How Does Municipal Governance Structure Affect Innovation and Knowledge Diffusion? Evidence from U.S. Metro Areas*

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Abstract

As declining state and federal aid forces regional governments to become more self-reliant, there is new interest in understanding factors that support regional resilience to economic and natural disasters. Using a sample of 365 metropolitan statistical areas, we examine one such factor: how regional government fragmentation shapes patented innovation, a known mechanism for bolstering resilience. While we find no evidence that the number of general-purpose governments (per capita) impact regional innovation, we do find that regions with a higher density of special-purpose governments have less inclusive innovation. This is true in terms both of who does the inventing and what is invented. Previous research links higher numbers of special-purpose government units to weaker economic performance; our results suggest higher numbers may also hinder regions' abilities to adapt to disruptions.

Keywords: fragmentation, polycentricity, regional resilience, innovation, economic development
JEL Classification Numbers: H1, H77, O3, R5

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1 Introduction

The severity of recent economic and natural disasters, such as the 2008 financial crisis and Hurricane Katrina, coupled with the continued decline in state and federal aid, have ignited interest in understanding how local governance affects a region's ability to recover and adapt. This is broadly known as regional resilience. The notion of regional resilience has gained popularity, in part, because it can be defined differently depending on the audience (Christopherson et al. 2010; Martin 2012). For instance, Pendall et al. (2010) argue that economic resilience comprises two separate, yet related concepts: first, the ability of a region to return to a pre-existing state of economic activity and, second, the responsive adaptations and adjustments of a region's complex systems.

While they do not all use the phrase "economic resilience," there are many studies that look at how economic activity returns to previous levels after an exogenous shock, including the large stream of literature stemming from Blanchard, Katz et al. (1992). Additional studies have looked at the underlying factors that create resilient regions. These include pre-shock conditions like capital, including human capital (Di Caro and Fratesi 2018) and industry diversity (Watson and Deller 2017), along with policy responses to the shock (Wolman et al. 2017).

It is also well established in the literature that regions in which innovation flourishes are more resilient to economic downturns and unanticipated shocks (Clark et al. 2010; Bristow and Healy 2018; Clark and Bailey 2018; Mustra et al. 2020). At the same time, the literature is sparse on the mechanisms explaining why this would be so. Several studies point to a notion of Schumpeterian innovation, where regions with innovative residents have the ability to learn, explore, and adapt to a changing economic environment (Filippetti et al. 2020; Mustra et al. 2020). Viewed through this lens, regions innovate and adapt to negative economic shocks due to local knowledge accumulation and dissemination.

In this paper, we combine data from the Census Bureau's quinquennial Census of Governments with detailed disambiguated patent data from the PatentsView Project to empirically examine the relationship between local governance structure and regional innovation. We focus on U.S. metropolitan statistical areas (MSAs) because approximately 95% of all patenting activity in the U.S. takes place within metro areas. We follow Lee and Wang (2020) and measure governance using both horizontal and vertical metrics of government fragmentation and dispersion. Fragmentation measures are based on the number of general-purpose and special-purpose governmental units per 100,000 people in the MSA, while fiscal dispersion measures are based on the distribution of government expenditures across the various units.

We leverage the disambiguated patent data to provide a perspective on innovation that is more nuanced than the overall rate of patented innovation. For example, we distinguish between patents awarded to inventors affiliated with organizations and those awarded to unaffiliated inventors. Within each subgroup, measures of innovation concentration are constructed based on the number of distinct inventors *and* the primary technology class of the patent awards. Recent work by Wagner and Pavlik (2020) shows that the concentration of patented innovation often varies greatly across metro areas, even when overall rates are similar. Understanding how governance structure affects innovation concentration (or diffusion) could have important implications for resilience because regions with more concentrated innovation, and thus a lack of diversification, may be more vulnerable to economic disruptions.

To account for potential simultaneity between innovation and local governance, we pursue an instrumental variables (IV) strategy to isolate a source of exogenous variation in the governance metrics. We instrument for current governance structure (1990 - present) using the region's diversity of places of worship in 1952 and governance structure metrics from 20 years earlier. We argue, and provide evidence, that these instruments satisfy the exclusion restriction because current inventors and ideas differ from the ideas and inventors from a generation ago.

Our results indicate that the presence of more general-purpose government units (per capita) are neutral for local innovation. That is, potential policies and institutions due to competition among local municipalities does not seem to influence the number of inventors or the range of products. However, consistent with the broader literature on vertical fragmentation, we find evidence that regions with a greater density of special-purpose government units have significantly less inclusive (or more concentrated) innovation both in terms of innovators and new products. This result appears to be driven more by the number of school districts in a metro area than by the number of other forms of special-district governments. We offer several potential channels through which additional local fragmentation in school districts could hinder inclusive innovation.

The implications of our results are clear. Previous work has found that communities that rely more heavily on special-purpose government units (school districts plus special districts) have weaker economic performance. Our results imply that they also have less inclusive innovation, making them potentially more vulnerable to sector-specific economic shocks or to the loss of a key innovator.

The following sections of the paper discuss the relationships between innovation, resilience, and governance, describe our data and identification strategy, present empirical results, and offer concluding remarks.

2 Background

2.1 Innovation and Resilience

There is significant variation in how regions recover from economic shocks and natural disasters (Hill et al. 2012). This has led policymakers and scholars increasingly to search for sources of economic resilience. In particular, a common question is this: what economic characteristics or government policies help a region withstand economic shocks and develop new growth paths? Despite the expanding literature, why some regions are more resilient than others remains an open question (Martin 2012; Christopherson et al. 2010; Martin and Sunley 2020). Thus far, empirical work on regional resilience has tended to concentrate on the structure of the local economy, in particular, regional industry characteristics like specialization (Palaskas et al. 2015), and complementarities of the industry mix (Cainelli et al. 2019), among others.

Understanding the structure of the local economy requires more than mere understanding of the characteristics of the industries within it. There is, for example, a well-established link between innovation, long-term economic growth and economic competitiveness (Bristow and Healy 2018). Recognition of this linkage has led to more research on the role that regional capacity for innovation plays on economic resilience after a region experiences a negative shock. For example, recent work by Filippetti et al. (2020) and Bristow and Healy (2018) provides evidence that more innovative regions either avoided the negative shock from the 2008 financial crisis or recovered quickly from it.

Scholars have gravitated towards the notion of Schumpeterian innovation to understand how innovation impacts economic resilience (Filippetti et al. 2020; Bristow and Healy 2018). According to Schumpeter, innovation, i.e. the ability and capacity to produce and disseminate new products, produces lasting endowment effects. The endowment effects result in capital accumulation by firms and knowledge spillovers to entrepreneurs, both of which can be leveraged during an adverse economic shock (Storper 2011). Evolutionary economic geographers have begun to flesh out an understanding of the role of innovation in regional economic evolution and resilience by drawing on the seminal work of (Schumpeter et al. 1939). In particular, a Schumpeterian notion of creative destruction has the negative shock acting as an economic driver because unproductive sectors or resources are replaced by creative entrepreneurs (Simmie and Martin 2010). In this view, innovators help regions adapt to changing circumstances and fuel economic revival.

Recent advances in understanding regional networks point to a related mechanism for innovation promoting economic resiliency. In this light, regions comprise networks of firms, industries, institutions, and people, all dependent on each other. Accordingly, urban population alone does not necessarily imply resilience; instead, what matters is how the relevant entities within the area are connected (Capello et al. 2015). The connectivity of the network brings together resources, knowledge and technological skills that can be harnessed either in a growing or a contracting regional economy (Cooke et al. 2011). For instance, Balland et al. (2015) examine patent applications in U.S. cities from 1975 to 2002 and find that cities with more diverse knowledge bases recover more quickly from economic shocks. Cappelli et al. (2021) generalize this concept and develop a measure of technological resilience – the ability to create and maintain knowledge over time. They find that areas with more technological resilience experienced smaller declines in unemployment during the 2008 financial crisis. A region's network of innovators and entrepreneurs could play a similar role. For instance, more locally connected innovators could take advantage of local resources and opportunities. Furthermore, locally connected innovators could reduce the likelihood that other high-skilled people leave the area during an economic downturn (Boschma 2015).

2.2 Local Governance, Economic Development and Innovation

The U.S. has one of the most decentralized forms of governance in the world, a unique structure that lends itself to lines of inquiry ranging from the optimal distribution of activities across governmental units to the appropriate use of policy to promote various economic objectives (Oates 1999). With state and federal aid to local governments shrinking by roughly 50% since the 1970s, there is new interest in understanding how increasingly self-reliant local governments can operate effectively.

Early perspectives on the fiscal federalism approach to municipal governance, such as Musgrave (1959) and Oates (1972), focused on what is now commonly referred to as the assignment problem: understanding what tax and expenditure functions should be performed by different levels of government. According to this work, when spillover effects to other jurisdictions or economies of scale are present, provision is optimized when either a higher level of government provides a service or when smaller levels of government coordinate their actions (or consolidate), thus internalizing the spillover and reaping the efficiency gains. Thus, the lack of coordination or the lack of a single overarching authority, often called fragmented local governance, is likely to be inefficient and to hinder economic growth.

Opponents of the regional or monocentric view argue that many municipal governments are essential for economic development. For instance, Ostrom et al. (1961), building on the earlier work of Tiebout (1956), argue that polycentric municipal government fosters competition and leads to more efficient public goods delivery better aligned with citizens' preferences. As Aligica and Tarko (2012) note, the polycentric view hinges on many independent decision-making centers that overlap and interact to form an organic social order.[1]

So while the monocentric view of governance points to overlapping and duplicated responsibilities as a key source of inefficiency, polycentrists assert the same mechanism is essential to ensure public sector competition (Aligica and Tarko 2012).[2] Furthermore, each type of governance structure can yield different institutions, policies and regulations that drive economic development and subsequent innovation.

Empirical evidence lacks consensus on whether polycentric or monocentric governance structure is best suited to promoting economic development and resiliency. For instance, Hammond and Tosun (2011) and Grassmueck and Shields (2010) find that a higher number of general-purpose governmental units (per square mile and per capita) is correlated with slower population, income, and employment growth. Goodman (2020b) and Stansel (2005) find that more government fragmentation is positively associated with growth. The geographic context also seems to matter, as

[1] An often cited criticism of polycentric governance is that it can lead to urban sprawl. See Carruthers and Ulfarsson (2003) for an overview of this work.

[2] The polycentricity approach to municipal governance is far more nuanced than we can address in this paper. See Aligica and Tarko (2012) for a more thorough discussion of the key principles and historical foundations.

Goodman (2020b) and Stansel (2005) find that metro areas grow more slowly when a large share of their total population is located in the principal city.

Other studies have addressed the governance question by capitalizing on the rare occasions when local governments have consolidated. In general, empirical evidence that consolidation improves economic development, services, or delivery has been somewhat sparse (Jimenez and Hendrick 2010; Carr and Feiock 1999). However, recent studies by Hall et al. (2020) and Egger et al. (2022), which rely upon modern causal inference methods, find evidence that consolidation enhances economic development in some situations.

While the literature on general-purpose government shows that the effects of fragmentation are mixed, there is greater agreement that more fragmentation in special-purpose governments may be detrimental to growth (Lee and Wang 2020; Goodman 2019, Berry 2008; Stansel 2006). For instance, Berry (2008) and Stansel (2006) find a strong positive relationship between the size of local governmental units and the number of overlapping special-purpose governments. Moreover, Lee and Wang (2020) find that median income and home prices recovered more slowly following the 2008 financial crisis in metro areas with more special-purpose governments (per capita). This suggests that special-purpose governments reduce regional resiliency. One limitation of this study, however, is that Lee and Wang (2020) offer no discussion of any theoretical mechanisms that would explain their findings.

Unlike general-purpose governments, special-purpose governments are comprised of school districts and special-districts governments. Common special-district governments include water- or fire-service zones, economic development districts, housing development authorities, and regional transportation authorities. Thus, special-purpose governments generally provide a single service and often overlap jurisdictions with other governmental units. They also typically have the authority to issue debt and collect taxes, tend to be less transparent, face little to no regional competition, are more likely to have unelected leaders, and accrue larger volumes of debt per capita than general-purpose government units (Martell 2007; Stansel 2006).

