Patent Intensity and Concentration: The Effect of Institutional Quality on MSA Patent Activity*

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Abstract

Patented innovation is a predominately local phenomena. It is also an indicator of economic growth. Using data on U.S. metropolitan statistical areas (MSAs), we examine the long-run effect of economic freedom, and each of its three components, on local patent activity. Using an instrumental variables approach for identification, we find that increased government spending is associated with reduced individual patent activity, though this effect is modest in magnitude. Our strongest results suggest that increased economic freedom significantly reduces patent concentration in both ownership and product types. This implies that economic freedom creates an environment conducive to diverse and diffused innovation and may provide a viable alternative to place-based economic development strategies. Our results are robust to a quantile regression instrumental variable analysis.

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1 Introduction

Patented innovation in the United States is highly concentrated within cities. According to the U.S. Patent and Trademark Office (USPTO), nearly 95% of all patents awarded to U.S. residents are granted to individuals who live in metropolitan areas. Patents are also an indicator of regional innovative activity.[1] Innovation increases economic dynamism, which has been shown to increase an economy's flexibility and ability to recover from negative productivity shocks (Decker et al. 2014). Innovation is also correlated with economic growth (e.g. Greenstone and Looney 2011). Enhancing our understanding of the effect of local government policies on patented innovation may help shape more effective economic development strategies.[2] This is the objective of this paper.

State and local governments regularly implement policies aimed at spurring growth within their localities. Enterprise Zones, for example, are the most prominent place-based policy. In 2008, forty of the U.S. states had their own enterprise zone programs (Ham et al. 2011). Many states also have broad R&D tax credit incentives (Wilson 2009). However, the benefit of these types of programs seem to be limited to the short-run (e.g. Givord et al. 2018). Furthermore, the effect of these programs is limited because they are generally accompanied by eligibility requirements outlined in the legislation.[3] Fostering an economic environment that is conducive to innovation without restriction may prove to be a viable alternative to these types of place-based policies. More specifically, we argue that local economic freedom facilitates the innovative environment local policy makers seek. Because an overwhelming majority of patented innovation occurs in urban areas, our focus is on metropolitan statistical areas (MSAs).

Institutions that are consistent with economic freedom "...provide an infrastructure for voluntary exchange, and protect individuals and their property from aggressors seeking to use violence,

[1]Because patent law is federal, within country variation in patents per-capita can be used as a proxy for regional differences in innovation. This is separate from the claim that patents increase innovative activity. Patent law that is too broad or strong can negatively affect innovation Moser (2013).

[2]While our focus is on local policy, we also acknowledge that the regional variation in patent activity can be affected by many other factors. For example, knowledge spillovers (Audretsch and Feldman 1996, Anselin et al. 1997, Acs et al. 2002, and Autant-Bernard and LeSage 2011) and labor migration (Almeida and Kogut 1999) can result in significant spatial spillovers in patenting activity. Similarly, social networks (Breschi and Lenzi 2016 and Crescenzi et al. 2016) and patenting networks (Peri 2005 and Kang and Dall'erba 2016a) are likely to result in spatial dependence as well. We consider and control for the potential for network effects and spillovers in our analysis following the recent work of Breschi and Lenzi (2016).

[3]These restrictions can make it difficult for small firms to benefit from R&D tax incentives. For example, Belenkiy et al. 2019 find that their R&D inequality index fell significantly when the U.S. revised its R&D policy with the Alternative Simplified Credit (ASC) legislation in 2009. This policy reduced, but did not eliminate, eligibility requirements. However, to the extent that there are any restrictions, the benefits of such policy will be limited.

coercion, and fraud to seize things that do not belong to them" (p. 406 Gwartney and Lawson 2003). The positive relationship between economic freedom, income, and entrepreneurship is well-documented at the cross-country level (Hall and Lawson 2014). These findings are echoed using analogous measures at the state and local levels (Karabegovic et al. 2006; Wiseman and Young 2013; Bologna 2014; Bologna et al. 2016). The commonly cited intuition behind these empirical results is that individuals residing within economically free areas are more likely to engage in wealth-creating innovation (Kreft and Sobel 2005). Thus, we expect these areas to have more patents per-capita as a result. In this paper, we test the effect of local economic freedom on patent intensity in metropolitan areas.[4]

We also explore the effect of local economic freedom on the distribution of patents across the population. That is, we examine if patent awards tend to be more concentrated in the hands of a few or if they are diffused throughout the population in regions with greater economic freedom. This is a variant of the idea that economic freedom and inequality are intricately related. To the extent that economic freedom increases economic opportunities, we expect to see a corresponding decrease in income inequality (Bennett and Vedder 2013).[5] Patent concentration (in ownership) is also an underutilized measure of market power (Watson and Holman 1970). Economically free societies are hypothesized to have the highest levels of market competition.A small number of researchers have tested this idea, finding some evidence in support (Claessens and Laeven 2003 and Klapper et al. 2006). The lack of research in this area likely stems from the difficulty in measuring competition (Boone (2008); Alexeev and Song 2013; Bologna 2017). By examining the effect on patent concentration, we can avoid the issue of arbitrarily categorizing firms according to their industry as in the traditional Herfindahl-Hirschman Index (HHI). Highly concentrated economic activity is likely associated with greater income inequality and monopoly power. We expect to see

