All regressions are limited to the sample of villages within urban areas and include city-fixed effects. The sample size falls substantially in Column 3 because of missing GHSL 1975 data for Sumatra. Robust standard errors, clustered at the subdistrict-level, are reported in parentheses. */**/*** denotes significant at the 10% / 5% / 1% levels. Robust standard errors, clustered at the subdistrict-level, are reported in parentheses. */**/*** denotes significant at the 10% / 5% / 1% levels.

**Table A.23:** Heterogeneous Effects of Density on Social Capital: Individual-Level Interactions (Soil IV)

| **Panel A: Trust in Neighbors** | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** |
|---|---|---|---|---|---|---|
| Log density | -0.058** | -0.055** | -0.052** | -0.027 | -0.053* | -0.050** |
| | (0.02) | (0.02) | (0.02) | (0.02) | (0.03) | (0.02) |
| … × Age: 41-65 | | -0.049** | | | | |
| | | (0.02) | | | | |
| … × Age: +65 | | -0.059** | | | | |
| | | (0.03) | | | | |
| … × Married | | | -0.050** | | | |
| | | | (0.02) | | | |
| … × Education: High | | | | -0.056** | | |
| | | | | (0.02) | | |
| … × Income: Middle | | | | | -0.044* | |
| | | | | | (0.02) | |
| … × Income: High | | | | | -0.058** | |
| | | | | | (0.03) | |
| … × Private | | | | | | -0.080*** |
| | | | | | | (0.03) |
| **Panel B: Community Trust and Participation** | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** |
| Log density | -0.075*** | -0.087*** | -0.079*** | -0.059*** | -0.057*** | -0.053*** |
| | (0.019) | (0.019) | (0.019) | (0.019) | (0.022) | (0.020) |
| … × Age: 41-65 | | -0.074*** | | | | |
| | | (0.018) | | | | |
| … × Age: +65 | | -0.055*** | | | | |
| | | (0.020) | | | | |
| … × Married | | | -0.082*** | | | |
| | | | (0.019) | | | |
| … × Education: High | | | | -0.080*** | | |
| | | | | (0.019) | | |
| … × Income: Middle | | | | | -0.058*** | |
| | | | | | (0.019) | |
| … × Income: High | | | | | -0.068*** | |
| | | | | | (0.020) | |
| … × Private | | | | | | -0.076*** |
| | | | | | | (0.021) |
| **Panel C: Intergroup Tolerance** | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** |
| Log density | -0.031 | -0.041 | -0.080* | -0.052 | -0.110** | -0.045 |
| | (0.046) | (0.044) | (0.044) | (0.046) | (0.054) | (0.050) |
| … × Age: 41-65 | | -0.043 | | | | |
| | | (0.045) | | | | |
| … × Age: +65 | | -0.059 | | | | |
| | | (0.048) | | | | |
| … × Married | | | -0.067 | | | |
| | | | (0.044) | | | |
| … × Education: High | | | | -0.045 | | |
| | | | | (0.043) | | |
| … × Income: Middle | | | | | -0.074 | |
| | | | | | (0.046) | |
| … × Income: High | | | | | -0.036 | |
| | | | | | (0.044) | |
| … × Private | | | | | | -0.050 |
| | | | | | | (0.048) |

*Notes:* This table reports mean effects and mean interaction terms for the impact of density on social capital, using soil quality variables and their interactions as instruments and including both the $\mathbf{W}_{2v}$ and $\mathbf{X}_v$ controls. For each panel, Column 1 replicates estimates from Table 4, Column 2, Row 3. See Appendix B.5 for more details on the estimation methodology and variables used for Columns 2-4. Robust standard errors, clustered at the subdistrict-level, are reported in parentheses. */**/*** denotes significant at the 10% / 5% / 1% levels.

**Table A.24:** Heterogeneous Effects of Density on Social Capital: City-Level Interactions (Soil IV)

| **Panel A: Trust in Neighbors** | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** |
|---|---|---|---|---|---|---|
| Log density | -0.058** | -0.034 | -0.056** | -0.060** | -0.030 | -0.051* |
| | (0.02) | (0.03) | (0.03) | (0.03) | (0.03) | (0.03) |
| … × Urban core: Large | | -0.046* | | | | |
| | | (0.02) | | | | |
| … × Sprawl (2000-2014): High | | | -0.051** | | | |
| | | | (0.02) | | | |
| … × Ethinic Frac: High | | | | -0.042* | | |
| | | | | (0.02) | | |
| … × Property Crime: High | | | | | -0.069*** | |
| | | | | | (0.02) | |
| … × Violent Crime: High | | | | | | -0.031 |
| | | | | | | (0.02) |
| **Panel B: Community Trust and Participation** | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** |
| Log density | -0.075*** | -0.065*** | -0.061*** | -0.085*** | -0.065*** | -0.076*** |
| | (0.019) | (0.021) | (0.020) | (0.024) | (0.019) | (0.021) |
| … × Urban core: Large | | -0.052*** | | | | |
| | | (0.019) | | | | |
| … × Sprawl (2000-2014): High | | | -0.054*** | | | |
| | | | (0.018) | | | |
| … × Ethinic Frac: High | | | | -0.062*** | | |
| | | | | (0.018) | | |
| … × Property Crime: High | | | | | -0.087*** | |
| | | | | | (0.019) | |
| … × Violent Crime: High | | | | | | -0.075*** |
| | | | | | | (0.018) |
| **Panel C: Intergroup Tolerance** | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** |
| Log density | -0.031 | -0.050 | -0.026 | -0.022 | -0.026 | -0.096* |
| | (0.046) | (0.042) | (0.050) | (0.070) | (0.049) | (0.057) |
| … × Urban core: Large | | -0.054 | | | | |
| | | (0.048) | | | | |
| … × Sprawl (2000-2014): High | | | -0.023 | | | |
| | | | (0.046) | | | |
| … × Ethinic Frac: High | | | | -0.024 | | |
| | | | | (0.042) | | |
| … × Property Crime: High | | | | | -0.053 | |
| | | | | | (0.049) | |
| … × Violent Crime: High | | | | | | -0.032 |
| | | | | | | (0.044) |

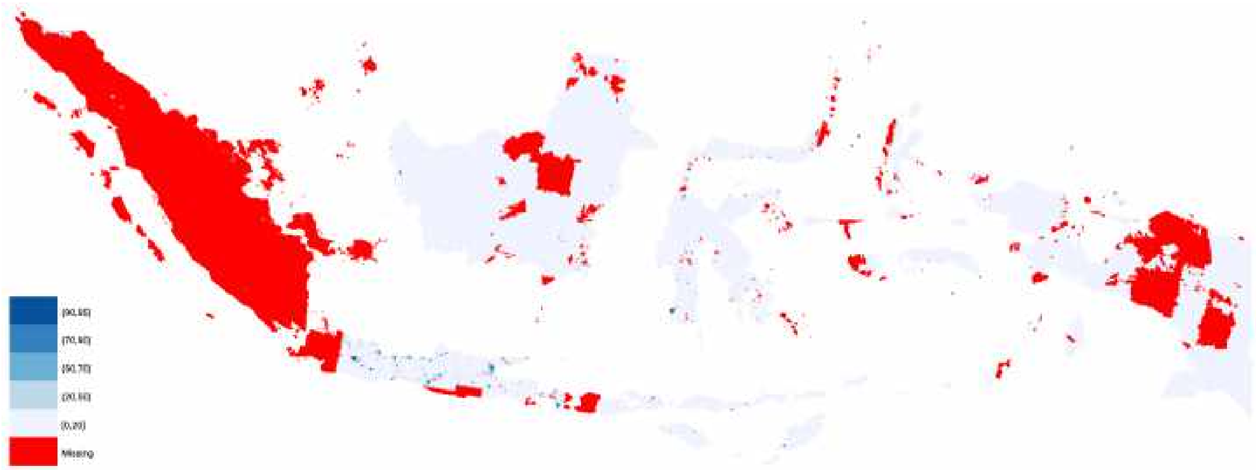
*Notes:* This table reports mean effects and mean interaction terms for the impact of density on social capital, using soil quality variables and their interactions as instruments and including both the $\mathbf{W}_{2v}$ and $\mathbf{X}_v$ controls. For each panel, Column 1 replicates estimates from Table 4, Column 2, Row 3. See Appendix B.5 for more details on the estimation methodology and variables used for Columns 2-4. Robust standard errors, clustered at the subdistrict-level, are reported in parentheses. */**/*** denotes significant at the 10% / 5% / 1% levels.