Special-purpose governments are also proliferating rapidly. Between 1987 and 2007, Jimenez and Hendrick (2010) found that 96% of the more than 8,100 new governmental units created in the U.S. were special-purpose governments. However, the reasons underlying their creation and dissolution is not well understood (Goodman 2020a). While some may solve inefficiencies arising from spillover effects or provide improved services demanded by residents, others may have emerged to circumvent tax, expenditure, and debt limitations faced by general-purpose governments (Goodman 2020a). If the transparency and accountability in special-purpose governments leads to more fiscal illusion for voters, then their continued (net) expansion would be consistent with Brennan and Buchanan (1980)'s Leviathan theory of government growth.

Our analysis focuses on the local concentration (or diffusion) of innovation in terms of inventor networks and types of products. There are plausible channels through which both polycentric and monocentric governance can result in policies and institutions that either help or hinder progress. For instance, decentralization of municipal government could produce competitive pressure that benefits inventors. This could come from a direct link where local municipalities provide services inventors need. Stokan and Deslatte (2019) show that horizontal fragmentation increases the use of economic development incentives to attract firms to a municipality, while more special-purpose districts yield fewer incentives but expand community development activities. Both of these mechanisms could yield stronger innovation networks. More broadly, local competition could produce a lower regional tax environment that is more conducive to inclusive innovation in the number of inventors and products. In a similar vein, if decentralization of governance leads to greater economic freedom, as research by Stansel (2013) suggests, then it may also support organic creation from a broader set of innovative firms and entrepreneurs.

In contrast, polycentric governance could lead to entrepreneurs and programs siloed within each municipality. This could result in weaker ties and information networks along with a less diverse array of products. Also, from an economic development perspective, individual regional governments could compete to "pick winners" and steer economic development toward local government-favored industry clusters (and firms) rather than enacting policies that promote a market-driven process. The focus on specific clusters could lead to more innovation (i.e. more patents in certain sectors), but a lower diversity of products.

The increased local competition with fragmented governance could also hinder effective regional collaboration for education, transportation networks, and workforce development, all of them helpful in facilitating knowledge spillovers. Thus, inventors are isolated and not benefiting from the region's broader knowledge base. Smaller governmental units are also at greater risk of fiscal distress if their tax base becomes too narrow or too heavily dependent on a single industry. For example, the collapse of the steel industry led to tremendous fiscal stress for some municipalities in Allegheny County, Pennsylvania, one of the most fragmented counties in the nation in terms of governmental units (Archibald and Sleeper 2008). Fiscal stress could then inhibit policies that incubate small innovative firms and entrepreneurs. Finally, polycentric governance could induce greater rent-seeking as firms that are more mobile pit municipalities against each other in an effort to gain (inefficient) subsidies.

More monocentric regions may also have advantages that spur innovation. The most obvious mechanisms are efficiency gains due to lower production costs and better policy coordination. Owing to their size, larger governments may also have greater access to state and federal funding, more capacity to promote economic development, and lower transactions costs in forming public-private partnerships that bolster economic development and resiliency (Archibald and Sleeper 2008). Thus, monocentric governance could utilize policies, such as innovation districts, to take advantage of a critical mass of innovators in their jurisdiction. This in turn could lead to more inclusive innovation.

As governments grow in size and influence, however, there is also a tendency for the regulatory regime to expand (Higgs 1991). This could lead to a reallocation of firm resources to satisfy compliance and reduce the incentive for innovation (Aghion et al. 2020). In addition, increased regulation could erode trust in government because it leads to more public corruption and regulatory capture (Taylor 2016; Holcombe and Boudreax 1991). As Taylor (2016) notes, interest groups, including industry trade groups, often support higher taxes, regulations, and more complex procurement policies that favor the status quo and ultimately retard scientific and technological progress.

As we discussed above, there are a range of potential mechanisms where the local governance structure, and related policies, institutions and regulations, can influence local innovation products and inventor networks. These mechanisms can have competing impacts on our measures of innovation. Next, we turn to the data and empirical strategy to shed empirical light on the relationship between local governance structure and innovation.

3 Data and Identification Strategy

3.1 Patented Innovation

Our innovation measures are derived from the detailed utility patent data provided by PatentsView Project, a collaborative effort between several universities, private-sector organizations, and the U.S. Patent and Trademark Office (USPTO). The PatentsView data are constructed from the USPTO records, covering both patent applications (2001-present) and granted patents (1976-present). This database differs from earlier iterations of data provided by the USPTO that assigned a unique identifier to individual patent awards only by applying a disambiguation algorithm to every patent's inventor(s), assignee(s), and lawyer(s).[3] These disambiguated data can then be merged to numerous data fields, allowing for a very nuanced examination of patented innovation that allows one to track the behavior of individual inventors and organizations across both space and time.

Over our sample period (1990-2018), there were more than 2.8 million unique patents awarded to more than 1.4 million U.S. residents representing more than 200,000 organizations (or assignees). Of these awards, roughly two-thirds were granted to organizations and more than 93% to inventors who lived in metro areas. One in four inventors (in MSAs) were unaffiliated with an organization. Collectively, these individuals were awarded roughly 14% of the patents granted to residents of metro areas over the nearly 30-year period we examine.

Because of the importance of knowledge diffusion in encouraging innovation, we capitalize on the disambiguated nature of the patent data and construct measures of inventor networks within and across MSAs. We do so following Breschi and Lenzi (2016), who propose measures of the size and interconnectedness of inventors when every inventor is treated as a distinct node in a broader network of inventors. The within-MSA, or regional inventor network, measure is given by:

$$\text{regional inventor network}_{\text{MSA}_{jt}} = \frac{\sum_{k=1}^{n} \sum_{\substack{l=1 \\ k \neq l}}^{n} \frac{1}{d_{kl}}}{n-1} \tag{1}$$

where d_{kl} is the geodesic distance between inventors k and l in MSA j at time t. The geodesic distance is the shortest path, or the minimum number of intermediaries, from any inventor k to every other inventor in the network. The regional inventor network measure is bounded by 0 and n, where 0 indicates that no inventor collaborated on a patent with any other inventor, and n implies that every inventor was a collaborator with every other inventor in the network. In short, larger values of the regional innovation network metric demonstrate a higher average level of collaboration within an MSA.

[3] A patent's assignee is the individual or organization that owns the legal property right to the patent. Patents are assigned to MSAs based on the residence of the inventor(s) and are fractionally weighted by the number of co-inventors. Patents where the primary product/technology class is design or plant are excluded.

Figure 1 shows the average rate of patented innovation per 100,000 residents (Panel A) and the average regional inventor network density (Panel B) by MSA. While there is more time-series variation in the regional inventor network measures, the majority of variation over our sample period occurs across space. In terms of overall patent intensity, for example, roughly 80% of the total observed variation between 1990 and 2018 is cross-sectional. This variation also indicates that even as some metro areas have become more (or less) innovative in the past 30 years, the relative ranking of most MSAs has been very stable.

[Insert Figure 1 here]

The link between patent intensity and inventor network density is also weaker than one might expect. While some MSAs, such as San Jose-Sunnyvale-Santa Clara, CA, and Burlington-South Burlington, VT, rank very high (top 10) in terms of both patent and network density, the simple correlation between these two metrics is just 0.52. Ann Arbor, MI, and Ames, IA, for example, are among the top 10 most innovative regions based on intensity, yet both fall outside the top 100 when it comes to collaboration. On the more extreme side, the Monroe, MI, and Greely, CO, MSAs are roughly 50th in the nation in terms of innovation intensity and fall outside the top 300 in terms of collaboration. Thus, these two metrics – innovation intensity and collaboration intensity – seem to be capturing distinct aspects of innovation that may be important for resilience.

Using an instrumental variables strategy for identification, Breschi and Lenzi (2016) study 331 MSAs over a relatively short time period (1995-1999) and find that MSAs with larger average inventor networks have higher rates of patented innovation. Similarly, in a panel of 355 MSAs from 2003-2014, Bennett et al. (2021) find that metro areas with larger innovation networks have significantly more high-growth firms, defined as those growing at least 20% per year for at least 5 consecutive years. They argue that regional inventor networks facilitate the flow of new knowledge and technologies to individuals, organizations, and, ultimately, to the entrepreneurs who create new products and services.

In addition to the more conventional measures of innovation, we also explore how innovation concentration (or diffusion) is affected by local governance structure. Wagner and Pavlik (2020) show that although overall *rates* of patented innovation may be similar across metro areas, the concentration of innovation, both in terms of technology classes and inventors, is often much different.

Using the unique identifiers for organizations and unaffiliated individuals in the raw patent data, we construct four distinct Herfindahl-Hirschman indices (HHI) to measure innovation concentration. The first two measures reflect the concentration of innovation across inventors, using each organization's (or individual's) share of the total patents awarded to their respective group.

The organization HHI measures treat each distinct organization as the unit of interest and ignores the number of inventors. Hence, if three organizations are each awarded one patent in MSA j in time t, the organization concentration HHI would be equal to 3,267 because each organization was responsible for generating one-third of the region's patents awarded to organizations. A limitation of this metric is that it excludes innovation from (unaffiliated) inventors who do not work for organizations. To address this issue, we also construct the HHI measures using the number of distinct inventors and ignore the number of organizations. For example, suppose that four inventors were awarded one patent in MSA j in time t. The inventor concentration HHI would be equal to 2,500 because each inventor was responsible for one-fourth of the region's innovation.

The second concentration metric is based on the primary technology class listed on the patent (the international patent classification or IPC) to assess the concentration of innovation. There are approximately 130 different IPC codes, and we refer to these HHI measures as organization production concentration and individual product concentration. If all the patents awarded to (organization or individual) inventors in MSA j have the same primary technology class, then the HHI value for this metric would equal 10,000.

From a resilience perspective, it is natural to expect a region with less concentrated (or more diffuse) innovation to be more resilient to economic disruptions. As a simple illustration, Baltimore, MD, and Bloomington, IN, are two metro areas that have nearly identical patent intensity rates, roughly 28 patents per 100,000 residents. (The national average is 26.) However, when one examines the concentration of innovation, the picture changes. In terms of product/technology classes among patents generated by organizations (which generate a majority of the patents), Baltimore's average HHI is 738 and Bloomington's is 4845. This means the range of products and services being created in Baltimore is more than 6 times as diverse as the range of products and services being created in Bloomington. Based on previous research (Balland et al. 2015), one would expect Baltimore's greater inclusive innovation to enhance the region's resilience to economic shocks relative to Bloomington, other factors constant.

Figure 2 plots the distribution of innovation concentration for the MSAs in our sample. Values in the figure reflect the annual average over the period from 1990 to 2018. Much like patent intensity, innovation concentration is much more likely to vary across regions than it is to vary over time, potentially reflecting persistent, deep-rooted expertise among organizations and technologies.

[Insert Figure 2 here]

The HHI measures are plotted ranking MSAs from least concentrated innovation (rank = 1) to most concentrated innovation (rank = 362). The least and most concentrated MSAs are labeled in each panel, along with MSAs at roughly the 34th and 68th percentiles. Among inventors (the two left panels), the New York-Newark-Jersey City MSA has the least concentrated (most inclusive) innovation among both organizations and unaffiliated individual inventors. In contrast, the Villages MSA in Florida and Beckley, WV, have the most concentrated (least inclusive) inventor indices, both in excess of 6,000. Innovation is fragile in these regions because so many of their patents come from only a few inventors/organizations.

In general, the data suggest that innovation tends to be more inclusive (less concentrated) in MSAs with higher rates of innovation. For instance, Silicon Valley, the San Jose-Sunnyvale-Santa Clara, CA, has the highest rate of patent intensity in the nation by a sizable margin *and* ranks second in the nation in terms of the diversity of organizations receiving patents. There are, however, some key exceptions. The Rochester, MN, metro area ranks 11th in the nation (in our sample) in terms of overall patent intensity, yet the region is in the 70% percentile in terms of the diversity of products and services being created. Similarly, the Carson City, NV, metro area ranks 56th in the nation in terms of intensity, and 224th in terms of diversity of organizational inventors. This last is because 20% of the region's patents have been awarded to only two firms, International Gaming Technology and General Electric.