[4]One argument against the use of patent law is that while patents may incentivize innovative activity by granting temporary monopoly rights, the political economy costs of the socially granted monopoly may outweigh these positive effects thereby reducing innovation (Boldrin and Levine 2013). It may be the case that a higher patent intensity signals significant rent-seeking behavior. However, it is unlikely that the rent-seeking costs are substantial in economically free environments where pure wealth transfers are relatively uncommon. Sobel (2008) offers evidence in support of this idea, finding the number of lobbying organizations per-capita to negatively correlate with economic freedom. Thus, increased patents in response to increased economic freedom are likely to be beneficial. Though, we encourage researchers to empirically test this idea.

[5]Despite this intuition, the evidence concerning economic freedom and inequality is mixed (Berggren 1999; Scully 2002; Ashby and Sobel 2008). A major reason for these mixed results is measurement error in inequality estimates. For example, Bennett and Nikolaev (2017) use six alternative measures of income inequality and find the relationship between inequality and economic freedom to be extremely sensitive to the measure employed. Therefore, by focusing on patent concentration, we avoid making arbitrary assumptions and are less reliant on the specific data source used.

less concentration (or more competition) in innovation when economic freedom is higher.

Lastly, we examine the effect of economic freedom on the distribution of patents across product or technology types.[6] We refer to this as a measure of product concentration. The benefits and costs of industry specialization versus diversity to the local economy have long been debated in the literature, but there is a general consensus that diversity at a disaggregated level yields positive economic growth.[7] As such, we utilize 450 different product classifications to measure the concentration of patents in specific technologies. To the best of our knowledge, we are the first to test the relationship between economic freedom and product concentration.

To the extent that economic freedom increases opportunities for a broader base of people, we expect economic freedom to result in a more diverse set of patents in terms of product/technology types. Furthermore, Mazzeo (2002)'s model of product variety provides another potential channel through which freedom could result in more diverse patent technologies. Mazzeo (2002) shows firms have a strong incentive to differentiate their products in response to increased competition. If greater economic freedom induces firms/inventors to differentiate their products to enhance their competitive advantage, then we may observe a wider variety of patent technologies as firms protect their innovations.

To estimate the effect of economic freedom on metro level patent intensity, patent ownership concentration, and patent product concentration we combine Stansel (2019)'s MSA-level economic freedom index with Li et al. (2014)'s detailed patent data. The patent data not only includes information concerning the simple rate of awards (intensity), but also the identity of the patent owner and product or technology class. We utilize the latter two pieces of information to construct separate HHI indices for patent ownership concentration and for patent product concentration among unique inventors.[8] Stansel's MSA-level economic freedom index is the local counterpart to the Fraser Institute's state-level (Economic Freedom of North America - EFNA) and country-level (Economic Freedom of the World -EFW) economic freedom indices. It follows the methodology

[6] Here we are distinguishing between industry concentration and firm concentration (e.g. competition). An economy could have a significant amount of competition despite production being heavily concentrated in a specific industry.

[7] Some researchers argue that a highly concentrated industrial presence encourages specialization, inducing economic growth (Marshall 1890; Arrow 1962; Romer 1986; Glaeser et al. 1992). Others, however, argue that industry diversity creates large knowledge spillovers that are conducive to innovative activity (Jacobs 1969). Beaudry and Schiffauerova (2009) survey the literature finding evidence in support of both theories, but more evidence in support of the Jacobs theory when diversity is measured at a more detailed level. We focus on this finely disaggregate level.

[8] We do this for both firms and for individuals separately.

of the EFNA index and is designed to provide a comprehensive measure of the extent to which individuals are allowed to engage in voluntary exchange.[9] The index can also be disaggregated into its three subcomponents of government spending, taxation, and labor market freedom.[10] We are interested in how the cross-sectional variation in economic freedom correlates with each of our patent measures at the MSA level. For some forms of innovation, such as renewable energies, variation in these local policies has been found to promote greater regional innovation (Corsatea 2016).

Both the economic freedom and the patent data are available for moderately long time spans (1972 - 2012 and 1975 - 2010, respectively). However, because we are interested in longer-run policy implications implied by cross-sectional variation, we average this data across all available years of interest. This long-run focus is common in the institutions and development literature as both are extremely persistent through time (see e.g., Acemoglu et al. 2001 and Spolaore and Wacziarg 2013). In our sample, we focus on the period from 1992-2007 and limit our analysis to the 272 MSAs that did not change geographic definitions between 2009 and 2015 due to data constraints.[11]

Using a cross-sectional regression, we regress our averaged patent measures on averaged economic freedom.[12] Our regressions all include state fixed effects so that we are able to focus on differences in local policy. Given the potential for simultaneity, we rely on an instrumental variables approach for identification by instrumenting for contemporaneous economic freedom with the region's economic freedom score from at least 20 years in the past plus the contemporaneous rate of pro-school choice campaign contributions from residents of the MSA.[13] The latter instrument is

[9] This index has been found to positively correlate with income (Bologna et al. 2016), entrepreneurship (Bologna 2014), local government credit ratings (Dove 2017), in-migration (Shumway 2018), and firm and job creation (Bennett 2019). These findings tend to confirm the results of the vast cross-country literature using the EFW index.