**Table A.25:** The Effect of Density on Trust: Model Regressions to Control for Sorting

| | **Dep Var: realized $p_0$** | | **Dep Var: realized $p_1$** | | **Dep Var: $r_0$** | | **Dep Var: $r_1$** | | **Dep Var: $\Pi_{\mathbf{inv}}$** | | **Dep Var: $\Pi_{\mathbf{tru}}$** | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** | **(7)** | **(8)** | **(9)** | **(10)** | **(11)** | **(12)** |
| Q (Density$^{-1}$) | 0.762*** | 1.372*** | 0.660*** | 2.367*** | 0.214*** | 0.652*** | 0.107*** | 0.457*** | 0.155*** | 0.404*** | 1.671*** | 5.316*** |
| | (0.005) | (0.027) | (0.002) | (0.013) | (0.007) | (0.012) | (0.003) | (0.008) | (0.006) | (0.012) | (0.005) | (0.031) |
| Q$^2$ (Density$^{-1}$) | | -0.610*** | | -1.707*** | | -0.437*** | | -0.349*** | | -0.249*** | | -3.645*** |
| | | (0.027) | | (0.012) | | (0.013) | | (0.005) | | (0.008) | | (0.028) |
| $\alpha$ (Group Share) | -0.447*** | -0.447*** | 0.037*** | 0.037*** | -0.094*** | -0.094*** | -0.022*** | -0.022*** | -0.113*** | -0.113*** | 1.086*** | 1.086*** |
| | (0.027) | (0.027) | (0.006) | (0.006) | (0.016) | (0.016) | (0.005) | (0.005) | (0.010) | (0.010) | (0.016) | (0.016) |
| R (Intolerant Share) | -1.027*** | -1.027*** | 0.029** | 0.029** | -0.232*** | -0.232*** | -0.013 | -0.013 | -0.047** | -0.047** | -0.583*** | -0.583*** |
| | (0.026) | (0.026) | (0.010) | (0.010) | (0.025) | (0.025) | (0.008) | (0.008) | (0.018) | (0.018) | (0.034) | (0.034) |
| $N$ | 8,400 | 8,400 | 8,400 | 8,400 | 8,400 | 8,400 | 8,400 | 8,400 | 8,400 | 8,400 | 8,400 | 8,400 |
| $N$ Clusters | 20 | 20 | 20 | 20 | 20 | 20 | 20 | 20 | 20 | 20 | 20 | 20 |
| Adjusted $R^2$ | 0.841 | 0.871 | 0.588 | 0.875 | 0.499 | 0.623 | 0.373 | 0.653 | 0.649 | 0.752 | 0.682 | 0.895 |
| Simulation FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

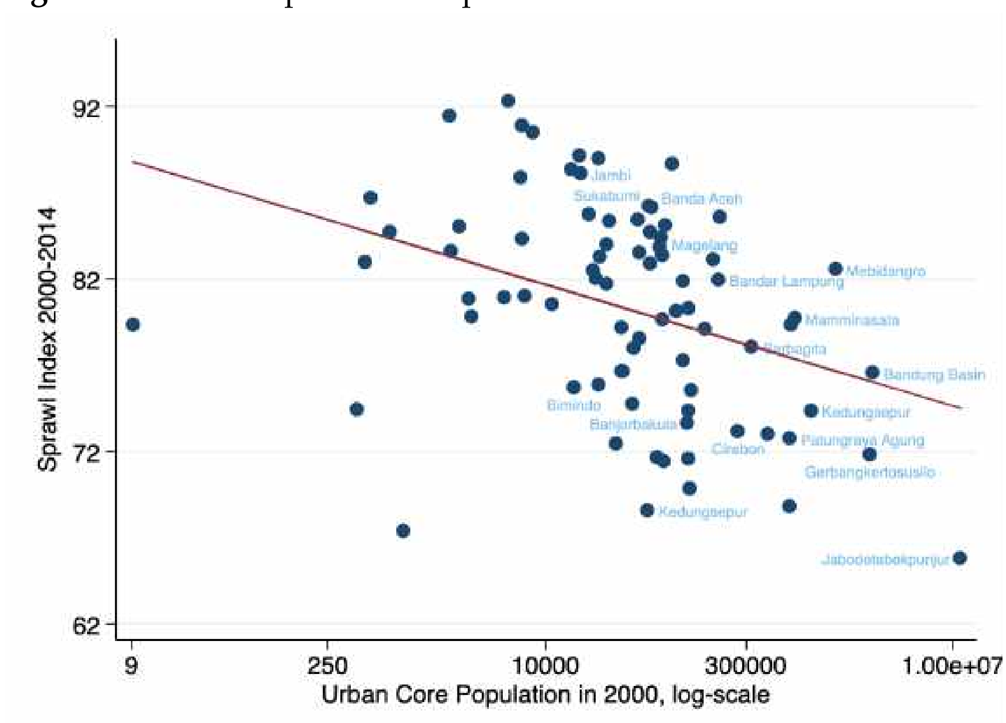
*Notes:* This table reports the effect of density on trust using the simulated data. Column (1), (3), (5), (7), (9), and (11) reports the linear specication results for outsomes shown in the header, while (2), (4), (6), (8), (10), and (12) reports the quadratic specication results. All regressions include simulation-fixed effects. Standard errors are clustered at the simulation-level, are reported in parentheses. */**/*** denotes significant at the 10% / 5% / 1% levels.

**Figure A.1:** GHSL 1975: Built Up Area



*Notes*: This figure plots the built up extent of villages in Indonesia using the GHSL 1975 data. Locations with a larger percentage of built up areas are shaded in darker blue. The red portions of this figure indicate areas where the 1975 data are missing. The figure assigns each village to the average of the GHSL 1975 raster for that village, using the 2010 village shapefile from BPS.