3.2 Governance Measures

We rely upon the Census Bureau's quinquennial Census of Governments to construct our measures of local government fragmentation. The Census of Governments is completed every 5 years (ending in 2 and 7) and covers the universe of governments. There are roughly 90,000 different governmental units, according to the Census Bureau. Table 1 shows the counts, by type, for 1992, 2007, and 2017. State and federal governmental units are omitted.

[Insert Table 1 here]

As noted by Jimenez and Hendrick (2010), the growth in governmental units has been fueled almost exclusively by expansions in special districts. Over our sample period, the number of special-district governments expanded by more than 5,100 (or 16%). The total number of governmental units has increased at a slower rate, primarily due to a trend in school district consolidation that dates to the 1960s. In 1967, for example, there were roughly the same number of school districts (21,264) as special districts (21,782). The shift toward special districts has been fairly widespread geographically and by function. For instance, if one decomposes the variation in general-purpose or special-purpose governments (including school districts) at the MSA level, more than 95% of the variation is spatial rather than temporal. In terms of function, the highest share of new special districts (between 1992 and 2017) have been for water services (16%), fire protection (15%), housing (8%), conservation (7%), and economic development (4%).[4]

We construct measures of both vertical and horizontal governmental fragmentation that follow from the literature (Lee and Wang 2020; Goodman 2019; Grassmueck and Shields 2010). Horizontal fragmentation attempts to capture the effect of having overlapping layers of responsibility in a given area. It is the number of general-purpose governments (counties, townships, and municipalities) per 100,000 residents. In contrast, the term vertical fragmentation has come to mean how dispersed government responsibilities are shared across different governmental units. The standard approach in the literature, which we follow, measures vertical fragmentation as the number of special districts and school districts in an MSA per 100,000 residents. As noted by Goodman (2019), much of the recent attention to polycentric governance has focused on vertical fragmentation because of the negative development consequences associated with a greater concentration of these governmental units.

In addition to the rate of governmental units, fragmentation is also evaluated using the distribution of expenditures. As Lee and Wang (2020) note, areas where few local governments bear most functional responsibilities are likely to be different from areas where service provision is shared

[4] The Census Bureau's Annual Survey of Government Finance relies on a much smaller sample of governments. For instance, the 2001 annual survey sampled 19,685 governments, of which 68.5% were school districts, 14.6% were special districts, 6.9% were counties, 5.9% were cities, and 3.6% were townships. Because the annual surveys significantly over-represent school districts and under-represent special districts, relying on their data to measure fragmentation would likely be misleading. The survey methodology for the Census of Governments may be found here: https://www.census.gov/programs-surveys/cog/technical-documentation/methodology.html [accessed: 11/2/2021]

more equally. The variable horizontal fiscal fragmentation is the Herfindahl-Hirschman index of the squared shares of direct governmental expenditures covered by the region's general-purpose governments. Similarly, vertical fiscal fragmentation is the sum of the squared shares of direct governmental expenditures undertaken by the MSA's school and special-district governments. In both instances, larger values indicate more concentrated government spending (more fiscal centralization).

3.3 Identification Strategy

Given our interest in exploring if observable differences in local governance structure explain the spatial distribution of innovation *across* different metro areas, we exploit the cross-sectional variation in the data by estimating a between regression. Specifically, our empirical regression has the form:

$$\bar{I}_{j,s} = \alpha + \eta \bar{X}_{j,s} + \delta \bar{G}_{j,s} + \mu_s + \bar{\varepsilon}_{j,s}, \tag{2}$$

where $\bar{I}_{j,s}$ denotes the (mean) innovation measure of interest for metropolitan area j located in state s. $\bar{X}_{j,s}$ denotes a vector of control variables for metropolitan area j located in state s that previous research suggests could be correlated with patented innovation. Our parameter of interest, $\bar{G}_{j,s}$ denotes our governance metric of interest (outlined in Section 3.2). We also include state-specific fixed effects (μ_s) to adjust for factors such as differences in non-compete enforcement and state tax policies related to innovation. Multi-state metro areas are assigned to the state where the most populous county is located. Finally, $\bar{\varepsilon}_{j,s}$ denotes the random disturbance term.

The between estimator regresses the average value of our innovation outcome of interest on the individual averages of the governance measures, state fixed effects, and our control variables. This specification eliminates the time-series variation in the data so that the estimated coefficients are identified using only the cross-sectional variation. This also allows one to overcome the challenges that arise because metro area patent intensity, concentration, and governance are so persistent over time (recall that 95% of the total variation in our metro fragmentation measures is cross-sectional).[5] Several recent studies on metro area patented innovation, including Wagner and Pavlik (2020) and

[5] If one were to use a two-way fixed effects framework, the inclusion of MSA-specific fixed effects would remove all the cross-sectional variation in the data. In this case, the coefficients would be identified from within-MSA variation over time.

Breschi and Lenzi (2016), follow the same estimation strategy.

Our full sample of (annual) data covers the period 1990 to 2018. Since the Census of Governments is available every five years, the fragmentation measures use data from the 1992, 1997, 2002, 2007, 2012, and 2017 censuses. Except for a few covariates, we estimate equation (2) using each MSA's annual average values from 1990 to 2018. This is roughly three decades, so our estimated coefficients can be interpreted as reflecting some long-run cross-sectional effect.

To adjust for observable differences in innovation, we include a broad set of control variables in $\bar{X}_{j,s}$. Following Carlino et al. (2007), we include each MSA's Herfindahl-Hirschman index of private sector employment (HHI employment) constructed from the Quarterly Census of Employment and Wages. The variable is scaled in thousands, and smaller values indicate a more diverse economy (at least based on the distribution of payroll jobs). Descriptive statistics, years of coverage used to construct the MSA averages, and the sources for all of our empirical variables are provided in Table 2. Our full sample covers 362 MSAs.

[Insert Table 2 here]

Prior work has shown that access to capital is important for innovation and patents (Mann and Sager 2007). To capture research funding and access to capital, we include real per capita university R&D spending (in thousands) and real per capita venture capital spending in the region.

The regression also includes the share of jobs in STEM fields (science, technology, engineering, and math) because these occupations are a key driver of innovation (Shambaugh et al. 2017). We follow Wagner and Pavlik (2020) and form this variable using the Census Bureau's definition of STEM occupations, along with the industry-occupation crosswalk file created by the Bureau of Labor Statistics. The crosswalk file provides estimates (based on national data) of the percentage of specific occupations in a given industry, which allows one to estimate the number of jobs in a specific occupation or set of occupations.[6] These 63 occupations are then mapped to employment levels in a given North American Industry Classification System (NAICS) sector using the national industry-occupation matrix created by the BLS.[7]

[6]The Census Bureau's definition of STEM occupations are available at the following URL: ¡https://www2.census.gov/programs-surveys/demo/guidance/industry-occupation/stem-census-2010-occ-code-list.xls¿ [Accessed: 12/8/2018].

[7]The BLS industry-occupation crosswalks by industry are available at the following URL: ¡https://www.bls.gov/emp/tables/industry-occupation-matrix-industry.htm¿ [Accessed: 12/8/2018].

In addition to STEM jobs, several variables are included to adjust for a metro area's economic development and dynamism. These include the MSA's net job creation rate, per capita GDP (in thousands of real dollars), and economic freedom index, as well as a measure of the human capital stock. We rely on the region's net job creation rate, from the Census Bureau's Business Dynamic Statistics database, to measure dynamism in the MSA. Since educational attainment has been shown to be a strong driver of innovation (Shambaugh et al. 2017), we include the percentage of adults ages 25 and older who hold college degrees as a control variable. The level of real per capita GDP will adjust for differences in economic development across regions, while the MSA's economic freedom index (Stansel 2019) will adjust for institutional differences that could foster innovation and bolster resilience. Economic freedom has been found to be positively related to income, entrepreneurship, and more diffuse innovation (Hall and Lawson 2014; Wagner and Pavlik 2020).[8]

There are also factors that could be correlated with innovation, or innovation concentration, such as a region's climate (for agricultural-related patents) or age. Newer MSAs may be disadvantaged relative to older metro areas if innovation is entrenched in historic evolution. The regressions include several variables to control for these effects. To adjust for potential entrenchment, we include the total number of patents awarded to an MSA between 1790 and 1910, and the median annual patent rate over this same period. We also include an MSA's average patent rate (from 1990-2018) for agricultural-related patents and health care patents. Health care-related patents often have more co-inventors, which could affect the network measures, while agricultural innovation may be dependent on local climate conditions and therefore be regional-specific.[9]

Knowledge diffusion and spillovers also play critical roles in fostering innovation (Breschi and Lenzi 2016; Anselin et al. 1997; Acs et al. 2002). We adjust for these factors using three different control variables. First, we include the number of jobs (in millions) in the MSA that are "export-based" to control for direct economic linkages to other areas. Second, we include each MSA's average population-weighted distance to every other MSA. This will adjust for the unobservable factors affecting innovation that are correlated with proximity to more people and potential inventors.

[8] The economic freedom index varies from 0 (least free) to 10 (most free) and is the average of scores given to three broad areas of governance: (1) spending; (2) taxation; and (3) labor market freedom. See Stansel (2019) for more details.

[9] Using the NBER patent subcategories, agricultural patents are category 11 and health care patents are categories 31 and 32.

Finally, we follow Breschi and Lenzi (2016) and include a measure of the size and interconnectedness of inventors within an MSA with inventors in other MSAs. This variable is analogous to our regional inventor network measure, except that it is based on the average geodesic distance between every inventor in MSA j and every inventor outside of MSA j. This variable is also bounded by 0 and w, where 0 indicates that no inventor in an MSA collaborated with any inventor outside the region, and w indicates that every inventor in the region collaborated with every inventor outside of it. This variable will help to capture the average spatial pattern of knowledge flows across metro areas.

Breschi and Lenzi (2016) also find that larger metro areas have higher rates of patent intensity. We include two variables to adjust for size differences across MSAs. The first is the region's total population (in millions), and the second is the percentage of the region's total population living in the largest county. This will account for differences in the relative size of a region's urban core.

Finally, due to the potential for simultaneity between local governance and innovation, we follow Wagner and Pavlik (2020) and Breschi and Lenzi (2016) and rely upon an instrumental variables strategy for identification. Since institutions like governance structure evolve slowly while innovation happens and spreads rapidly, we instrument for the average value of each governance measure (formed using data from 1992 to 2017) using the value from 1972.[10] We also include a second instrument for each governance measure, the MSA's Herfindahl-Hirschman index of church denominations, based on data from the 1952 Survey of Churches and Church Membership.[11] The HHI for church denominations provides a metric reflecting the diversity of religious preferences in the community. If these preferences are persistent over time, which seems reasonable, then we would expect the diversity of churches in 1952 to be correlated with fragmentation of local governance in subsequent generations. Results of the first-stage regressions are shown in Appendix Table A.1.

Valid instruments must also satisfy the exclusion restriction. We argue that governance structure from 20 years in the past coupled with the region's diversity of churches 40 years in the past will be unrelated to *current* innovation because the inventors and ideas are, for all practical purposes, unrelated. For instance, Wagner and Pavlik (2020) note that the median inventor is awarded one patent, and that fewer than 2% of inventors in the U.S. have ever been awarded patents 20

[10]The Census of Governments provides counts of the number of governmental units, by county, dating back to 1942. However, the first year that detailed financial data are provided by governmental unit is 1972.

[11]The number of churches by denomination is provided at the county level in the Survey of Churches and Church Membership. All the empirical variables used in this paper, including our HHI church measure, use the 2015 MSA definitions from the Office of Management and Budget when aggregating county-level data is required.

years apart. Additionally, Mehta et al. (2010) examined the citation "age profile" of patents and found that frequency of citation peaks one year after a patent is awarded and falls to a number statistically indistinguishable from zero 15 years afterward. Based on this evidence, we believe we are justified in assuming that current patented innovation is unrelated either to a community's historical religious diversity or to its local governance structure a generation ago.