[10] See Stansel (2019) for further details concerning the variables included in each category.

[11] Because of our focus on cross-sectional variation, control variables are extremely important. We rely on the Economic Census for our controls, many of which are not available until 1992. In addition, because the economic freedom index is only available on a 5-year basis, we end our analysis at 2007. Some control variables are also only available for MSAs using the 2009 geographic definitions. This will all be discussed in detail in Section 3 of the paper.

[12] While we utilize long-run averages to focus on cross-sectional variation, it is important to note that the absence of patents in our annual data is rare. Kang and Dall'erba (2016b) utilize a Tobit estimator to explore the role of knowledge spillovers in county level patent creation. A Tobit estimator is necessary in this case because 438 counties within their sample do not produce a patent. Because our focus is on a larger geographical area (MSAs), we do not face the same censorship problem. If we had annual data on economic freedom and could estimate a full panel from 1992 - 2007 for our 272 MSAs (a total of 4,352 observations), we would only have 145 instances of 0 values for individual patent awards (3.3% of the sample) and 87 instances of 0 values for firms (1.9% of the sample).

[13] Similar to Breschi and Lenzi (2016), as a robustness check we also identify coefficients by replacing our external instruments with instruments constructed from our underlying data following the method proposed by Lewbel (2012). These alternative instrumental variables regressions identify coefficients using heteroskedastic covariance restrictions rather than an assumption of exogeneity. These results echo our main findings and provide evidence that the

intended to capture citizen preference for government size and scope and is unlikely independently related to patented innovation.[14] We also test the robustness of our findings using instrumental variable quantile regressions.

We find some evidence of government crowd out in that less government spending (as indicated by a higher score in that component of the index) increases patent intensity. However, this effect is strong only for individual intensity (patents awarded to individual inventors per 100,000 residents) and is relatively modest. Our results also suggest that economic freedom (and its components) significantly decreases the concentration of innovation ownership across both firms and individuals. In other words, we are less likely to see a small numbers of distinct firms (or individuals) possess a majority of the patents in areas with high levels of economic freedom. The innovation is diffused across more unique inventors. Similarly, we also find that economic freedom is associated with significant decreases in the concentration of innovation across product types for both firms and individuals. This finding is robust to whether we focus on the patent's primary technology class or use all technology classes. Thus, not only do we see more patent activity and a wider variety of firms and individuals that are doing the innovating, those that are innovating are producing a wider variety of products.

While we test the robustness all of our results with an instrumental variable analysis, reverse causation remains a concern in the cases of ownership and product concentration in particular. Regional specialization in production is a long run, and extremely persistent, phenomena. If areas with high levels of product concentration also tend to experience a high degree of firm concentration, we may see lower economic freedom as a result. Similarly, areas with significant patent ownership concentration may have firms with significant market power and an incentive to restrict economic freedom as protection from competitive forces. To test for this possibility, we follow Autor et al. (2013) and estimate the effect of past changes in concentration on future changes in economic freedom finding no evidence of this reverse effect.[15] Given the long-run nature of our study, our results suggest that increased economic freedom may be a non-temporary viable alternative to

coefficients we estimate are not simply an artifact of a single identification strategy. The alternative regressions are available upon request.

[14] Rather, it is likely general preference for school choice reflects a deeper ideological preference for government size and scope. This preference will only influence patented innovation through its effect on economic freedom.

[15] Specifically, we regress the change in innovation diversity from 1976-1991 on the change in economic freedom from 1992-2007. The results, which are available in Appendix Tables A.2 through A.4, show no evidence that past changes in innovation concentration are correlated with future economic freedom.

traditional place-based economic development policies if increased, diverse innovation is the goal.

The rest of the paper will proceed as follows. We discuss our data in Section 2. Our empirical strategy is presented in Section 3 where we also outline our identifying assumptions. Results are presented in Section 4. We conclude and discuss policy implications in Section 5.

2 Data

2.1 Patent Data

Our patent measures are derived from Li et al. (2014)'s disambiguation of the U.S. Patent and Trademark Office's (USPTO) publicly available data that span the period from 1975 to 2010.[16] While the USPTO assigns a unique identifier to every distinct patent, they do not assign unique identifiers based on either inventors or assignees, making it difficult to study how patenting activity by specific inventors or organizations evolves over space and time. A patent's assignee is the individual or organization that owns the legal property right to the patent.