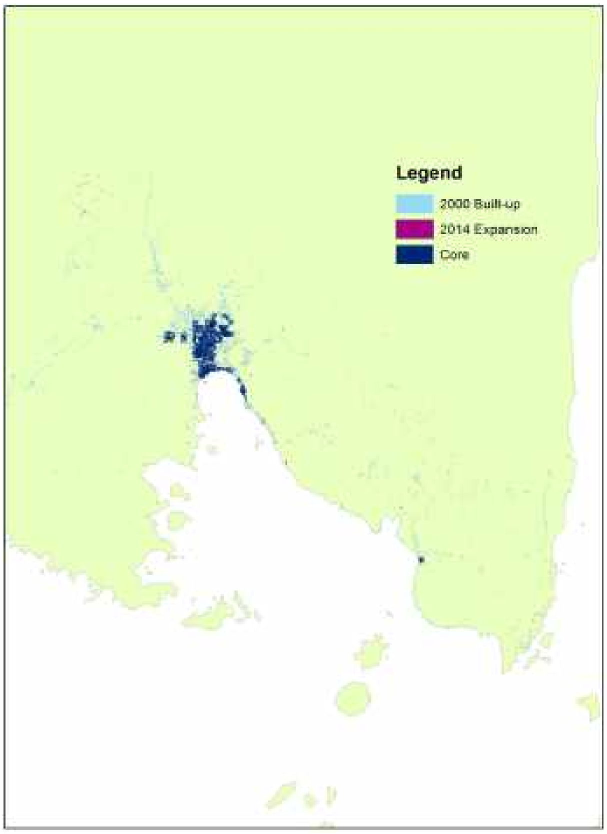
**Figure A.2:** Urban Sprawl vs. Population of the Urban Core Area in 2000



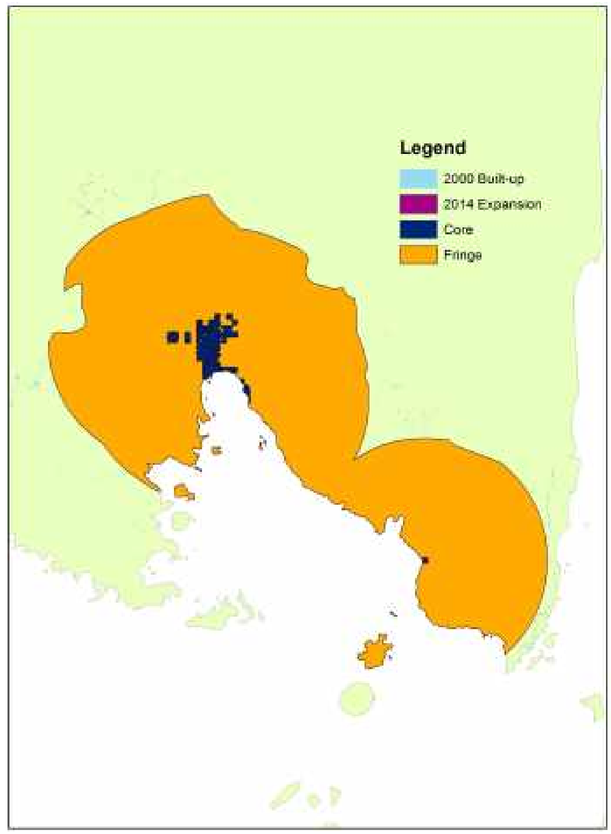

*Notes*: This figure presents a scatterplot of the relationship between urban sprawl (from 2000-2014) and the population of the urban core area of each city in 2000. The estimated semi-elasticity of the linear regression line is $-1.02$ (p-value .00). Each point in the scatterplot represents a different city. The horizontal axis is expressed in log-scale.

**Figure A.3:** Bandar Lampung Core and Fringe Identification

**(A)** From Built-Up to the Core



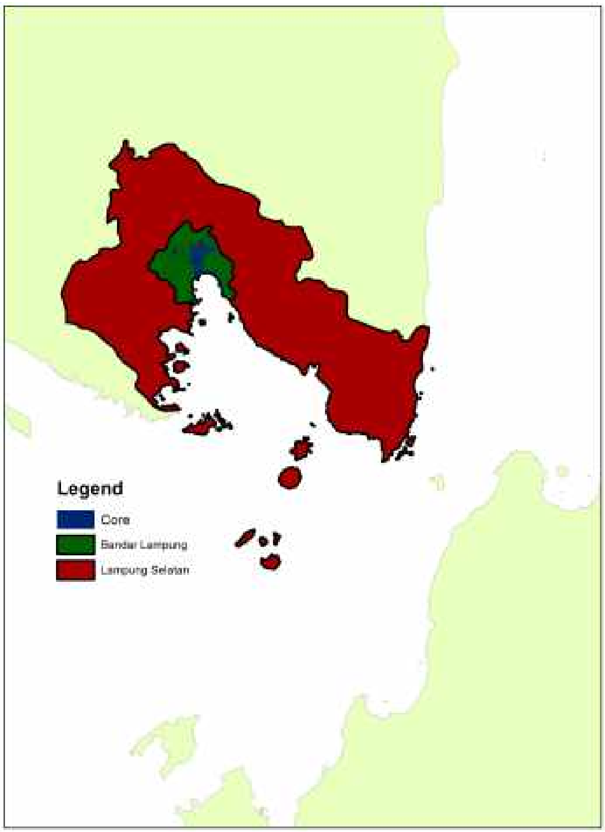

**(B)** Adding the Fringe



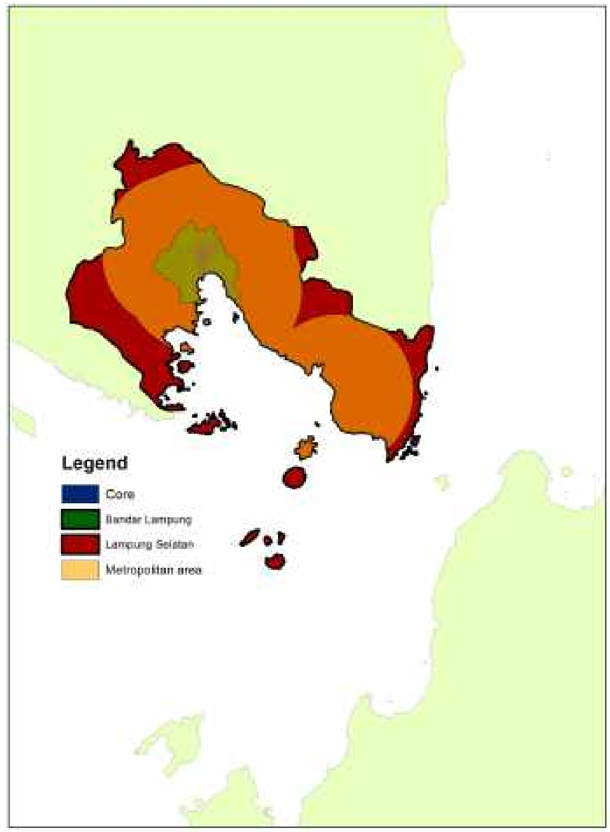

*Notes*: This figure illustrates the procedure we follow to identify core and fringe of a metropolitan area from the built-up raster data. We use the metropolitan region corresponding to the city of Bandar Lampung as an example. Panel A reports the pixels in the map covered by built-up in 2000 (light blue) and those corresponding to new built-up by 2014 (dark violet). The light green polygon in the background depicts the Southern tip of Sumatra. The pixels of 2000 built-up areas identified as core by Burchfield et al. (2006) methodology are indicated in dark blue. For this city, a major core is visible at the center of the map, while a second smaller satellite core can be seen moving South-East along the shore. Panel B simply adds the fringe constructed around this core (in orange). The fringe is obtained as a 20km buffer around the core, which is then intersected with boundaries of the administrative units belonging to this metropolitan area. Bandar Lampung comprises two administrative regions, as described in Appendix Figure A.4.