4 Empirical Results

The instrumental variables results are presented in Tables 3 through Table 6. Each regression includes an unreported constant term and state fixed effects. Standard errors are clustered at the state-level. The Cragg-Donald F-statistic for the strength of the instruments is reported, along with the p-value from the Sargan over-identification test statistic for the exogeneity of the instruments. Finally, each regression also reports the p-value from a Moran's I test for residual spatial correlation using an inverse distancing weighting matrix. We find no evidence of significant residual spatial correlation in any of the regressions ($p \leq 0.05$), suggesting that the across-MSA inventor network measure and weighted population distance variable are sufficiently controlling for spatial spillovers between MSAs.

For each outcome variable, we estimate five separate regressions: one with each of the four governance fragmentation measures included separately as a regressor, and one regression including all four governance variables simultaneously. The first-stage F-statistic for the strength of the instruments is 3965.0 for horizontal fragmentation, 327.0 for vertical fragmentation, 43.5 for horizontal fiscal dispersion, and 143.6 for vertical fiscal dispersion. These values easily surpass the latest threshold guidance from Andrews et al. (2019) regarding weak instruments. Finally, it is worth noting that in the 35 regressions shown in Tables 3 through 6 we never observe a p-value from the over-identification test that is below 0.10. Hence, at least empirically, the instruments are both strong and exogenous.

Focusing on the regional inventor work (Table 3), we find that larger MSAs, MSAs with more STEM jobs, and those with greater economic freedom have larger average inventor networks. We also find that MSAs with inventors who collaborate more with inventors from other MSAs have larger local networks. MSAs with larger urban cores, and those closer to other large MSAs (based on population), have significantly smaller regional inventor networks.

[Insert Table 3 here]

In terms of the governance metrics, we find little consistent evidence that the size of an MSA's average regional inventor network is dependent on local governance structure. Column (2) in Table 3 indicates that the presence of more special-district governments (per 100,000 residents) lowers the size of a region's inventor network. However, this finding is fragile because it does not hold when all the governance metrics are included in the same regression (column 5).

Regression results of the patent intensity rate are shown in Table 4. There are 10 total columns, the first 5 of which apply to the rate of patents among organizational inventors, and the last to the patent rate among unaffiliated individual inventors. Recall from Section 3.1 that organizational inventors make up roughly two-thirds of the inventor pool and generate around 85% of total patent awards.

[Insert Table 4 here]

Consistent with prior literature, the results in Table 4 show that metro areas with a larger share of STEM occupations, more export-based jobs, higher economic freedom, and larger university R&D expenditures have higher rates of patented innovation. After adjusting for these observable factors, the results in Table 4 indicate that fragmentation of local governance does not significantly affect the *rate* of patented innovation among either organizations or individuals.

Our innovation concentration results are presented in Tables 5 and 6. The outcome variables for Table 5 measure the concentration (or diffusion) of innovation among distinct organizations and individuals, while Table 6 shows the results for innovation concentration among product (or technology) classes for organizations and unaffiliated individuals.

[Insert Table 5 here]

[Insert Table 6 here]

Regarding the control variables, we find consistent evidence that MSAs with a higher share of STEM jobs, greater economic freedom, and more per capita university R&D expenditures have significantly less concentrated (more inclusive) innovation, both in terms of distinct inventors (Table 5) and inventions (Table 6). We find that innovation is more concentrated, again both in terms of inventors and inventions, in metro areas where a greater share of the population is in the urban core, in metro areas that are more economically concentrated (in terms of jobs), and in places where regional inventors collaborate more often with inventors outside the region.

These results point to consistent evidence that local governance affects the *concentration* of innovation. Based upon columns (5) and (10) in Tables 5 and 6, we find that a higher number of special-purpose governments (per 100,000 residents) significantly increases the concentration of innovation for organizations and individuals. In terms of distinct inventors (Tables 5), our results indicate that a one standard deviation increase in the number of special-purpose governments increases the HHI concentration for organizations and individuals by 251 and 336, respectively. This explains approximately 20 percent of the variation for the one standard deviation change in the HHI concentration of inventors.

The magnitude is similar when we focus on the HHI concentration of products (Table 6). The estimated coefficients in columns (5) and (10) suggest that a one standard deviation increase in the number of special-purpose governments raises the HHI for product concentration by 308 for organizations and 326 for individuals. This explains roughly 20 percent of the one standard deviation change in the HHI concentration of products being created in metro areas.

The finding that a greater concentration of special-purpose governments reduces inclusive innovation is consistent with the broader literature showing that population, employment, and home-price growth are weaker in metro areas with more special-purpose governments (Lee and Wang 2020; Goodman 2020b; Stansel 2006). Considering all the results jointly, we find that local governance is unrelated to the level or rate of local innovation. However, in regions with more vertical fragmentation – meaning there is more dispersion in responsibilities across governmental units – we find that innovation is more concentrated among who is inventing and what products are being created.

4.1 A Closer Look at Inclusive Innovation and Special-Purpose Governments

In this section, we decompose the vertical fragmentation measure into the two major components, special-district governments and school districts, to provide greater evidence on the mechanisms(s) underlying our baseline results. Because we only find evidence linking a higher number of special-purpose governments (per capita) to less inclusive innovation, we also limit our analysis to outcome variables measuring the HHI of patent concentration among inventors and technologies.

As we did with the baseline empirical specification, we treat the number of special-district/school districts (per 100,000 residents) as being endogenously determined with innovation. Instruments include the HHI of church denominations in the MSA in 1952 and the number of special-district/school districts per 100,000 residents in 1972. For these regressions, the first-stage F statistics are 292.2 (special-district governments) and 327.4 (school districts). The regression results are presented in Tables 7 and 8.

[Insert Table 7 here]

[Insert Table 8 here]

The results from columns (3) and (6) in Tables 7 and 8 include both vertical fragmentation metrics in the same regression. These specifications strongly suggest that the concentration of school districts rather than special-district governments is behind the finding that vertical fragmentation is detrimental to inclusive innovation.

There are at least two potential mechanisms that could explain this result. First, metro areas with greater governmental fragmentation have been shown to have higher than average levels of total government spending and taxation. (Goodman 2019). The presence of more school districts, typically funded by property taxes, might cause individuals and firms to divert resources to tax bills and away from activities that drive innovation, thus making innovation less inclusive at the margin. This explanation is similar in spirit to the study by Aghion et al. (2020), who find that French firms operating just below a certain regulatory threshold innovate significantly more than the firms operating just above it.

In addition, there is an established literature indicating that metro areas with more fragmented school districts tend to have less equitable distribution of school resources and educational attainment (Holme and Finnigan 2013). This could mean a smaller pool of potential innovators compared to areas with greater equality of educational opportunities, ultimately contributing to an environment of less inclusive innovation.

Furthermore, local school district fragmentation can reduce diversity along racial and socio-economic lines (Bischoff 2008; Clotfelter 2004). This could reduce inclusive innovation through a reduction in the so-called diversity dividend due to reduced interactions between both adults and children from different backgrounds (Syrett and Sepulveda 2011).

The literature on school district fragmentation is extensive, and our results suggest that more work is needed to isolate the mechanisms at work. As noted above, more districts might lead to greater competition for the same tax base, which in turn could hinder learning outcomes. Alternatively, there is a growing body of work linking diversity (broadly defined) to greater innovation and entrepreneurship (Karlsson et al. 2021). If greater school district segregation is being driven by racial division, then, if results from business organizations extend to the broader population, this could lead to less innovation, as our results suggest.

5 Conclusion and Policy Discussion

Economic and natural disasters have led both policymakers and scholars to explore ways that regions can recover and adapt. The extant literature has looked at how regions organize their governance structures to influence economic development and how innovation can shape economic resilience. However, to the best of our knowledge, there has not been scholarship linking the structure of a region's municipal governance to innovative capacity and inclusiveness.

There are a variety of mechanisms through which decentralization or consolidation of regional governance may impede or promote innovative activity. For instance, those who promote polycentric local governance, in the vein of Ostrom et al. (1961), point to competition among governments yielding greater local economic freedom and services that meet the needs of local entrepreneurs and innovators. We note, however, that decentralized governance does not come without potential negatives like barriers to collaboration across governmental units, the attempt to "pick winners," and the potential for rent-seeking by innovative firms.

Meanwhile, those who advocate municipal consolidation argue it allows for greater policy coordination and capacity, among other benefits. Here again, we note potential negatives: an expanded regulatory regime, public corruption, and regulatory capture by innovative firms that proves harmful to the broader innovation ecosystem.

Apparently, a multitude of mechanisms are at play. These lead us to examine empirically the role local governance structure plays in fostering several measures of innovation in U.S. metro areas. We focus on the variation across metro areas, identifying the impact using an instrumental variable strategy with lagged measures of municipal governance structure. Our results show no compelling evidence that the regional governance structure affects innovation rates either for firms or for unaffiliated individuals. However, we do find consistent evidence that local governance affects the concentration of innovation in a region. In particular, we estimate a robust relationship between vertical fragmentation (i.e. a higher number of special-district governmental units) and concentration of innovation for organizations and individuals, holding other measures of local governance constant. For instance, our results indicate that a one standard deviation increase in the number of special-district governments increases the HHI concentration for organizations and individuals by 251 and 336, respectively. This explains approximately 20 percent of a one standard deviation change in the HHI concentration of inventors.

In particular, our results show that the number of school districts per 100,000 residents (rather than the number of special districts overall) drives the finding that governmental fragmentation leads to less inclusive innovation. This result is unexpected, considering that over time, school districts have been consolidating while other forms of special purpose governments have been expanding. We offer two potential channels to explain this result. First, when school district fragmentation increases delivery costs, innovators may divert resources away from innovation to pay local tax bills. Second, if school district fragmentation results in greater inequality in delivery and student outcomes, this inequality could reduce the region's pool of potential local innovators. Both mechanisms could lead to less inclusive regional innovation, making local communities more vulnerable to economic disruptions.

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Table 1: Number of Local Governments in the U.S.

Type	1992	2007	2017	%Δ 1992-2017
County	3,043	3,032	3,025	-0.6
Municipality	19,285	19,489	19,426	0.7
Township	16,656	16,475	16,173	-2.9
Special District	31,555	35,566	36,694	16.3
School District	14,422	13,742	13,448	-6.8

Source: Census of Governments, U.S. Census Bureaus. Counts include only subnational governments. The Census Bureau defines special-purpose governments as the sum of special districts and school districts.