The National Bureau of Economic Research (NBER), building on the work of Hall et al. (2001), Beeson (2017), and others, provides a crosswalk file linking the raw assignee from patent records to Compustat data so that the name and address of patent assignees are standardized (see Beeson 2017 for details). Every patent award includes more than 60 fields including a unique patent number (assigned by the USPTO), the inventor (or inventors), the residential address of the inventor, one or more product/technology classifications categorizing the innovation, and most also include an assignee because the majority of patents are assigned to organizations rather than to individuals. The NBER crosswalk gives researchers a method for tracking *organizations* that have been awarded patents over time. Li et al. (2014) use the standardized assignee from the NBER crosswalk file along with the combination of the inventors city, state, country, and zip code (all required by the USPTO) and a disambiguation algorithm to identify unique *inventors*. The full disambiguated dataset, which includes more than 9.3 million records covering more than 4.2 million unique patent awards, gives researchers the ability to track the same individual inventors across both time and space and is freely available at Harvard's Dataverse.[17] Just like the raw USPTO data, there are more records

[16] Li et al. (2014)'s disambiguation begins in 1975 when the USPTO began to record patent records electronically. Recently Petralia et al. (2016) have geocoded the pre-electronic records dating back to 1836. These more-limited data are available at Harvard's Dataverse: https://dataverse.harvard.edu/dataverse/HistPat.

[17] The complete disambiguated dataset, including the raw data files and code, is available on Harvard's Dataverse at the following URL: https://hdl.handle.net/1902.1/15705.

than unique awards because each inventor of a multi-inventor patent has a separate record in the USPTO database.

We limit our focus to patent awards with at least one inventor who resides in the U.S. because of our interest in the spatial organization of patented innovation within the US. Over the entire sample period disambiguated by Li et al. (2014), more than 4.7 million records exist for patents with U.S. residents covering roughly 2.1 million distinct patent awards. In terms of a high-level overview, roughly 65% of the patent awards are granted to inventors assigned to a specific firm or organization, while the remaining 35% of patents are awarded to individual inventors who are not affiliated with an organization. For the 35 years in the full dataset, Li et al. (2014) are able to identify nearly 180,000 unique organizations and more than 1.3 million unique inventors who were granted patents. So while unaffiliated individual inventors represent a non-trivial share of the patented inventors, the majority of innovation within the U.S. is driven by organizations in metropolitan areas.

Due to data limitations of our control variables, which we describe in depth in Section 3, our empirical work centers on a sample of 272 metropolitan statistical areas over the period from 1992 to 2007. We use the latitude and longitude fields created by Li et al. (2014) from an inventor's residential address on the patent application to map individual patent records to MSAs. If a patent has multiple inventors, then we fractionally weight the patent by the number of co-inventors. Since design and plant patents are fundamentally different from utility patents, we also exclude all patents where the primary product/technology class is design or plant.[18] The mean annual rate of unique patents awarded to resident-inventors of these MSAs (per 100,000 residents) is shown below in Figure 1. Darker colors indicate MSAs that have higher average annual rates of patenting activity from 1992 to 2007.

[Insert Figure 1 here]

As the figure shows, there is considerable heterogeneity across MSAs in terms of patent intensity, with the strongest innovation centers generally being located in the northeast and west coast. The mean and median rates of (unique) patent awards per MSA are 23.2 and 13.0 over the period from 1992 to 2007, indicating the skewed distribution of the spatial location of innovation.

[18] In the full sample (1975-2010), patents with a primary class of design or plant account for roughly 3% of all patents.

Although there is year-to-year variation in patent intensity within metro areas, most of the observed variation is due to differences across MSAs rather than over time.[19] In other words, the relative ranking in terms of patent intensity is quite stable over our sample period. The San Jose, CA metro area has the highest rate of patent intensity every year between 1992 and 2007, with rates ranging from a low of 101.2 in 1992 to a high of 471.8 in 2006. Similarly, the Carson City, NV MSA is never ranked higher than 262 (out of 272 MSAs) in terms of patent intensity in a single year of the sample. The largest variation we observe in terms of relative rankings across years is in the Cleveland, TN metro area. The MSA's patent intensity peaked at 30.7 in 1992 (43rd highest in the nation) and reached a low of 1.6 in 2007 (258th in the nation). The decline in Cleveland, TN was also not monotonic as the region ranked 230th in overall patent intensity in 1997 and 117th in relative intensity as recent as 2004.

In terms of the breakdown between organizational inventors who are working for an assignee (such as an employee of IBM) and unaffiliated individual inventors, the mean annual rate of patents generated by firms is 19.1 per 100,000 residents compared to a rate of 4.2 patents for individual inventors without an assignee organization over our sample. While one might think that the innovation centers measured by overall patent intensity would create an environment that may boost unaffiliated individual inventors, there is actually limited overlap between the top metro areas for overall innovation and individual innovation. Table 1 shows the metro areas ranked in the top 5% of our sample in terms of average overall patent rates and individual patent rates (those unaffiliated at the time of the award) from 1992 to 2007.