**Figure A.4:** Bandar Lampung Core-Fringe and Administrative Boundaries

**(A)** CORE VS. ADMIN. UNITS




**(B)** METRO AREA AND ADMIN. BOUNDARIES




*Notes*: This figure is a continuation of Appendix Figure A.3 and illustrates how the metropolitan area identified by the Burchfield et al. (2006) methodology compares to the boundaries of the administrative units corresponding to it. The metropolitan area encompasses two administrative regions, which can be seen in Panel A. The dark green unit is the city (*kota*) of Bandar Lampung, while the crimson unit is the district (*kabupaten*) of Lampung Selatan. The core of the metropolitan area from Figure A.3 is also reported in dark blue. It is important to observe that the main portion of the core does not overlap with the administrative boundaries of the *kota*, being actually smaller, while the secondary part completely lies within the *kabupaten*. In Panel B, the identified metropolitan area is superimposed onto the administrative definition of it. The figure shows that the identified metropolitan area is also smaller than the simple union of the two administrative units. Moreover, it is evident that the area is delimited by the administrative boundaries when the radius of the fringe exceeds those boundaries.

# B Empirical Strategy Appendix

## B.1 An IV Estimator for $\theta$

Recall that $\widetilde{\mathbf{X}}_{iv} \equiv [\mathbf{X}_i, \mathbf{X}_v, \mathbf{W}_{2v}]$ collects observed variables that do not include density. An IV estimator for $(\theta, \widetilde{\beta})$ solves the following two moment equations:

$$\begin{aligned}
0 &= \mathbf{Z}'(\mathbf{y} - \widehat{\theta}_{IV} \log \text{density} - \widetilde{\mathbf{X}}\widehat{\widetilde{\beta}}_{IV}) \\
0 &= \widetilde{\mathbf{X}}'(\mathbf{y} - \widehat{\theta}_{IV} \log \text{density} - \widetilde{\mathbf{X}}\widehat{\widetilde{\beta}}_{IV}).
\end{aligned}$$

The second equation can be used to solve for $\widehat{\widetilde{\beta}}_{IV}$ as follows:

$$\widehat{\widetilde{\beta}}_{IV} = \left(\widetilde{\mathbf{X}}'\widetilde{\mathbf{X}}\right)^{-1} \widetilde{\mathbf{X}}' \left(\mathbf{y} - \widehat{\theta}_{IV} \log \text{density}\right).$$

Plugging this expression into the first equation gives us the following expression for the IV estimator of $\theta$, our parameter of interest:

$$\widehat{\theta}_{IV} = \left(\mathbf{Z}'\mathbf{M}_{\widetilde{\mathbf{X}}} \log \text{density}\right)^{-1} \mathbf{Z}'\mathbf{M}_{\widetilde{\mathbf{X}}}\mathbf{y}$$

where $\mathbf{M}_{\widetilde{\mathbf{X}}} = \left(\mathbf{I} - \widetilde{\mathbf{X}}\left(\widetilde{\mathbf{X}}'\widetilde{\mathbf{X}}\right)^{-1}\widetilde{\mathbf{X}}'\right)$ is the standard orthogonal projection matrix for $\widetilde{\mathbf{X}}$.

## B.2 Bias of $\widehat{\theta}_{IV}$

An expression for the bias of $\widehat{\theta}_{IV}$ is the following:

$$\begin{aligned}
\text{Bias}\left(\widehat{\theta}_{IV}\right) &= \mathbb{E}\left[\widehat{\theta}_{IV}\right] - \theta \\
&= \mathbb{E}\left[\left(\mathbf{Z}'\mathbf{M}_{\widetilde{\mathbf{X}}} \log \text{density}\right)^{-1} \mathbf{Z}'\mathbf{M}_{\widetilde{\mathbf{X}}}\mathbf{y}\right] - \theta \\
&= \mathbb{E}\left[\left(\mathbf{Z}'\mathbf{M}_{\widetilde{\mathbf{X}}} \log \text{density}\right)^{-1} \mathbf{Z}'\mathbf{M}_{\widetilde{\mathbf{X}}}\ \mathbb{E}\left[\mathbf{y} \,\middle|\, \mathbf{Z}, \widetilde{\mathbf{X}}, \log \text{density}\right]\right] - \theta \\
&= \mathbb{E}\left[\left(\mathbf{Z}'\mathbf{M}_{\widetilde{\mathbf{X}}} \log \text{density}\right)^{-1} \mathbf{Z}'\mathbf{M}_{\widetilde{\mathbf{X}}}\ \left(\theta \log \text{density}_v + \widetilde{\mathbf{X}}_{iv}\widetilde{\beta} + \mathbb{E}\left[u_{iv} \,\middle|\, \mathbf{Z}, \widetilde{\mathbf{X}}, \log \text{density}\right]\right)\right] - \theta \\
&= \theta + 0 + \mathbb{E}\left[\left(\mathbf{Z}'\mathbf{M}_{\widetilde{\mathbf{X}}} \log \text{density}\right)^{-1} \mathbf{Z}'\mathbf{M}_{\widetilde{\mathbf{X}}}\ \mathbb{E}\left[u_{iv} \,\middle|\, \mathbf{Z}, \widetilde{\mathbf{X}}, \log \text{density}\right]\right] - \theta \\
&= \mathbb{E}\left[\left(\mathbf{Z}'\mathbf{M}_{\widetilde{\mathbf{X}}} \log \text{density}\right)^{-1} \mathbf{Z}'\mathbf{M}_{\widetilde{\mathbf{X}}}\ \mathbb{E}\left[u_{iv} \,\middle|\, \mathbf{Z}, \widetilde{\mathbf{X}}, \log \text{density}\right]\right] \\
&= \mathbb{E}\left[\left(\mathbf{Z}'\mathbf{M}_{\widetilde{\mathbf{X}}} \log \text{density}\right)^{-1} \mathbf{Z}'\mathbf{M}_{\widetilde{\mathbf{X}}}\ \mathbb{E}\left[\underbrace{x_i^U}_{\text{(A)}} + \underbrace{w_v^U}_{\text{(B)}} + \underbrace{\eta_{vi}}_{\text{(C)}} + \underbrace{\xi_{vi}}_{\text{(D)}} \,\middle|\, \mathbf{Z}, \widetilde{\mathbf{X}}, \log \text{density}\right]\right]
\end{aligned}$$

This bias expression contains four terms, which we describe separately. For term (A), the sorting model described by Altonji and Mansfield (2018), together with their assumptions A1-A5, delivers their proposition 1, which is namely that the expectation of $x_v^U$ is linearly dependent on $\mathbf{X}_v$, the group-level observables. This means that we have the following:

$$\text{(A)}: \qquad \mathbb{E}\left[\left(\mathbf{Z}'\mathbf{M}_{\widetilde{\mathbf{X}}} \log \text{density}\right)^{-1} \mathbf{Z}'\mathbf{M}_{\widetilde{\mathbf{X}}}\mathbb{E}\left[x_i^U \,\middle|\, \mathbf{Z}, \widetilde{\mathbf{X}}, \log \text{density}\right]\right] = 0$$

since the expectation of $x_i^U$ is in the space spanned by the columns of $\widetilde{\mathbf{X}}$.