Figure 1: Patent Intensity and Innovation Networks by MSA: Average 1990-2018

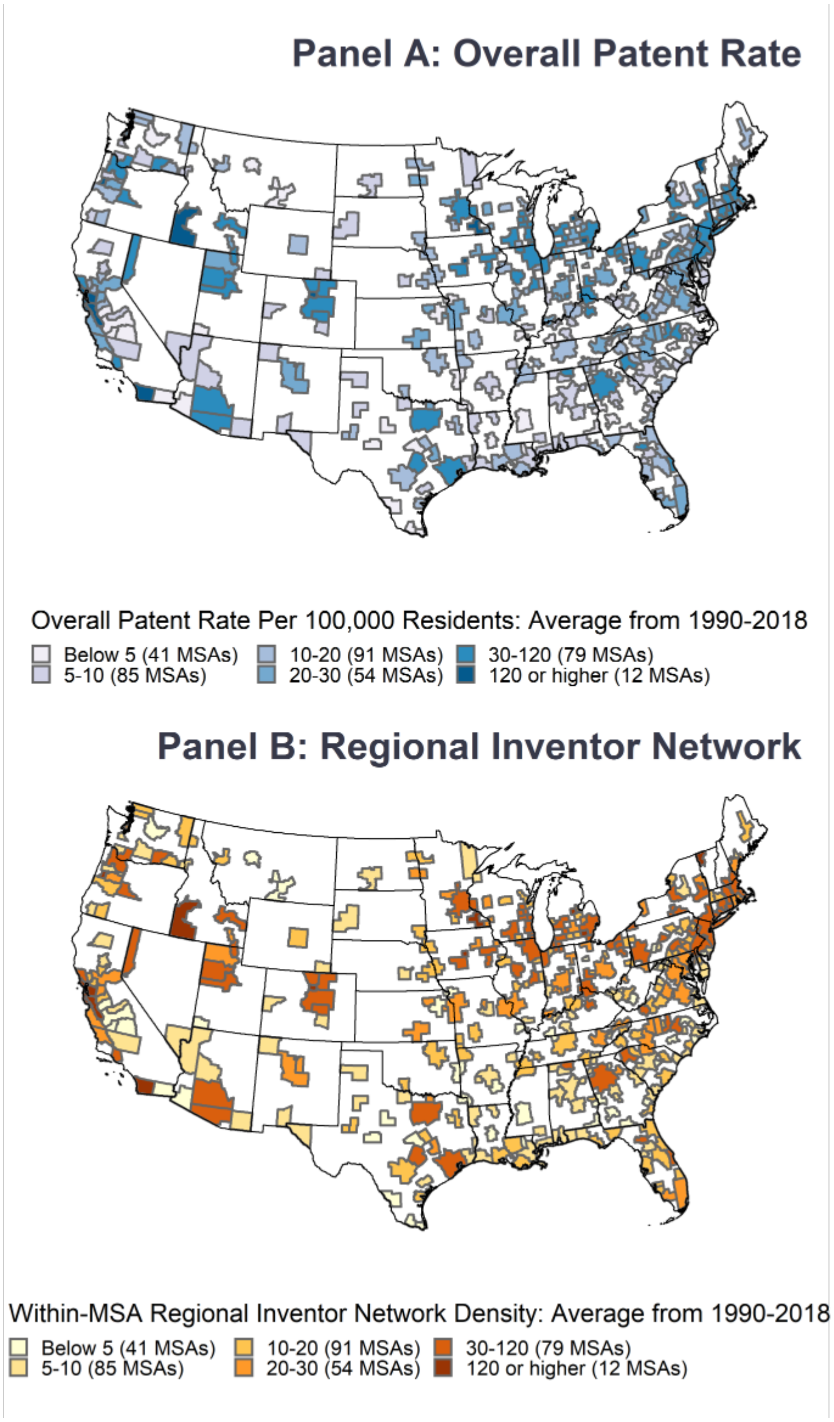

Figure 2: Inventor and Product Innovation Concentration by MSA: Average 1990-2018

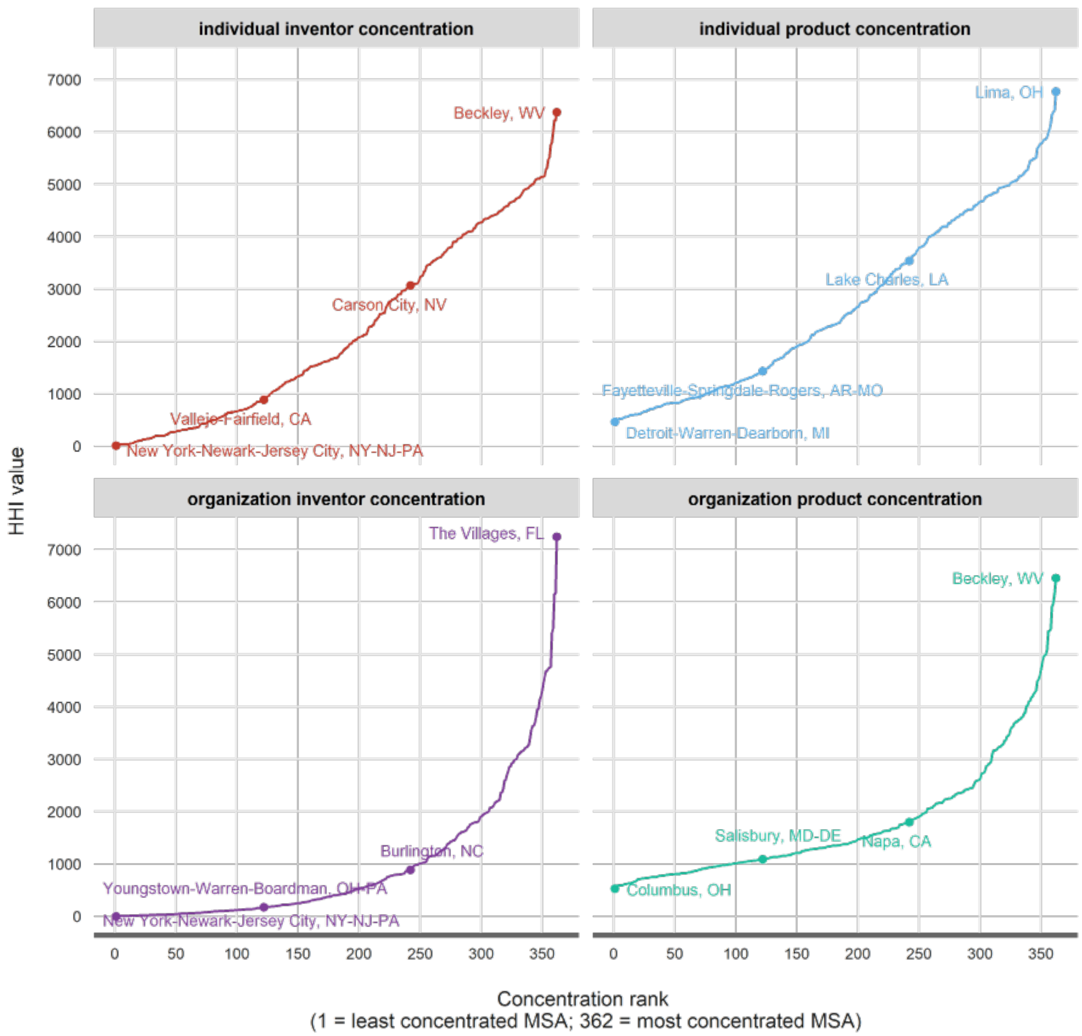

Table 2: Descriptive Statistics and Data Sources

Variable	Mean	Std Deviation	Years of Coverage
regional inventor network	1.259	1.655	1990-2018
organization patent rate	22.628	32.778	1990-2018
individual patent rate	3.588	2.118	1990-2018
organization concentration	962.388	1272.269	1990-2018
individual concentration	2181.349	1723.456	1990-2018
organization product concentration	1777.298	1162.772	1990-2018
individual product concentration	2692.449	1671.846	1990-2018
horizontal fragmentation	11.840	12.360	1992-2017
vertical fragmentation	17.325	15.221	1992-2017
horizontal fiscal dispersion	31.681	10.514	1992-2017
vertical fiscal dispersion	0.361	0.151	1992-2017
share of jobs in STEM occupations	2.718	0.903	1990-2018
economic freedom: overall	6.533	0.726	1992-2017
venture capital per capita	0.296	0.773	1990-2018
percent 25 and older with degree	18.565	8.539	2005-2007
per capita university r & d spending	0.066	0.194	1990-2018
across-MSA inventor network	0.192	0.438	1990-2018
net job creation rate	1.330	0.960	1990-2018
HHI employment	1.104	0.260	1990-2018
export jobs	3.953	1.525	2003-2007
population (millions)	0.610	1.396	1990-2018
largest county population share	79.327	22.008	1990-2018
real per capita GDP	16.945	4.985	1990-2018
weighted population distance	426.741	138.898	1990-2018
historical patent rate	3.363	3.497	1790-1910
historical patent sum (000s)	2.024	9.684	1790-1910
agricultural patent rate	0.059	0.175	1990-2018
health care patent rate	2.076	3.607	1990-2018

Notes: The full sample includes 362 metropolitan statistical areas (MSAs). Years of coverage indicates the number of years used to construct the average of each MSA's variable of interest. All dollar variables were converted into real terms using the CPI (2018 = 100). Regional innovation network, across-MSA inventor network, patent rates (per 100,000 residents), and innovation concentration measures were constructed using data from the PatentsView project. MSA economic freedom is from the Fraser Institute and is available in economic census years (ending in 2 or 7). The horizontal/vertical fragmentation and dispersion variables were constructed from the Census Bureau's Census of Governments, which is also available only in years ending in 2 or 7. The share of jobs in STEM occupations was constructed from the Quarterly Census of Earnings and Wages. Net job creation rate is from the Census's Business Dynamic Statistics program. University r&d spending (in thousands) per capita is from the National Science Foundation. Venture capital spending is from Dow Jones Venture Source. The percentage of the population ages 25 and older with a graduate degree was constructed using data from IPUMS for 2005-2017. MSA employment in export industries is from the Brookings Institution. GDP data are from the Bureau of Economic Analysis. MSA population data and the largest county's share of total population are from the Census Bureau. Distances between MSAs, used to construct the weighted population distance variable, are based on the distance between the MSA's most populated counties. The Herfandahl-Hirschman Index of employment (in thousands) uses supersectors from the Quarterly Census of Earnings and Wages data. Historial patent data were obtained from the HistPat Dataset, version 8, available at Harvard's Dataverse.

Table 3: Regional Governance Structure and Inventor Networks

	Dependent variable:				
	regional inventor network				
	(1)	(2)	(3)	(4)	(5)
	2SLS	2SLS	2SLS	2SLS	2SLS
share of jobs in STEM occupations	0.470***	0.486***	0.541***	0.532***	0.448***
	(0.140)	(0.143)	(0.139)	(0.136)	(0.139)
economic freedom: overall	0.493***	0.454**	0.425**	0.478***	0.381*
	(0.179)	(0.182)	(0.204)	(0.174)	(0.199)
venture capital per capita	-0.096	-0.105	-0.113*	-0.118	-0.120
	(0.070)	(0.071)	(0.067)	(0.077)	(0.076)
percent 25 and older with degree	0.011	0.008	0.008	0.011	0.010
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
per capita university r & d spending	-0.719	-0.634	-0.672	-0.643	-0.751*
	(0.445)	(0.445)	(0.430)	(0.441)	(0.424)
across-MSA inventor network	0.308*	0.304*	0.317*	0.294*	0.341*
	(0.171)	(0.175)	(0.180)	(0.176)	(0.195)
net job creation rate	0.009	0.010	0.033	0.024	0.005
	(0.087)	(0.087)	(0.090)	(0.086)	(0.087)
HHI employment	-0.119	-0.166	-0.193	-0.155	-0.172
	(0.275)	(0.272)	(0.277)	(0.280)	(0.274)
export jobs	0.051	0.049	0.025	0.028	0.050
	(0.061)	(0.064)	(0.059)	(0.065)	(0.064)
population (millions)	0.229	0.218	0.241	0.231	0.175
	(0.167)	(0.164)	(0.169)	(0.162)	(0.163)
largest county population share	-0.013**	-0.013***	-0.013**	-0.010*	-0.008
	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)
real per capita GDP	-0.016	-0.016	-0.015	-0.015	-0.008
	(0.018)	(0.018)	(0.018)	(0.018)	(0.017)
weighted population distance	-0.003***	-0.003***	-0.003**	-0.003***	-0.003**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
historical patent rate	-0.014	-0.018	-0.021	-0.021	-0.007
	(0.022)	(0.020)	(0.020)	(0.019)	(0.022)
historical patent sum (000s)	0.003	0.005	0.002	0.007	0.010
	(0.023)	(0.023)	(0.023)	(0.022)	(0.023)
agricultural patent rate	0.234	0.259	0.234	0.253	0.225
	(0.451)	(0.457)	(0.459)	(0.446)	(0.466)
health care patent rate	0.078**	0.078**	0.079**	0.077**	0.075**
	(0.036)	(0.035)	(0.035)	(0.035)	(0.035)
horizontal fragmentation	-0.017*				-0.013
	(0.010)				(0.012)
vertical fragmentation		-0.011**			-0.007
		(0.005)			(0.007)
horizontal fiscal dispersion			-0.021		-0.023
			(0.022)		(0.021)
vertical fiscal dispersion				-0.597	-1.278*
				(0.740)	(0.704)
N	362	362	362	362	362
Adj. R^2	0.631	0.628	0.621	0.627	0.623
IV Sargan P	0.501	0.451	0.462	0.438	0.691
Cragg-Donald F-stat	3965.035	327.017	43.465	143.590	
Moran's I p-value	0.067	0.071	0.063	0.067	0.088

This table presents the effect of various measures of regional governance fragmentation on the a region's (within-MSA) regional innovation network. Every governance fragmentation variable is treated as endogenous using the region's Herfandahl-Hirschman index of church denominations from 1952 and the endogenous variable's value from 1972 as instruments. The row 'Cragg-Donald F-statistic' denotes the first-stage F statistic for the strength of the instruments. The row 'IV Sargan' shows the p-value from the Sargan test under the null hypothesis that at least one of the instruments is uncorrelated with the error term. The row 'Moran's I p-value' reports the p-value of residual spatial correlation using an inverse distance weighting matrix. Standard errors are in parantheses and are clustered at the state dimension. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level. Models were estimated with a constant term and state fixed effects that are not reported. Most variables are the average over the period from 1990 to 2018. See the notes to Table 1 for exceptions, variable definitions, and sources.