[Insert Table 1 here]

Overall intensity, which is the same data illustrated in Figure 1, is the average annual rate of unique patents awarded in the MSA. Individual intensity is the average annual rate of unique patents awarded to unaffiliated individuals in the MSA at the time an award was made.[20] Blank

[19] In terms of a simple analysis of variance, nearly 80% of the total variation in overall patent intensity between 1992 and 2007 is from the cross-sectional variation in the data. Moreover, the Spearman rank correlation coefficient for overall patent intensity between 1992 and 2007 (5-year averages) is 0.90.

[20] If the assignee field of a patent record includes an organization, even a limited liability corporation, then we classify the patent as having been awarded to a firm. We classify patents as being awarded to an unaffiliated individual when the assignee field is blank. It is also worth noting that it is possible for an individual inventor to be awarded multiple patents where one or more patents are assigned to an organization and one or more patents are unassigned (indicating individual ownership).

cells in Table 1 indicate that a metro area was *not* in the top 5% of innovative regions for the column of interest. For example, the average rate of individual patent awards in Reno, NV was 11.9 per 100,000 residents making it tied for the second most innovative metro area for individual inventors (behind San Jose, CA). Since Reno's overall intensity value is blank in Table 1, this means that Reno was not one of the top 5% most innovative regions for patenting overall. In contrast, the Boise City, ID metro area has an overall average patent rate of 264.1, which is the second highest overall rate in the country trailing only San Jose. Unaffiliated inventors in Boise City also generate patents at an average annual rate of 9.9, making it one of the top 5% most innovative regions overall *and* for individual inventors. In addition to Boise City, ID, only the Boulder, CO, Corvallis, OR, San Francisco, CA, and San Jose, CA metro areas turn out to be innovation hot spots overall and for individuals. This raises the question of whether or not different factors may play a role in affecting how much innovation occurs for organizations and individuals and where the innovation is located.

In addition to intensity, the questions of who is innovating and what is being created may also be important considerations. We shed more light on the production of patented innovation by also exploring differences in the concentration (or diffusion) of both inventor innovation and product innovation across metropolitan areas. Since we are able to identify unique firms and individuals, we calculate a separate Herfindahl-Hirschman index (HHI) of patent concentration within metropolitan areas for firms and individual inventors. Of course, if a single firm generates all of the unique patents awarded to firms in a given MSA in a given year, the HHI value would be equal to 10,000. We refer to to this variable as *innovation concentration firms* in the paper. In contrast, if three firms have an equal share of the unique patents assigned to firms in a given MSA and year, then the concentration score for the MSA would equal 3267. If an organizational patent has co-inventors located in different MSAs, then we fractionally weight the firm's invention by the number of co-inventors.

Limiting the scope of inquiry to only innovation intensity may inadvertently conceal valuable information about a region's entrepreneurial ecosystem. The bordering metro areas of Salisbury and Dover, Delaware provide a simple illustration of this point. In terms of average annual patent intensity by firms, Salisbury and Dover are very similar with rates of 5.8 and 4.4 respectively over the period from 1992 to 2007. However, if you calculate the HHI for patenting firms, Salisbury has a average annual value of 654.1 compared to Dover's average annual value of 1609.2. Hence, while both regions have roughly the same rate of innovation by firms, innovation in Salisbury is much less concentrated (on average) across distinct firms than in neighboring Dover. Can local policies alter this landscape? These are important questions that, to date, have remain unexplored.

In addition to inventor concentration, we also calculate separate HHIs for firms and individuals using the U.S. Patent Classification System major product classification code that is referred to as a *class*. The product classes delineate one technology from another.[21] These variables we construct, which we call *product concentration firms* and *product concentration individuals*, measure the market concentration of unique patents awarded to firms and individuals based on the product/technology classification. There are more than 450 different product classifications so there can be considerable heterogeneity across metro areas in terms of the type of innovation that one observes. For instance, the Pittsfield and Springfield, Massachusetts metro areas have a similar average annual rate of firm innovation at 15.5 and 14.0, respectively. In terms of product diversity however, the average annual product concentration value (or HHI using the primary technology class on the patent) for Pittsfield is 344.3 and the average annual concentration value for Springfield is 72.8. Much like the case with inventor diffusion, these concentration metrics reveal that Springfield's innovation environment among firms is much less concentrated (on average) in terms of the products/technologies being created than in the Pittsfield metro area.

Similar to patent intensity, most of the observed variation in both inventor and product innovation concentration is across metro areas rather than over time. Figure 2 plots the average annual concentration metrics (or HHIs) for all MSAs, where the horizontal axis indicates a metro area's ranking (1 = least concentrated) and the vertical axis shows the HHI value (for the entire sample). Since nearly half of all patents are assigned to more than one product/technology class, we explore product innovation concentration using only the primary class (which we call *narrow*) and using every technology class listed on the patent (which we call *broad*).[22] Panel A shows the skewness of product concentration for products by firms using all technology classes and Panel B shows the skewness of product concentration for products by firms using only the primary technology classes.