For term (C), note that $W_{2v}$ is defined as a vector of village-level characteristics not mechanically related to sorting, so $W_{2v}$ is uncorrelated with $\eta_{vi}$ by definition. Hence, we can write:

$$\eta_{vi} = \mathbf{X}_i \mathbf{P}_{\mathbf{X}_i} + e$$

where $\mathbf{P}_{\mathbf{X}_i}$ is a projection matrix and $e$ is the orthogonal component, which is mean zero given $\widetilde{\mathbf{X}}$.[49] This means that $\eta_{vi}$ is in the space spanned by the columns of $\widetilde{\mathbf{X}}$ and hence term (C) is zero:

$$\text{(C)}: \qquad \mathbb{E}\left[\left(\mathbf{Z}'\mathbf{M}_{\widetilde{\mathbf{X}}}\text{log density}\right)^{-1}\mathbf{Z}'\mathbf{M}_{\widetilde{\mathbf{X}}}\mathbb{E}\left[\eta_{vi}\,\middle|\,\mathbf{Z}, \widetilde{\mathbf{X}}, \text{log density}\right]\right] = 0$$

For term (D), we assumed that $\xi_{vi}$ was unpredictable given all unobservables in the model, so that by construction, we have:

$$\text{(D)}: \qquad \mathbb{E}\left[\xi_{vi}\,\middle|\,\mathbf{Z}, \widetilde{\mathbf{X}}, \text{log density}\right] = 0.$$

So, we are left with the following expression for the bias in $\widehat{\theta}_{IV}$:

$$\text{Bias}\left(\widehat{\theta}_{IV}\right) = \mathbb{E}\left[\left(\mathbf{Z}'\mathbf{M}_{\widetilde{\mathbf{X}}}\text{log density}\right)^{-1}\mathbf{Z}'\mathbf{M}_{\widetilde{\mathbf{X}}}\;\mathbb{E}\left[w_v^U\,\middle|\,\mathbf{Z}, \widetilde{\mathbf{X}}, \text{log density}\right]\right]$$

So, in order for our IV to be unbiased, a sufficient condition is that conditional on $\mathbf{Z}$ and the other observed individual and village-level variables, $w_v^U$ is mean zero.

$$\mathbb{E}\left[w_v^U\,\middle|\,\mathbf{Z}, \widetilde{\mathbf{X}}, \text{log density}\right] = 0$$

What this amounts to is that our density shifters, namely soil quality of the village or lagged population measures, need to be uncorrelated with unobservables that influence overall village-level social capital. We discuss the plausibility of this assumption in the main text of the paper.

### B.3 Mean Effects Analysis

Our estimate of the mean effects of density on groups of related outcomes is based on the procedure in Kling et al. (2007) (see footnote 22). Let $k = 1, ..., K$ index outcome variables for a group of related outcomes (e.g. trust in neighbors, inter-ethnic tolerance, etc.). Let $\mathbf{Y} = [\mathbf{y}_1', \mathbf{y}_2', ..., \mathbf{y}_K']'$ denote a stacked vector of $K$ social capital outcomes for that group. Let $\mathbf{X}$ be denoted as follows:

$$\mathbf{X} = \begin{bmatrix} \mathbf{X}_1 & 0 & ... & 0 \\ 0 & \mathbf{X}_2 & ... & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & ... & \mathbf{X}_K \end{bmatrix}$$

where $\mathbf{X}_k$ consists of the control variables for outcome $k$. In our initial regression, this will only include individual-specific controls $\mathbf{X_i}$, predetermined community characteristics $\mathbf{W_{2v}}$ and the city-specific intercepts, but later regressions will add $\mathbf{X_v}$. Also stack the independent variables as follows:

$$\mathbf{D} = \begin{bmatrix} \text{log density} & 0 & ... & 0 \\ 0 & \text{log density} & ... & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & ... & \text{log density} \end{bmatrix}$$

[49] This is equation (11) in Altonji and Mansfield (2018).

After stacking and appropriately arranging the variables, we can estimate mean effects using the following single regression:

$$\mathbf{Y} = \mathbf{X}\beta + \mathbf{D}\theta + \varepsilon \tag{13}$$

With OLS, this is straightforward, but with IVs, we need to use an appropriately stacked vector:

$$\mathbf{Z} = \begin{bmatrix} \mathbf{Z}_1 & 0 & ... & 0 \\ 0 & \mathbf{Z}_2 & ... & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & ... & \mathbf{Z}_K \end{bmatrix}$$

After estimating the parameters of this regression (with OLS or IV), we obtain the mean effect estimate as follows:

$$\tau = \frac{1}{K}\sum_{k=1}^{K}\frac{\theta_k}{\sigma_k}$$

where $\sigma_k$ is the standard deviation of $\mathbf{y}_k$. We ignore sampling variation in $\sigma_k$ when estimating $\tau$.

## B.4 IFLS Panel Specification (SUR System)

Another approach to dealing with sorting is to use a two-step estimator (Combes et al., 2010). In the first step, we estimate local fixed effects of social capital, which condition out the impact of individual-specific effects and the effect of time-varying individual-level observables. We then average the residuals from this regression, and estimate a cross-sectional regression of the average social capital measures (averaged over village years) on our density measure in 2010.

Let $k = 1, ..., K$ denote a group of related social capital outcomes, and let $Y_{it}^k$: social capital outcome $k$ for individual $i$ at time $t$. The vector $\mathbf{x}_{it}$ consists of time-varying individual-level characteristics for individual $i$, such as that individual's educational attainment at time $t$, their marital status at time $t$, age at time $t$, and household size at time $t$. We first stack the outcome variables in a vector, $\mathbf{Y} = [\mathbf{y}_1', \mathbf{y}_2', ..., \mathbf{y}_K']'$. Let $\mathbf{X}$ be denoted as follows:

$$\mathbf{X} = \begin{bmatrix} \mathbf{X}_1 & 0 & ... & 0 \\ 0 & \mathbf{X}_2 & ... & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & ... & \mathbf{X}_K \end{bmatrix}$$

where $\mathbf{X}_k$ consists of the control variables for outcome $k$ (e.g. the time-varying individual-level controls). Let $\mathbf{D}$ be a matrix individual fixed effects for outcome $k$ (i.e. $d_i$), specific to each individual and outcome:

$$\mathbf{D} = \begin{bmatrix} \mathbf{D}_1 & 0 & ... & 0 \\ 0 & \mathbf{D}_2 & ... & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & ... & \mathbf{D}_K \end{bmatrix}$$

Let $\mathbf{A} = [\alpha_{jt}]$ denote a row vector of effects for each village and year (e.g. the $\alpha_{jt}$'s). This is common to all outcomes.

In the first step of the (Combes et al., 2010) estimator, we estimate $\alpha_{jt}$ for all equations using a SUR system:

$$\mathbf{Y} = \mathbf{X}\beta + \mathbf{D}\theta + \mathbf{A} + \varepsilon \tag{14}$$

The $\mathbf{A}$ vector will contain the $\alpha_{jt}$ estimates, which are estimates of the social capital index for each village and year, after conditioning out individual fixed effects and time-varying individual-level observables.[50]

Next, in the second step, we form the cross-sectional average of these village-year fixed effects:

$$\alpha_j = \frac{1}{T}\sum_{t=1}^{T}\alpha_{jt}$$

We then use $\alpha_j$ as the independent variable in the following regression:

$$\alpha_j = \mathbf{W}_{2v}\beta_2 + \theta \log \text{density}_v + \Delta\varepsilon_i$$

where we instrument log density$_v$ with our 2 sets of instruments.