Table 4: Regional Governance Structure and Innovation Rates

	Dependent variable:									
	organization patent rate					individual patent rate				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
share of jobs in STEM occupations	12.933***	11.394**	11.798***	11.717***	11.996**	0.627***	0.554***	0.552***	0.548***	0.621***
	(4.909)	(4.569)	(4.446)	(4.332)	(4.784)	(0.169)	(0.162)	(0.153)	(0.152)	(0.183)
economic freedom: overall	11.350***	11.131***	12.078***	11.187***	10.956***	0.985***	0.995***	0.919***	0.991***	0.869***
	(3.358)	(3.313)	(3.623)	(3.290)	(3.709)	(0.323)	(0.332)	(0.356)	(0.316)	(0.324)
venture capital per capita	1.303	1.551	1.552	1.291	1.214	0.406***	0.421***	0.417***	0.421***	0.395***
	(3.869)	(3.841)	(3.893)	(4.006)	(4.018)	(0.125)	(0.128)	(0.127)	(0.135)	(0.129)
percent 25 and older with degree	-0.147	-0.145	-0.110	-0.105	-0.160	-0.011	-0.010	-0.012	-0.010	-0.015
	(0.198)	(0.196)	(0.209)	(0.204)	(0.226)	(0.014)	(0.014)	(0.016)	(0.015)	(0.017)
per capita university r & d spending	13.146	11.808	12.153	11.621	13.943	0.894	0.795	0.754	0.795	0.877
	(12.281)	(12.252)	(12.576)	(12.266)	(12.792)	(0.607)	(0.610)	(0.577)	(0.617)	(0.583)
across-MSA inventor network	7.215**	7.565**	7.217**	7.509**	7.176**	-0.335	-0.318	-0.288	-0.316	-0.299
	(3.186)	(3.354)	(3.459)	(3.436)	(3.589)	(0.229)	(0.235)	(0.244)	(0.234)	(0.230)
net job creation rate	-0.562	-0.993	-0.916	-0.898	-0.950	-0.089	-0.108	-0.102	-0.109	-0.085
	(2.124)	(2.190)	(2.218)	(2.221)	(2.099)	(0.120)	(0.122)	(0.121)	(0.122)	(0.117)
HHI employment	-11.854**	-11.335**	-10.863*	-11.228*	-11.947**	0.047	0.092	0.048	0.091	-0.025
	(5.637)	(5.660)	(5.772)	(5.788)	(5.419)	(0.292)	(0.299)	(0.318)	(0.298)	(0.319)
export jobs	4.244***	4.759***	4.640***	4.554***	4.587***	-0.073	-0.050	-0.053	-0.048	-0.075
	(1.234)	(1.132)	(1.133)	(1.159)	(1.305)	(0.056)	(0.059)	(0.056)	(0.054)	(0.063)
population (millions)	-1.590	-2.142	-1.829	-2.278	-2.356	0.128*	0.109	0.099	0.105	0.100
	(1.460)	(1.564)	(1.556)	(1.772)	(1.903)	(0.075)	(0.073)	(0.070)	(0.087)	(0.091)
largest county population share	0.090	0.072	0.081	0.137	0.119	0.010**	0.009**	0.009**	0.010	0.011
	(0.069)	(0.066)	(0.066)	(0.101)	(0.107)	(0.004)	(0.004)	(0.004)	(0.008)	(0.008)
real per capita GDP	-0.126	-0.103	-0.133	-0.050	-0.097	0.017	0.018	0.020	0.018	0.021
	(0.583)	(0.580)	(0.594)	(0.609)	(0.614)	(0.020)	(0.020)	(0.019)	(0.022)	(0.021)
weighted population distance	-0.014	-0.019	-0.020	-0.018	-0.016	0.000	0.000	0.000	0.000	0.000
	(0.021)	(0.021)	(0.022)	(0.022)	(0.022)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
historical patent rate	-0.947*	-0.767*	-0.829*	-0.759	-0.864*	-0.101**	-0.092**	-0.089**	-0.091**	-0.097**
	(0.487)	(0.461)	(0.450)	(0.467)	(0.518)	(0.041)	(0.041)	(0.037)	(0.044)	(0.044)
historical patent sum (000s)	-0.063	-0.062	-0.056	0.006	0.044	-0.008	-0.009	-0.011	-0.009	-0.008
	(0.192)	(0.200)	(0.211)	(0.224)	(0.236)	(0.009)	(0.009)	(0.011)	(0.014)	(0.015)
agricultural patent rate	-3.397	-3.631	-3.500	-3.668	-2.932	0.020	-0.002	-0.023	-0.001	0.007
	(7.520)	(7.875)	(7.678)	(7.710)	(7.469)	(0.398)	(0.412)	(0.440)	(0.412)	(0.426)
health care patent rate	4.164***	4.143***	4.149***	4.118***	4.132***	0.183***	0.182***	0.182***	0.182***	0.182***
	(1.192)	(1.209)	(1.216)	(1.199)	(1.145)	(0.059)	(0.061)	(0.061)	(0.061)	(0.058)
horizontal fragmentation	0.272				0.371	0.020*				0.026*
	(0.217)				(0.245)	(0.010)				(0.013)
vertical fragmentation		-0.097			-0.266*		0.001			-0.008
		(0.103)			(0.144)		(0.009)			(0.010)
horizontal fiscal dispersion			0.219		0.209			-0.025		-0.029
			(0.381)		(0.466)			(0.050)		(0.050)
vertical fiscal dispersion				-14.620	-9.664				-0.036	-0.251
				(15.925)	(18.105)				(1.818)	(1.611)
N	362	362	362	362	362	362	362	362	362	362
Adj. R^2	0.667	0.665	0.663	0.662	0.661	0.636	0.633	0.633	0.632	0.631
IV Sargan P	0.091	0.138	0.113	0.152	0.100	0.191	0.254	0.296	0.257	0.233
Cragg-Donald F-stat	3965.035	327.017	43.465	143.590		3965.035	327.017	43.465	143.590	
Moran's I p-value	0.390	0.353	0.439	0.333	0.324	0.570	0.614	0.691	0.609	0.617

This table presents the effect of various measures of regional governance fragmentation on a region's rate of patented innovation (per 100,000 residents). Every governance fragmentation variable is treated as endogenous using the region's Herfandahl-Hirschman index of church denominations from 1952 and the endogenous variable's value from 1972 as instruments. The row 'Cragg-Donald F-statistic' denotes the first-stage F statistic for the strength of the instruments. The row 'IV Sargan' shows the p-value from the Sargan test under the null hypothesis that at least one of the instruments is uncorrelated with the error term. The row 'Moran's I p-value' reports the p-value of residual spatial correlation using an inverse distance weighting matrix. Standard errors are in parantheses and are clustered at the state dimension. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level. Models were estimated with a constant term and state fixed effects that are not reported. Most variables are the average over the period from 1990 to 2018. See the notes to Table 1 for exceptions, variable definitions, and sources.

Table 5: Regional Governance Structure and Innovation Concentration: Inventors

	Dependent variable:									
	organization concentration					individual concentration				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
share of jobs in STEM occupations	-468.340***	-446.641***	-533.749***	-527.927***	-414.242***	-892.045***	-875.981***	-1009.927***	-1001.308***	-833.930***
	(76.556)	(73.467)	(74.133)	(75.638)	(77.783)	(116.771)	(110.116)	(118.929)	(117.877)	(116.750)
economic freedom: overall	-560.183***	-497.966***	-525.715***	-547.320***	-479.047***	-536.363***	-442.410***	-415.286**	-524.382***	-357.137*
	(142.141)	(128.070)	(156.773)	(137.191)	(147.043)	(161.783)	(164.854)	(189.794)	(164.648)	(191.508)
venture capital per capita	33.779	39.133	47.815	53.666	48.842	-2.284	8.849	25.766	22.788	23.700
	(45.393)	(54.336)	(52.120)	(56.385)	(58.717)	(86.066)	(104.511)	(98.312)	(104.386)	(111.998)
percent 25 and older with degree	-6.354	-2.417	-4.455	-6.206	-4.599	18.608*	24.731**	23.771**	19.944*	23.251**
	(9.043)	(9.086)	(9.346)	(9.123)	(9.707)	(10.390)	(9.646)	(9.324)	(10.460)	(9.892)
per capita university r & d spending	-461.049*	-544.310**	-523.148**	-534.458**	-483.258*	-1630.749***	-1775.112***	-1704.762***	-1766.118***	-1632.928***
	(250.931)	(258.469)	(241.135)	(229.805)	(255.077)	(368.228)	(380.408)	(330.466)	(327.620)	(368.601)
across-MSA inventor network	1520.164***	1516.262***	1523.276***	1533.495***	1503.140***	885.282***	883.225***	867.093***	910.307***	837.563***
	(511.991)	(502.416)	(507.026)	(504.592)	(488.774)	(319.312)	(305.051)	(319.573)	(315.469)	(297.780)
net job creation rate	-77.895	-66.798	-97.670	-92.922	-58.762	-198.170**	-185.897**	-239.028***	-226.535***	-182.528**
	(71.184)	(67.801)	(74.742)	(70.518)	(67.027)	(80.435)	(78.234)	(81.938)	(78.443)	(78.001)
HHI employment	602.448***	655.148***	655.412***	637.252***	639.695***	702.079**	789.712***	830.480***	763.616***	798.749***
	(208.599)	(217.510)	(216.436)	(211.859)	(200.494)	(292.346)	(304.261)	(299.112)	(296.079)	(277.088)
export jobs	-4.713	-16.128	17.698	16.981	-20.130	206.530***	194.714***	249.938***	242.683***	193.998***
	(35.756)	(33.166)	(34.218)	(35.366)	(36.218)	(51.203)	(51.724)	(54.533)	(48.374)	(55.331)
population (millions)	-108.999**	-78.803*	-123.641**	-113.563**	-47.615	-236.651***	-196.142***	-256.142***	-261.288***	-150.593*
	(51.111)	(47.484)	(50.880)	(56.975)	(53.087)	(70.695)	(67.734)	(72.116)	(75.446)	(80.443)
largest county population share	8.253***	8.741***	7.714***	5.603**	5.088*	21.822***	22.380***	21.122***	19.733***	17.804***
	(2.489)	(2.420)	(2.369)	(2.796)	(2.990)	(3.062)	(2.616)	(2.704)	(4.137)	(4.816)
real per capita GDP	14.244	13.953	14.110	13.191	9.163	13.745	13.557	11.272	14.478	4.554
	(15.419)	(14.960)	(16.033)	(16.767)	(16.679)	(22.576)	(21.975)	(23.843)	(25.221)	(25.593)
weighted population distance	0.177	0.097	-0.127	-0.074	0.130	1.940	1.763	1.254	1.532	1.663
	(0.766)	(0.724)	(0.783)	(0.770)	(0.732)	(1.240)	(1.234)	(1.423)	(1.361)	(1.270)
historical patent rate	-1.728	-2.027	5.330	4.518	-9.189	82.099***	83.693***	92.574***	95.206***	71.257**
	(11.289)	(10.490)	(13.059)	(12.718)	(11.395)	(26.865)	(25.770)	(27.714)	(27.725)	(28.142)
historical patent sum (000s)	14.332**	11.354	14.494*	10.968	6.927	31.357***	26.750***	33.293***	28.943***	23.319**
	(7.272)	(7.226)	(7.411)	(7.782)	(8.252)	(8.602)	(8.787)	(9.294)	(9.503)	(10.277)
agricultural patent rate	-535.260***	-563.694***	-543.552***	-553.048***	-551.213***	-827.606***	-874.363***	-824.240***	-857.730***	-830.918***
	(134.696)	(171.117)	(135.356)	(129.903)	(171.296)	(235.680)	(281.014)	(259.521)	(245.163)	(285.300)
health care patent rate	1.949	2.264	1.080	2.140	4.725	3.300	3.544	1.804	2.268	6.879
	(16.595)	(18.339)	(17.935)	(18.265)	(17.917)	(25.130)	(28.725)	(28.195)	(27.563)	(28.438)
horizontal fragmentation	15.809**				8.599	27.617**				15.537
	(7.685)				(7.506)	(13.500)				(14.079)
vertical fragmentation		18.621**			16.545**		27.764***			22.090**
		(7.808)			(7.687)		(6.755)			(9.060)
horizontal fiscal dispersion			10.093		3.938			38.227		29.045
			(19.335)		(21.084)			(27.390)		(31.793)
vertical fiscal dispersion				496.119	978.679				233.829	1299.267
				(653.167)	(654.632)				(879.080)	(1203.581)
N	362	362	362	362	362	362	362	362	362	362
Adj. R^2	0.648	0.657	0.643	0.649	0.665	0.634	0.641	0.614	0.625	0.655
IV Sargan P	0.292	0.298	0.373	0.365	0.172	0.165	0.142	0.145	0.104	0.266
Cragg-Donald F-stat	3965.035	327.017	43.465	143.590		3965.035	327.017	43.465	143.590	
Moran's I p-value	0.350	0.452	0.312	0.368	0.431	0.127	0.191	0.128	0.174	0.145