[21] An overview of the U.S. Product Classification System is available at: https://www.uspto.gov/sites/default/files/patents/resources/classification/overview.pdf.

[22] From a practical perspective, if a patent has 3 product/technology classes listed then we treat this as three distinct patents for the purposes of measuring product concentration. We also fractionally weight all of the concentration measures by the number of co-inventors.

Similarly, Panels C and D show the product concentration distribution for individual inventors using all technology classes (Panel C) and using only the primary class (Panel D). Finally, Panels E and F show the distribution of inventor concentration for firms and individuals, respectively.

[Insert Figure 2 here]

While the data do suggest that innovation tends to be less concentrated in terms of both inventors and products in metro areas that have higher patent intensity (which also tend to be larger MSAs in terms of population), there are some notable exceptions. For instance, the Corvallis, OR metro area has the third highest rate of overall and firm intensity in the nation but its concentration score for firm inventors is at the 25th percentile nationwide because a large fraction of patents in the region are awarded to a single firm (Hewlett-Packard). On the other hand, metro areas like San Jose, CA, Boulder, CO, and Ann Arbor, MI are all very highly ranked innovation centers for both firms and individuals, *plus* they are among the leading regions for having a more diversified pool of inventors and products/technologies.

2.2 Economic Freedom Measures

Our measures of economic freedom come from Stansel (2019). Stansel quantifies the level of economic freedom across 382 metropolitan statistical areas following the methodology of the Economic Freedom North America index (Stansel et al. 2018).[23] The aggregate index is constructed on a scale of 0 (least free) to 10 (most free) and is the simple average of the scores given to three broad areas of governance: (1) spending; (2) taxation; and (3) labor market freedom.[24] All three categories capture the extent to which government decisions replace individual voluntary exchange. Each broad area contains three separate indicators; each scored on a standardized scale from 0 to 10, which are then averaged together for an overall area score. Area 1, government spending, includes, as percentages of personal income, government consumption expenditures, transfers and subsidies, and insurance and retirement payments. Area 2, taxation, includes, as percentages of personal income, income and payroll tax revenue, sales tax revenue, and revenue from property tax and other taxes. Both of these two areas include equivalent state-level estimates of each that are added to the local-level estimates. Because our regressions include state-fixed effects we will

[23] Stansel (2019) uses the 2015 geographic definitions of MSAs throughout for consistency.

[24] See Stansel (2019) for a detailed description of the variables included within each category. We will only define them briefly in this paper.

focus on local-level variation alone. Lastly, Area 3, labor market freedom, includes minimum wage income as a percentage of personal income per-capita, government employment as a percentage of total employment, and private union density. Like Area 1 and Area 2, the government employment indicator also adds in the state-level equivalent. In our analysis, we will focus on aggregate freedom as well as each of the three index areas. The aggregate MSA level economic freedom index, along with each of the three components, is available in 5-year increments from 1972 - 2012.[25]

There are many additional policies that affect innovative activity within a given MSA. However, many of these policies are state specific. Non-compete laws, for example, are governed by state law. Thus, because we are controlling for state-fixed effects we are able to focus on local policies alone. However, there are many cases where these state-level policies are not implemented uniformly across the entire state. Importantly, because this within state variation in incentives (e.g. tax cuts) mostly stems from rural versus urban distinctions (Bartik 2018), focusing only on metropolitan areas allows us to control for much of this variation. Lastly, we control for federal and university R&D spending within each MSA to control for differential involvement at the federal level. Thus, the remaining variation between local policies relevant to innovative activity should stem from variation in economic freedom alone.

3 Empirical Strategy and Identification

Since we are interested in exploring a potential link between economic freedom and patented innovation *across different metro areas*, we leverage the cross-sectional variation in our data by estimating a between regression. Specifically, our empirical model has the form:

$$\bar{p}_{j,s} = \alpha + \eta \bar{X}_{j,s} + \delta \bar{EF}_{j,s} + \mu_s + \bar{\varepsilon}_{j,s}, \tag{1}$$

where $\bar{p}_{j,s}$ denotes the mean patent outcome variable of interest for metropolitan area j located in state s, $\bar{X}_{j,s}$ is a vector of the mean value of control variables for metropolitan area j located in state s, $\bar{EF}_{j,s}$ is the mean value of our economic freedom variable of interest for metropolitan area j located in state s, μ_s is a state fixed effect, and $\bar{\varepsilon}_{j,s}$ is the random disturbance term. The between estimator regresses the average value of our patent variable of interest on the individual averages of

[25]The data are restricted to five-year increments because Stansel (2019) relies on the Census of Governments for fiscal information. The Census is only conducted every five-years.

our control and economic freedom measures. This formulation eliminates the time-series variation in the data so that our estimated coefficients are identified using only the cross-sectional variation. We include state fixed effects in equation 1 to absorb the effects of state factors such as corporate tax rates and R&D tax credits that may influence patented innovation. Multi-state metro areas are assigned to the state where its most populous county is located.