### B.5 Heterogeneous Effects (SUR System)

To estimate heterogeneous effects of density, we add a matrix of levels terms,

$$\mathbf{M} = \begin{bmatrix} \mathbf{M}_1 & 0 & ... & 0 \\ 0 & \mathbf{M}_2 & ... & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & ... & \mathbf{M}_K \end{bmatrix}$$

where $\mathbf{M}_K$ consists of the level variables for outcome $k$, and a stacked vector of interaction terms with density,

$$\mathbf{N} \equiv \mathbf{M}\cdot\mathbf{D} = \begin{bmatrix} \mathbf{M}_1\cdot\mathbf{D}_1 & 0 & ... & 0 \\ 0 & \mathbf{M}_2\cdot\mathbf{D}_2 & ... & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & ... & \mathbf{M}_K\cdot\mathbf{D}_K \end{bmatrix}$$

to (13), and we estimate the following regression using our instrument set which is augmented by interactions between $\mathbf{M}$ and the original instruments:

$$\mathbf{Y} = \mathbf{X}\beta + \mathbf{M}\gamma + \mathbf{D}\theta + \mathbf{N}\theta_1 + \varepsilon \tag{15}$$

Then we obtain the mean effect estimates for the reference group, $\tau$, and for the interaction terms, $\tau_1$, as follows:

$$\tau = \frac{1}{K}\sum_{k=1}^{K}\frac{\theta_k}{\sigma_k} \qquad \tau_1 = \frac{1}{K}\sum_{k=1}^{K}\frac{\theta_{1k}}{\sigma_k}$$

where $\sigma_k$ is the standard deviation of $\mathbf{y}_k$.

We report estimates of the mean effects and the interaction terms in Table 7 and Table 8. Below, Appendix Table B.1 describes how we construct different variables used in this heterogeneity analysis.

[50] Note that we can also use a single-index approach in the first step, where we form an average of the dependent variables, $Y_{it} = \frac{1}{K}\sum_{k=1}^{K} Y_{it}^k$, and just use this in a single regression to estimate $\alpha_{jt}$. The results of this approach are shown in Appendix Table A.22.

**Table B.1:** Summary Statistics: Mechanism Variables (SUSENAS 2012)

| **Panel A: City level** | **Description** | **Dataset** | **Mean (sd)** | **N** |
|---|---|---|---|---|
| Urban core size | The area size ($km^2$) of the urban core area. Cities where core area sizes are above median are classified as large core. | GHSL 2000/2014 and authors' calculation | 41.91 (135.93) | 76 |
| Sprawl Index, 2000-2014 | The sprawl index created using GHSL built-up data in 2000 and 2014. Cities are classified as high (low) sprawl cities if the index is above (below) the sample median. | GHSL 2000/2014 and authors' calculation | 80.11 (6.05) | 76 |
| Ethnic Fractionalization | The ethnic fractionalization index defined in city level. Cities are classified as high (low) ethnic fractionalized cities if ethnic fractionalization index is above (below) the sample median. | Census 2010 | 0.35 (0.30) | 76 |
| Poverty crime risk | The city-level probability that a community within the city reports any incidence of property crime, weighted by population. Property crimes include theft and fraud. Cities are classified as suffering high (low) property crime risk if this index is above (below) the sample median. | PODES 2011 | 0.63 (0.17) | 76 |
| Violent crime risk | The city-level probability that a community within the city reports any incidence of violent crime. Violent crimes include theft with violence, abuse, rape and homicide. Cities are classified as suffering high (low) violent crime risk if the index is above (below) the sample median. | PODES 2011 | 0.23 (0.14) | 76 |
| **Panel B: Individual level** | **Description** | **Dataset** | **Mean (sd)** | **N** |
| Age | Age of individuals. People are classified into three groups, younger than 40 years old, aged between 41 to 60 years old and older than 65 years old. | SUSENAS 2012 | 48.29 (13.69) | 23,819 |
| Married (1 0) | If the individual is married or not. | SUSENAS 2012 | 0.81 (0.39) | 23,819 |
| Education | Years people spend in school. Individuals are classified as high (low) educated if school year is above (below) the sample median. | SUSENAS 2012 | 8.33 (4.60) | 23,819 |
| Income | Monthly net income (k Rupiah), in money and goods, earned by individuals from the main job. Individuals are classified into high, middle and low income according to the 66 and 33 quantiles of the income distribution. | SUSENAS 2012 | 2045.84 (2985.17) | 19,610 |
| Private commuting mode to work (1 0) | If the commuting mode people choose to go to work is private or not. Private modes include private cars, private motorcycles and official cars. Non-private modes include non-motorized transportation and public transportation. | SUSENAS 2012 | 0.47 (0.50) | 19,995 |

*Notes:* This table reports titles, descriptions for constructions, and summary statistics for the variables used in mechanism analysis for the SUSENAS data (2012). Summary statistics were computed using data only from the sample of communities comprising metropolitan areas.

# C Model Appendix

## C.1 Nash Equilibrium

This section discusses the Nash equilibrium strategies of investors and trustees, building on results established by Manapat et al. (2013). We assume throughout that individuals are rational and aim to maximize profits. Consider a investor and a trustee are playing a within-group game with benefit $\theta_1$; similar results will also apply to cross-group interactions. Recall that investor makes the transfer if $r > 1/\theta_1$ and obtains a payoff of $r\theta_1 > 1$. Conversely, she does not make the transfer if $r < 1/\theta_1$. The probability that an interactions are not anonymous is given by $Q$.

Given this setup, the investor's payoff is given by

$$\Pi^{\text{Inv}} = \begin{cases} 1 - (1 - \theta_1 r_1)(p_1 - p_1 Q), & \text{if } r_1 \leq 1/\theta_1 \\ 1 - (1 - \theta_1 r_1)(p_1 - p_1 Q + Q), & \text{if } r_1 > 1/\theta_1 \end{cases},$$

while the trustee's payoff is given by

$$\Pi^{\text{Tru}} = \begin{cases} \theta_1 (1 - r_1)(p_1 - p_1 Q), & \text{if } r_1 \leq 1/\theta_1 \\ \theta_1 (1 - r_1)(p_1 - p_1 Q + Q), & \text{if } r_1 > 1/\theta_1 \end{cases}.$$

If $r_1 > 1/\theta_1$, the investor's profit increases with $p_1$, so the equilibrium strategy is $p_1 = 1$. If $r_1 < 1/\theta_1$, investor's profit decreases with $p_1$, and the investor maximizes profits by choosing $p_1 = 0$. Since investor's profit is monotonic in $p_1$, the equilibrium strategy is either $p_1 = 1$ or $p_1 = 0$.

Consider the following situations based on different values of $Q$:

**Case 1: No Information.** When investors have no information at all, $Q = 0$, the profits of trustees and investors are,

$$\Pi^{\text{Inv}} = 1 - (1 - \theta_1 r_1) p_1$$
$$\Pi^{\text{Tru}} = \theta_1 (1 - r_1) p_1$$

If $p_1 = 1$, the trustee chooses not return anything to maximize profit. But when trustee returns nothing, investor should choose $p_1 = 0$. So there is no Nash equilibrium when $p_1 = 1$. If $p_1 = 0$, suppose the trustee returns $r_1 > 1/\theta_1$. Then, the investor has incentives to increase $p_1$ to 1 to increase profit. So the only Nash equilibrium is $p_1 = 0$, $r_1 < 1/\theta_1$.