This table presents the effect of various measures of regional governance fragmentation on the concentration (or diffusion) of a region's innovation among distinct inventors. The dependent variables are the Herfandahl-Hirschman indices of concentration among distinct organizational or individual inventors. Larger values indicate more concentrated innovation. Every governance fragmentation variable is treated as endogenous using the region's Herfandahl-Hirschman index of church denominations from 1952 and the endogenous variable's value from 1972 as instruments. The row 'Cragg-Donald F-statistic' denotes the first-stage F statistic for the strength of the instruments. The row 'IV Sargan' shows the p-value from the Sargan test under the null hypothesis that at least one of the instruments is uncorrelated with the error term. The row 'Moran's I p-value' reports the p-value of residual spatial correlation using an inverse distance weighting matrix. Standard errors are in parantheses and are clustered at the state dimension. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level. Models were estimated with a constant term and state fixed effects that are not reported. Most variables are the average over the period from 1990 to 2018. See the notes to Table 1 for exceptions, variable definitions, and sources.

Table 6: Regional Governance Structure and Innovation Concentration: Products

	Dependent variable:									
	organization product concentration					individual product concentration				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
share of jobs in STEM occupations	-426.526***	-390.624***	-493.490***	-487.625***	-367.364***	-829.690***	-820.712***	-954.891***	-947.751***	-770.099***
	(72.339)	(69.635)	(74.595)	(73.947)	(71.005)	(112.078)	(108.466)	(115.350)	(115.599)	(112.846)
economic freedom: overall	-510.794***	-438.893***	-452.413***	-500.717***	-400.620***	-521.431***	-425.861***	-420.590**	-509.316***	-372.271**
	(135.683)	(120.035)	(145.571)	(132.982)	(140.888)	(154.536)	(159.821)	(180.171)	(158.731)	(182.884)
venture capital per capita	14.967	19.179	30.416	32.302	30.846	-25.798	-13.130	2.697	0.478	-3.890
	(55.612)	(61.923)	(59.552)	(64.513)	(63.807)	(84.809)	(104.474)	(98.379)	(103.417)	(110.437)
percent 25 and older with degree	-0.484	3.949	2.142	-0.046	2.652	19.809*	26.117***	24.473***	21.329**	23.744**
	(8.358)	(8.225)	(8.623)	(8.457)	(8.936)	(10.411)	(9.619)	(9.495)	(10.469)	(9.897)
per capita university r & d spending	-543.212***	-627.358***	-591.940***	-618.689***	-569.825**	-1532.962***	-1688.022***	-1629.412***	-1679.286***	-1546.093***
	(210.566)	(223.443)	(208.877)	(193.275)	(223.042)	(352.934)	(359.914)	(306.942)	(312.657)	(346.164)
across-MSA inventor network	1237.763***	1230.767***	1231.627***	1251.587***	1212.717***	736.153**	735.750***	728.037**	763.235***	698.452**
	(457.922)	(445.392)	(453.545)	(452.714)	(433.366)	(292.138)	(277.216)	(291.871)	(288.834)	(272.163)
net job creation rate	-140.135**	-124.407*	-162.424**	-155.761**	-120.223*	-150.236**	-139.726*	-191.174**	-180.943**	-132.298*
	(66.125)	(63.975)	(69.147)	(65.845)	(65.828)	(74.897)	(72.192)	(76.653)	(74.112)	(71.303)
HHI employment	577.139***	632.825***	644.268***	612.215***	634.152***	650.596**	743.286***	771.460***	716.926***	729.555***
	(182.223)	(193.770)	(190.132)	(184.325)	(178.512)	(264.506)	(276.908)	(273.517)	(270.993)	(254.004)
export jobs	9.653	-7.051	33.779	30.926	-7.668	213.168***	203.537***	257.850***	251.973***	198.288***
	(35.194)	(35.478)	(37.712)	(35.275)	(36.413)	(54.849)	(57.302)	(59.420)	(52.804)	(59.223)
population (millions)	-127.574***	-89.382**	-139.863***	-136.618**	-59.235	-264.153***	-225.190***	-288.102***	-291.938***	-184.740**
	(47.665)	(42.870)	(49.464)	(54.696)	(46.655)	(67.317)	(63.948)	(68.046)	(72.571)	(78.786)
largest county population share	7.690***	8.368***	7.244***	5.716**	4.938	21.344***	21.833***	20.472***	19.285***	17.768***
	(2.429)	(2.425)	(2.423)	(2.652)	(3.033)	(2.959)	(2.488)	(2.625)	(4.095)	(4.924)
real per capita GDP	25.516*	25.016**	24.505*	25.151*	19.916	12.877	12.797	11.301	13.859	5.158
	(13.036)	(12.735)	(13.915)	(14.042)	(14.179)	(21.430)	(20.876)	(22.841)	(24.431)	(24.872)
weighted population distance	0.228	0.172	-0.138	-0.015	0.130	1.665	1.459	1.001	1.227	1.468
	(0.736)	(0.692)	(0.731)	(0.713)	(0.699)	(1.162)	(1.157)	(1.341)	(1.287)	(1.168)
historical patent rate	-8.472	-10.143	-2.125	-1.624	-16.621	81.843***	84.366***	94.026***	96.125***	72.035***
	(12.277)	(10.688)	(13.508)	(13.087)	(12.001)	(23.490)	(22.298)	(25.057)	(25.015)	(24.235)
historical patent sum (000s)	14.206**	10.834*	15.015**	11.763	7.013	35.046***	30.311***	36.328***	32.706***	27.172***
	(6.193)	(6.109)	(6.868)	(7.140)	(7.008)	(7.646)	(7.717)	(8.364)	(8.823)	(9.568)
agricultural patent rate	-660.502***	-690.886***	-661.819***	-678.073***	-676.243***	-781.117***	-830.362***	-786.161***	-813.488***	-790.282***
	(171.918)	(221.549)	(186.359)	(164.218)	(229.431)	(260.257)	(307.499)	(277.241)	(259.137)	(305.892)
health care patent rate	4.696	5.210	3.834	4.521	7.453	5.060	5.207	3.438	3.846	8.353
	(16.067)	(18.142)	(17.761)	(17.759)	(17.888)	(24.276)	(28.082)	(27.490)	(27.089)	(27.230)
horizontal fragmentation	15.842**				6.038	29.743**				18.646
	(6.287)				(5.522)	(13.430)				(14.185)
vertical fragmentation		21.750***			20.257***		28.085***			21.458**
		(6.997)			(6.835)		(7.437)			(9.663)
horizontal fiscal dispersion			18.181		9.932			31.168		20.389
			(20.115)		(21.113)			(27.339)		(31.869)
vertical fiscal dispersion				327.397	923.371				204.306	1164.198
				(630.093)	(632.519)				(904.526)	(1226.659)
N	362	362	362	362	362	362	362	362	362	362
Adj. R^2	0.595	0.612	0.581	0.593	0.617	0.618	0.624	0.598	0.606	0.640
IV Sargan P	0.991	0.984	0.924	0.867	0.750	0.294	0.252	0.237	0.188	0.420
Cragg-Donald F-stat	3965.035	327.017	43.465	143.590		3965.035	327.017	43.465	143.590	
Moran's I p-value	0.390	0.538	0.328	0.399	0.501	0.132	0.206	0.142	0.173	0.161

This table presents the effect of various measures of regional governance fragmentation on the concentration (or diffusion) of a region's innovation among distinct product/technology classes. The dependent variables are the Herfandahl-Hirschman indices of concentration among distinct product classes of patents awarded to organizations or individual inventors. Larger values indicate more concentrated innovation. Every governance fragmentation variable is treated as endogenous using the region's Herfandahl-Hirschman index of church denominations from 1952 and the endogenous variable's value from 1972 as instruments. The row 'Cragg-Donald F-statistic' denotes the first-stage F statistic for the strength of the instruments. The row 'IV Sargan' shows the p-value from the Sargan test under the null hypothesis that at least one of the instruments is uncorrelated with the error term. The row 'Moran's I p-value' reports the p-value of residual spatial correlation using an inverse distance weighting matrix. Standard errors are in parantheses and are clustered at the state dimension. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level. Models were estimated with a constant term and state fixed effects that are not reported. Most variables are the average over the period from 1990 to 2018. See the notes to Table 1 for exceptions, variable definitions, and sources.