Our full sample of (annual) data covers the period from 1992 to 2007. Since the economic freedom measures are only available every five years, 1992 is the earliest Economic Census year that control variables are also available. The patent data are available through 2010, however since we only observe metro economic freedom in 2007 and 2012 we end our empirical sample in 2007. With the exception of six variables (discussed below), equation 1 is estimated using the annual average values for our metropolitan areas from 1992 to 2007. This is a relatively long time period (16 years) so our estimated coefficients can be thought of as reflecting more of a long-run cross-sectional effect.

We assess the effects of local economic freedom on innovation using several patent outcome measures. First, we focus on the overall intensity of patent generation (per 100,000 residents), firm intensity of unique awards (those assigned to organizations), and individual intensity (those unassigned to organizations). These regressions will yield insights into how local institutions influence innovation among organizations and individuals. Second, we estimate equation 1 using our aforementioned measures of innovation concentration by inventors, *innovation concentration firms* and *innovation concentration individuals*, as outcome variables. These specifications will reveal the role local institutions play in shaping the competitiveness of patented innovation among local inventors. Finally, we utilize our product concentration measures, *product concentration narrow* and *product concentration broad*, for both firms and individuals to assess how local economic freedom affects the competitiveness of product innovation. The *narrow* concentration measure uses only the patent's primary technology class while the *broad* measures uses every technology class listed on the patent.

We include a diverse set of regressors ($\bar{X}_{j,s}$) in equation 1 to adjust for observable differences across metropolitan areas that one might expect to be correlated with innovation. This begins with two measures of R&D in the area, the sum of university R&D spending within a metro area and the total spending at federally funded R&D centers located in the MSA. Both variables were constructed using data from the National Science Foundation and enter the regressions scaled in thousands of dollars per capita. We also include the dollar amount of all commercial and industrial loans outstanding in the MSA (scaled by the number of establishments) since access to capital may be important in fostering innovation. Descriptive statistics and the sources for all of our empirical variables are provided in Table 2.[26]

[Insert Table 2 here]

Since science, technology, engineering, and math jobs (otherwise known as STEM) are known to be an important driver of innovation, we estimate the share of total employment in metro areas that is STEM-related and include this variable as a control in equation 1. We construct our *STEM employment* variable using data from the Census Bureau and Bureau of Labor Statistics (BLS). STEM occupations are defined following the current standard for the American Community Survey that was created by the Census Bureau in 2010.[27] 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.[28] The industry-occupation matrix provides an estimate of the percentage of jobs in a given industry that are in a specific occupation. For example, nuclear engineers are classified as STEM and have an occupation code of 17-2161. The industry-occupation matrix shows that NAICS sectors Utilities (221), Professional and Technical Services (541), and Waste Management and Remediation Services (562) employ nuclear engineers. The industry-occupation matrix also shows that nuclear engineers are estimated to account for 0.1% of total employment in sector 541, 0.1% of total employment in sector 562, and 1.3% of total employment in sector 221. Using the industry-occupation relationships, we estimate the total number of jobs in STEM occupations at the county level using employment data from the Quarterly Census of Earnings and Wages (QCEW) (at the 3-digit NAICS level) annually from 1992 to 2007. We then aggregate the county-level data in each MSA to obtain an estimate of the total number of jobs and total STEM jobs in the region.[29]

[26] Only one individual was awarded a patent in the Carson City, NV metro area during our sample (in 2006). As a result, the MSA's *innovation concentration firms*, *product concentration* measures values are zero. We re-estimated our regressions omitting the MSA and it had no discernible effect on the estimated magnitudes or statistical significance of our findings.

[27] 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].

[28] 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].

[29] All of our variables are geographically consistent and use the 2015 Office of Management and Budget definitions

In addition to STEM employment, we follow Carlino et al. (2007) and include the metro area's net-migration rate, establishment density, and a measure of economic diversification as controls. The net-migration rate is defined as the number of in-migrants less the number of out-migrants (per 10,000 people) net of any within-MSA movements. This ensures that we are only capturing population flows from outside of an MSA. This variable is constructed using the Internal Revenue Service's county-to-county Statistics of Income data. Establishment density is the number of business establishments in the MSA reported by the QCEW per square mile of land area in the MSA. Greater density may allow for greater knowledge or people flows and therefore correlate with more innovation. Finally, we adjust for economic diversification of a region by including each MSA's Herfindahl-Hirschman index of private sector employment. We refer to this variable as *HHI employment* and it was calculated from the QCEW (aggregating from individual counties due to definitional changes) for the following sectors: construction, education and health services, financial activities, information, leisure and hospitality, manufacturing, natural resources and mining, professional and business services, and trade, transportation and utilities. Since larger metro areas also tend to be more innovative (Breschi and Lenzi 2016), we include the MSA's total population (scaled in 100,000s) to control explicitly for differences in size.