**Case 2: Full Information.** When both investor and trustee have full information, $Q = 1$,

$$\Pi^{\text{Inv}} = \begin{cases} 1, & \text{if } r_1 \leq 1/\theta_1 \\ \theta_1 (1 - r_1), & \text{if } r_1 > 1/\theta_1 \end{cases}$$
$$\Pi^{\text{Tru}} = \begin{cases} 0, & \text{if } r_1 \leq 1/\theta_1 \\ \theta_1 (1 - r_1), & \text{if } r_1 > 1/\theta_1 \end{cases}$$

Now, the investor's profit is not affected by her strategy $p_0$. The trustee always has incentives to return more than $1/\theta_1$. But to maximize profit, trustee only returns slightly more than needed, $r_1 = 1/\theta_1 + \epsilon$. So any $p_1 \in [0, 1]$ with $r_1 = 1/\theta_1 + \epsilon$, is a Nash equilibrium.

**Case 3: Intermediate Information.** Finally, consider the case $0 < Q < 1$. If the trustee chooses to return $r_1 = 1/\theta_1 + \epsilon$, and if the investor always transfers $p_1 = 1$, the investor has no incentive to decrease $p_1$, since $r_1 > 1/\theta_1$. The trustee has no incentives to increase $r_1$, since it only decreases her fraction of the transfer.

Now, we want to see if the trustee also has no incentives to decrease $r_1$. For the trustee to not reduce $r_1$, the following inequality should hold,

$$\theta_1(1 - 1/\theta_1 - \epsilon)(p_1 - p_1 Q + Q) \geq \theta_1(1 - r_1)(p_1 - p_1 Q)$$

where $r_1 < 1/\theta_1$. Since $p_1 = 1$ and $\epsilon > 0$, we have,

$$Q > \frac{1/\theta_1 - r_1}{1 - r_1}$$

and $\frac{1/\theta_1 - r_1}{1-r_1} \leq t$ when $0 \leq r_1 \leq 1/\theta_1$. So when $Q \geq 1/\theta_1$, trustee has no incentives to reduce $r_1$, and $p_1 = 1$ and $r_1 = 1/\theta_1 + \epsilon$ is a Nash equilibrium. When $Q < 1/\theta_1$, both $p_1 = 0, r_1 = 0$ and $p_1 = 1, r_1 = 1/\theta_1 + \epsilon$ are Nash equilibria. □

When investors have no information at all, $Q = 0$, investors never transfer, $p_1 = 0$, and trustees return nothing, $r_1 = 0$. When the probability that an investor knows the trustee's return increases, buy still small, $Q \leq 1/\theta_1$, the population oscillates between $p_1 = 0, r_1 = 0$ and $p_1 = 1, r_1 = 1/\theta_1 + \epsilon$. When $Q$ is sufficiently large, $Q \geq 1/\theta_1$, the benefits of trustees are realized. Trustees return a fraction of the transfer that is slightly larger than $1/\theta_1$. Then investors usually trust and make the transfer even when they don't have information. As $Q$ keep increasing, it is less likely that investors need to make blind transfer, so that relevance of $p_1$ decreases. Eventually, when $Q = 1$, investors always have information about trustees and $p_1$ is no longer relevant.

## C.2 Simulation Results by Group

Each panel in Figure C.1 plots payoffs of or strategies for investors and trustees for group A and group B separately. Investors' payoffs and strategies are depicted in solid lines and trustees' are in dashed lines. Group A outcomes are marked in red and group B outcomes are marked in blue. Panels A and B show that the payoffs and strategies of group A and B are the same in a evenly divided community, where $\alpha = 0.5$. But the payoffs and strategies of group A and B diverge when one group becomes larger than other (i.e. when $\alpha = 0.8$) as depicted in Panels C and D.

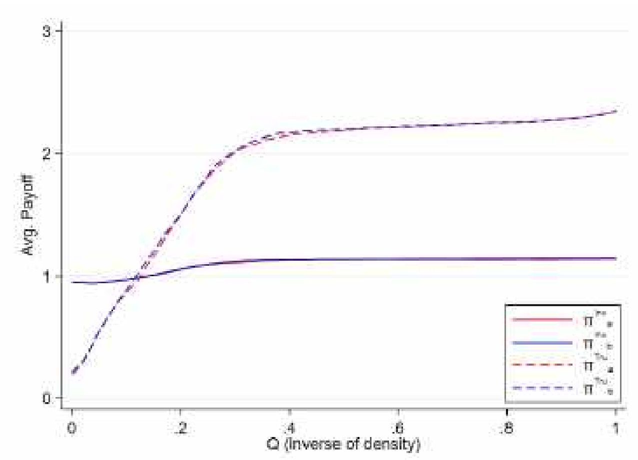
In the own-group game, the larger group $A$ seems to be playing optimally, as $r_{1,A}$ increases to $1/\theta 1 = 1/4$ when $Q$ increases, and $p_{1,A}$ rises until $Q = 1/\theta 1 = 1/4$, after which it falls. However, the smaller group $B$ has trustees that return larger amounts $r_{1,B} > 1/4$, meaning that investors can keep larger amounts and earn higher profits. We conjecture that this is because the smaller group has less opportunity for learning, given that they are a smaller group. In the cross-group game, group $B$ trustees seem to be returning slightly less than $r_{0,B} = 1/\theta_0 = 1/3$, and this leads to lower levels of cross-group investment for group A ($p_{0,A}$). Conversely, group $A$ trustees are returning higher levels at $r_{0,A} \approx 0.4$, and group B investors are investing larger amounts.

## C.3 Investors' Strategies: $\widetilde{p}$ vs. $p$

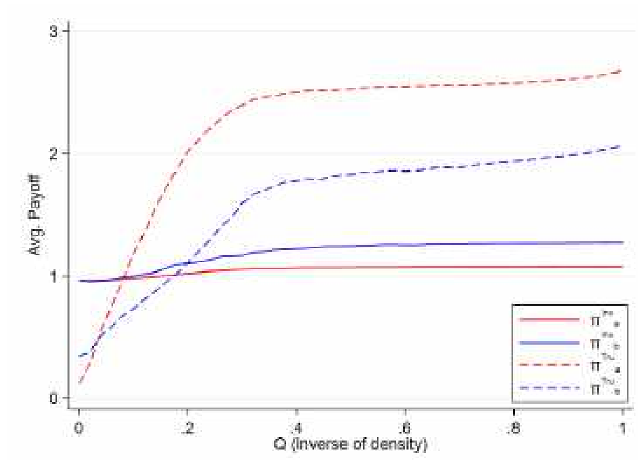
In Figure C.2 compares investors' strategies under no information, $p_0$ and $p_1$, (Panels A-D) with the realized trust outcomes, $\widetilde{p}_0$ and $\widetilde{p}_1$. The key difference between these figures is that as $Q$ increases, $p_0$ and $p_1$ begin to fall back to 0.5. This is because $p_0$ and $p_1$ refer to strategies that investors play in games of imperfect information. As density falls and $Q$ increases, those strategies do not govern payoffs, and they face no selection pressure in the evolutionary game. Hence, $p_0$ and $p_1$ converge to their prior distributional means of 0.5.