Table 7: Innovator Concentration and Special-Purpose Governments

	Dependent variable:					
	organization concentration			individual concentration		
	(1)	(2)	(3)	(4)	(5)	(6)
	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
share of jobs in STEM occupations	-465.529***	-458.568***	-440.908***	-912.571***	-866.608***	-856.732***
	(74.858)	(65.637)	(69.232)	(111.009)	(107.583)	(104.974)
economic freedom: overall	-509.293***	-513.099***	-498.784***	-465.165***	-449.272**	-441.291**
	(132.735)	(130.414)	(128.664)	(166.644)	(175.509)	(176.890)
venture capital per capita	44.509	25.115	29.191	17.064	-19.810	-17.584
	(54.380)	(52.413)	(54.554)	(103.505)	(101.228)	(102.803)
percent 25 and older with degree	-3.097	-1.808	-1.452	23.430**	26.954***	27.156***
	(9.017)	(9.388)	(9.375)	(9.758)	(9.575)	(9.568)
per capita university r & d spending	-552.797**	-541.831**	-548.097**	-1786.149***	-1772.076***	-1775.546***
	(255.168)	(266.571)	(268.520)	(370.568)	(374.932)	(380.246)
across-MSA inventor network	1517.319***	1531.081***	1522.773***	887.026***	903.923***	899.320***
	(500.817)	(518.125)	(511.448)	(305.272)	(326.193)	(323.403)
net job creation rate	-76.573	-55.351	-55.086	-202.755**	-154.317**	-154.115**
	(68.480)	(69.457)	(69.159)	(79.713)	(76.151)	(76.810)
HHI employment	658.590***	619.522***	634.682***	792.210***	729.821**	738.185**
	(218.662)	(220.194)	(221.494)	(304.916)	(304.773)	(306.940)
export jobs	-8.244	-15.086	-20.411	209.494***	184.912***	181.922***
	(34.309)	(30.241)	(31.492)	(49.476)	(55.274)	(54.377)
population (millions)	-95.216*	-62.175	-60.783	-224.597***	-147.507**	-146.646**
	(48.828)	(47.077)	(47.053)	(69.203)	(62.141)	(61.986)
largest county population share	8.347***	9.140***	9.173***	21.697***	23.547***	23.568***
	(2.394)	(2.480)	(2.471)	(2.658)	(2.828)	(2.759)
real per capita GDP	13.630	17.048	15.791	13.276	18.852	18.159
	(15.166)	(15.030)	(14.907)	(22.449)	(21.352)	(21.432)
weighted population distance	0.051	0.134	0.144	1.682	1.887	1.893
	(0.726)	(0.795)	(0.770)	(1.277)	(1.268)	(1.257)
historical patent rate	-1.519	4.176	0.593	85.434***	92.178***	90.192***
	(10.309)	(11.786)	(10.476)	(26.241)	(25.272)	(25.398)
historical patent sum (000s)	12.524*	9.021	9.504	28.642***	21.547***	21.808***
	(7.332)	(6.618)	(6.921)	(8.785)	(8.124)	(8.148)
agricultural patent rate	-573.647***	-527.666***	-544.612***	-886.496***	-811.532***	-820.875***
	(164.026)	(149.888)	(165.249)	(267.925)	(269.112)	(272.486)
health care patent rate	1.175	4.728	3.928	1.908	8.572	8.135
	(18.482)	(17.410)	(17.919)	(28.848)	(26.200)	(26.691)
vertical fragmentation, special purpose	19.194**		10.059	26.183***		5.566
	(9.375)		(9.491)	(8.592)		(8.559)
vertical fragmentation, school districts		65.539***	50.216*		121.963***	113.575***
		(21.691)	(25.711)		(22.464)	(25.247)
N	362	362	362	362	362	362
Adj. R^2	0.655	0.650	0.654	0.635	0.646	0.646
IV Sargan P	0.343	0.238	0.243	0.119	0.219	0.215
Cragg-Donald F-stat	292.191	327.369		292.191	327.369	
Moran's I p-value	0.444	0.426	0.451	0.182	0.270	0.263

This table presents the effect of various measures of regional governance fragmentation on the concentration (or diffusion) of a region's innovation among distinct inventors. The dependent variables are the Herfandahl-Hirschman indices of concentration among distinct organizational or individual inventors. Larger values indicate more concentrated innovation. Every governance fragmentation variable is treated as endogenous using the region's Herfandahl-Hirschman index of church denominations from 1952 and the endogenous variable's value from 1972 as instruments. The row 'Cragg-Donald F-statistic' denotes the first-stage F statistic for the strength of the instruments. The row 'IV Sargan' shows the p-value from the Sargan test under the null hypothesis that at least one of the instruments is uncorrelated with the error term. The row 'Moran's I p-value' reports the p-value of residual spatial correlation using an inverse distance weighting matrix. Standard errors are in parantheses and are clustered at the state dimension. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level. Models were estimated with a constant term and state fixed effects that are not reported. Most variables are the average over the period from 1990 to 2018. See the notes to Table 1 for exceptions, variable definitions, and sources.

Table 8: Innovation Concentration and Special-Purpose Governments

	Dependent variable:					
	organization product concentration			individual product concentration		
	(1) 2SLS	(2) 2SLS	(3) 2SLS	(4) 2SLS	(5) 2SLS	(6) 2SLS
share of jobs in STEM occupations	-409.003***	-409.965***	-384.554***	-857.665***	-813.532***	-802.616***
	(71.209)	(64.579)	(66.911)	(108.757)	(104.178)	(102.041)
economic freedom: overall	-449.560***	-459.697***	-439.115***	-448.838***	-434.133**	-425.306**
	(123.987)	(124.388)	(120.764)	(161.042)	(169.953)	(171.154)
venture capital per capita	25.371	4.351	10.182	-4.821	-41.463	-38.988
	(62.080)	(60.389)	(61.853)	(103.218)	(101.703)	(103.390)
percent 25 and older with degree	3.280	4.399	4.913	24.802**	28.254***	28.476***
	(8.212)	(8.448)	(8.403)	(9.777)	(9.569)	(9.574)
per capita university r & d spending	-637.979***	-624.331***	-633.324***	-1699.197***	-1684.895***	-1688.739***
	(221.318)	(225.368)	(230.128)	(350.798)	(361.045)	(365.531)
across-MSA inventor network	1231.031***	1248.354***	1236.429***	739.580***	756.806**	751.708**
	(442.978)	(464.079)	(453.667)	(277.388)	(299.167)	(295.568)
net job creation rate	-134.826**	-113.926*	-113.511*	-156.763**	-109.011	-108.803
	(63.281)	(67.479)	(66.033)	(73.899)	(70.165)	(70.752)
HHI employment	637.995***	592.562***	614.301***	745.831***	683.276**	692.551**
	(194.374)	(192.502)	(195.211)	(278.646)	(275.143)	(278.343)
export jobs	0.835	-3.571	-11.241	218.467***	194.585***	191.283***
	(36.197)	(33.360)	(34.779)	(54.971)	(60.359)	(59.775)
population (millions)	-106.811**	-74.709	-72.652	-253.946***	-178.013***	-177.083***
	(43.996)	(45.449)	(44.124)	(65.491)	(57.235)	(57.109)
largest county population share	7.950***	8.721***	8.769***	21.143***	22.966***	22.988***
	(2.436)	(2.391)	(2.405)	(2.540)	(2.602)	(2.533)
real per capita GDP	24.552*	28.496**	26.693**	12.511	18.095	17.327
	(12.884)	(12.929)	(12.725)	(21.317)	(20.376)	(20.369)
weighted population distance	0.125	0.202	0.217	1.378	1.579	1.585
	(0.678)	(0.786)	(0.746)	(1.200)	(1.194)	(1.181)
historical patent rate	-9.979	-2.745	-7.890	86.121***	93.015***	90.815***
	(10.880)	(11.515)	(10.712)	(22.777)	(22.277)	(21.964)
historical patent sum (000s)	12.137*	8.453	9.142	32.224***	25.195***	25.485***
	(6.196)	(5.949)	(6.014)	(7.732)	(7.071)	(7.046)
agricultural patent rate	-703.695***	-650.621***	-674.917***	-842.654***	-767.576***	-777.939***
	(214.896)	(194.759)	(218.701)	(291.911)	(296.951)	(301.533)
health care patent rate	3.944	7.819	6.674	3.551	10.178	9.692
	(18.375)	(16.892)	(17.708)	(28.257)	(25.510)	(26.069)
vertical fragmentation, special purpose	23.482***		14.435	26.503***		6.168
	(8.596)		(9.067)	(9.365)		(9.086)
vertical fragmentation, school districts		71.720***	49.792*		121.319***	112.000***
		(21.336)	(25.816)		(20.438)	(22.836)
N	362	362	362	362	362	362
Adj. R^2	0.609	0.598	0.608	0.618	0.629	0.631
IV Sargan P	0.936	0.866	0.890	0.214	0.365	0.359
Cragg-Donald F-stat	292.191	327.369		292.191	327.369	
Moran's I p-value	0.504	0.563	0.578	0.190	0.304	0.296

This table presents the effect of various measures of regional governance fragmentation on the concentration (or diffusion) of a region's innovation among distinct product/technology classes. The dependent variables are the Herfandahl-Hirschman indices of concentration among distinct product classes of patents awarded to organizations or individual inventors. Larger values indicate more concentrated innovation. Every governance fragmentation variable is treated as endogenous using the region's Herfandahl-Hirschman index of church denominations from 1952 and the endogenous variable's value from 1972 as instruments. The row 'Cragg-Donald F-statistic' denotes the first-stage F statistic for the strength of the instruments. The row 'IV Sargan' shows the p-value from the Sargan test under the null hypothesis that at least one of the instruments is uncorrelated with the error term. The row 'Moran's I p-value' reports the p-value of residual spatial correlation using an inverse distance weighting matrix. Standard errors are in parantheses and are clustered at the state dimension. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level. Models were estimated with a constant term and state fixed effects that are not reported. Most variables are the average over the period from 1990 to 2018. See the notes to Table 1 for exceptions, variable definitions, and sources.

Table A.1: First-Stage Regression Results

	Dependent variable:			
	horizontal fragmentation	vertical fragmentation	horizontal dispersion	vertical dispersion
	(1)	(2)	(3)	(4)
	OLS	OLS	OLS	OLS
share of jobs in STEM occupations	-0.387**	-1.279**	0.532	-0.006
	(0.179)	(0.578)	(0.539)	(0.007)
economic freedom: overall	0.556**	0.684	-2.785***	-0.006
	(0.232)	(0.725)	(1.057)	(0.013)
venture capital per capita	0.060	-0.065	-0.118	-0.012***
	(0.074)	(0.234)	(0.387)	(0.004)
percent 25 and older with degree	0.005	-0.050	-0.049	0.000
	(0.018)	(0.042)	(0.059)	(0.001)
per capita university r & d spending	-0.332	1.000	-1.139	0.000
	(0.558)	(1.324)	(2.407)	(0.028)
across-MSA inventor network	0.198	-0.222	0.529	0.013
	(0.256)	(0.408)	(0.398)	(0.012)
net job creation rate	-0.011	0.060	0.025	0.002
	(0.101)	(0.369)	(0.424)	(0.009)
HHI employment	0.809**	0.074	-2.911**	0.009
	(0.319)	(1.292)	(1.249)	(0.027)
export jobs	0.061	0.210	-0.240	0.001
	(0.067)	(0.284)	(0.276)	(0.004)
population (millions)	-0.087	-0.689*	-0.108	-0.016***
	(0.093)	(0.390)	(0.310)	(0.004)
largest county population share	0.002	0.002	-0.021	0.002***
	(0.004)	(0.014)	(0.015)	(0.000)
real per capita GDP	-0.015	0.031	0.087	0.001
	(0.019)	(0.111)	(0.093)	(0.002)
weighted population distance	-0.002	-0.005	0.002	0.000*
	(0.002)	(0.006)	(0.005)	(0.000)
historical patent rate	0.040	0.262***	0.145*	0.002**
	(0.051)	(0.097)	(0.076)	(0.001)
historical patent sum (000s)	-0.004	0.050	-0.062*	0.002***
	(0.010)	(0.047)	(0.037)	(0.000)
agricultural patent rate	-0.176	3.710*	0.505	-0.010
	(0.398)	(2.245)	(2.103)	(0.032)
health care patent rate	0.023	-0.003	-0.025	-0.001
	(0.023)	(0.086)	(0.102)	(0.001)
hhi churches	0.007	-0.022	0.074*	0.000
	(0.011)	(0.037)	(0.042)	(0.001)
horizontal fragmentation, 1972	0.879***			
	(0.021)			
vertical fragmentation, 1972		0.806***		
		(0.083)		
horizontal fiscal dispersion, 1972			0.400***	
			(0.050)	
vertical fiscal dispersion, 1972				0.589***
				(0.057)
N	362	362	362	362
Adj. R^2	0.631	0.628	0.621	0.627
First-Stage F	3965.035	327.017	43.465	143.590

This table presents the first-stage regressions. Outcome variables are the MSA averages using data from the Census Bureau's Census of Governments in 1992, 1997, 2002, 2007, and 2017. Instruments are the values of the outcome variables from 1972 and the MSA's Herfandahl-Hirschman index of church denominations from 1952. The row 'First-Stage F' denotes the Cragg-Donald statistic for the strength of the instruments. Standard errors are in parantheses and are clustered at the state dimension. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level. Models were estimated with a constant term and state fixed effects that are not reported. Most covariates are the average over the period from 1990 to 2018. See the notes to Table 1 for exceptions, variable definitions, and sources.