**Figure C.1:** How Lower Density Increases Trust (By Group)

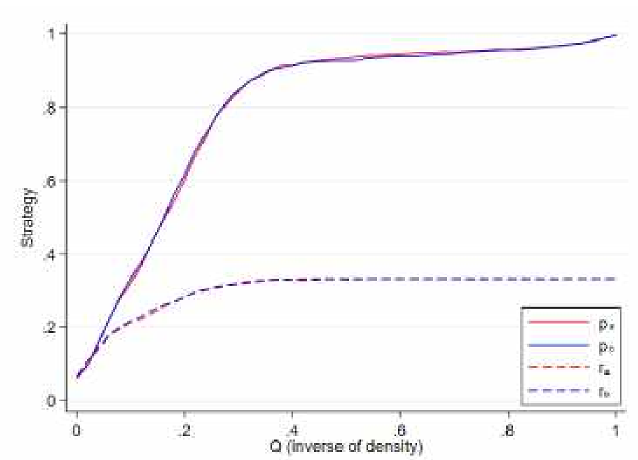
**(A)** PROFITS, $\alpha = 0.5$



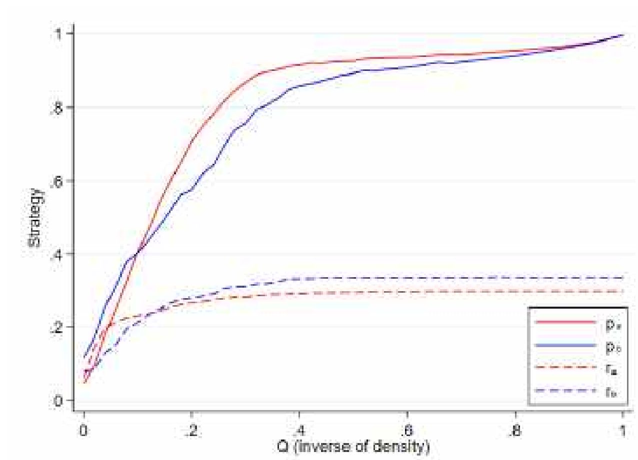

**(C)** PROFITS, $\alpha = 0.8$




**(B)** $\widetilde{p}, r$, $\alpha = 0.5$



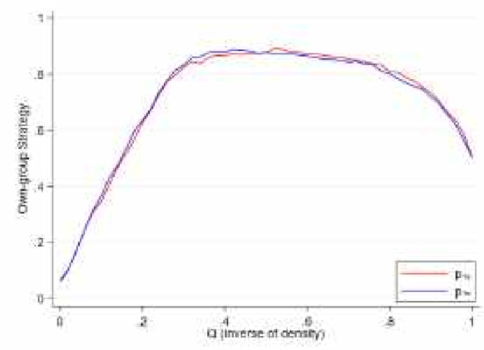

**(D)** $\widetilde{p}, r$, $\alpha = 0.5$



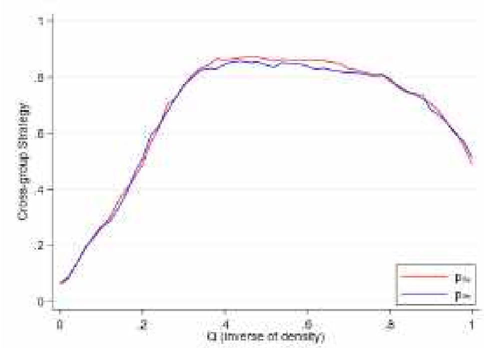

*Notes*: For each simulation, we use the following parameters: the total population size $N = 100$, the mutation rate $\mu = 0.01$, and the selection intensity $\beta = 20$. Results are averaged over the last 80 percent of 50 simulation runs, where each run consists of 50,000 rounds.

**Figure C.2:** Investors' Strategies: $\widetilde{p}$ vs. $p$

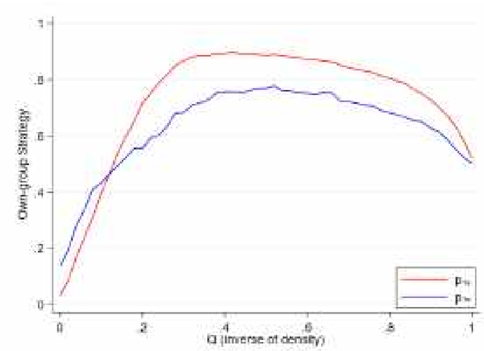
**(A)** $p_1$, $\alpha = 0.5$



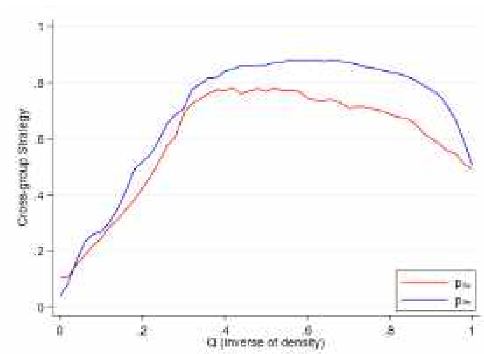

**(B)** $p_0$, $\alpha = 0.5$



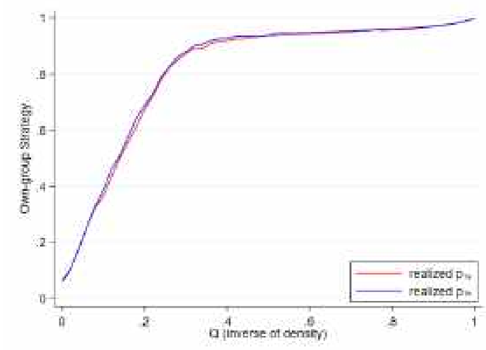

**(C)** $p_1$, $\alpha = 0.8$



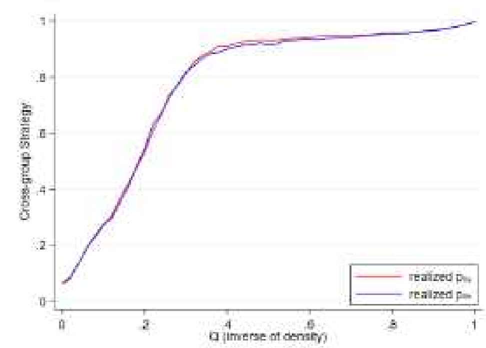

**(D)** $p_0$, $\alpha = 0.8$



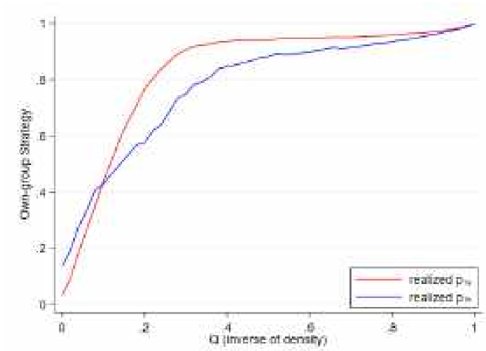

**(E)** $\widetilde{p}_1$, $\alpha = 0.5$



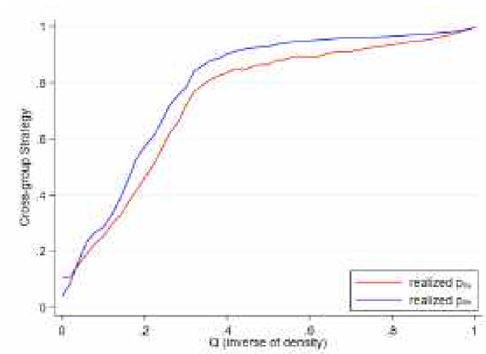

**(F)** $\widetilde{p}_0$, $\alpha = 0.5$




**(G)** $\widetilde{p}_1$, $\alpha = 0.8$




**(H)** $\widetilde{p}_0$, $\alpha = 0.8$




*Notes*: For each simulation, we use the following parameters: the total population size $N = 100$, the mutation rate $\mu = 0.01$, and the selection intensity $\beta = 20$. Results are averaged over the last 80 percent of 50 simulation runs, where each run consists of 50,000 rounds.