We also include several variables to account for a metro area's level of development and economic dynamism. These include the MSA's level of per capita GDP (in thousands of dollars), its reallocation rate and net job creation rate from the Census's Business Dynamic Statistics program. The reallocation rate is a region's job creation rate plus job destruction rate less the absolute value of net job creation rate. Larger values indicate more job dynamism in the MSA in the sense that labor is re-purposed to alternative uses more quickly. Since start-up and younger firms generate jobs more quickly than older firms, we include the net job creation rate to adjust for these effects. We also include the percentage of adults ages 25 and older who hold graduate degrees as a control because a recent Brookings Institution report (Shambaugh et al. 2017) notes that nearly three-quarters of patent holders have at least a master's degree. The final dynamism controls we include, which are from Chetty et al. (2014), include the share of income earned by the top 1% of income earners in the region and the MSA's (estimated) rate of upward mobility. These variables capture

for metropolitan statistical areas. All variables using the Quarterly Census of Earnings and Wages (QCEW) data are constructed by aggregating data at the county level since the QCEW's published metro area data are not geographically consistent over time.

differences in the concentration of resources and opportunities across regions.[30]

Since many previous studies have documented the important role knowledge diffusion and spillovers play in encouraging innovation, we include several controls along these dimensions. First, we include the share of economic activity in the MSA that is export-based to adjust for direct economic linkages to the outside world. Second, following the work of Breschi and Lenzi (2016) we include several variables to adjust for observable differences in the co-invention networks of different regions. These variables include the density of inventors in the MSA, a measure of the size and interconnectedness of inventors within each MSA (internal social proximity), and a measure of the size and interconnectedness of inventors within an MSA with inventors in other MSAs (external social proximity).[31] We define the density of inventors as the total number of patent holders in an MSA (in the prior year) relative to the MSA's land area. The internal and external social proximity metrics treat individual inventors as nodes in a network and capture the average social distance between inventors within the same MSA and the average social distance between inventors in different MSAs. As Breschi and Lenzi (2016) show, the internal social proximity measure for year t in MSA j may be expressed as:

$$\text{internal social proximity}_{\text{MSA}_{jt}} = \frac{\sum_{i=1}^{n} \sum_{\substack{k=1 \\ i \neq k}}^{n} \frac{1}{d_{ik}}}{n} \tag{2}$$

where d_{ik} is the geodesic social distance that separates inventor i from k in the co-invention network. The internal social proximity score is bounded by 0 and n, where a value of 0 indicates that no patent holders at time t in MSA i collaborated with one another and a value of n indicates that every patent holder at time t collaborated with every other patent holder (in the same MSA). The external social proximity metric is analogous except that the geodesic distance is calculated between inventor i in MSA j and every other inventor outside of MSA j.[32] In a cross-section of 331 MSAs, Breschi and Lenzi (2016) find that regions with a greater density of inventors and more

[30] The share of income earned by the top 1% and upward mobility were obtained from https://opportunityinsights.org/data/, which is repository for all of the data used in Chetty et al. (2014). We use their county-level estimates and take the simple mean of all counties within an MSA to arrive at an MSA value. These variables are available as a single point estimate that is based on data from 1996-2012.

[31] These measures control for the connectivity between MSAs, but they do not account for the origin of ideas as in Peri (2005) and Kang and Dall'erba (2016a). An interesting avenue for future research would be to explore if more economically free areas tend to have more patents where the ideas originated within that area.

[32] See Breschi and Lenzi (2016) for a more comprehensive description of these measures.

connected networks have higher rates of patented innovation.

The number of metropolitan areas we examine in our sample, 272, is dictated by the variables in the Census's Business Dynamic Statistics (BDS) program. The BDS data are available annually beginning in 1977 but the variables are constructed using the Office of Management and Budget's (OMB) 2009 definition of MSAs. OMB defined 382 MSAs in their 2015 definitions, of which 272 MSA area definitions remained unchanged from 2009. The other 110 MSAs are either newly defined metro areas or they experienced either the addition or subtraction of one or more counties to their area's geographic definition.[33]

Since the potential for simultaneity exists between innovation and economic freedom, we pursue an instrumental variables (IV) strategy to isolate a source of exogenous variation in our economic freedom measures. To accomplish this we depend on the fact that institutions are generally slow to evolve while innovation tends to evolve very rapidly. For instance, recent work by Mehta et al. (2010) shows that the peak citation period for a patent occurs only one year after the patent was awarded and then begins to decline fairly sharply. This suggests that knowledge transfers both spread and die very rapidly. Since shifts in government policies tend to evolve much more slowly, we instrument for the average annual value of an MSA's economic freedom index (from 1992-2007) using the region's 1972 score. This is the oldest observed value of an MSA's economic freedom score and it is at least 20 years earlier than any of the observed data in our regression. Given that patent knowledge is dispersed very quickly and that fewer than 2% of all inventors (including all organizational inventors) in Li et al. (2014)'s full disambiguated dataset were awarded patents over a time horizon that spanned at least 20 years, the 1972 economic freedom score should be unrelated to patent awards 20-35 years in the future because the awards reflect different ideas *and* different inventors.

To capture contemporaneous preferences for the size and scope of government activity within MSAs, we also instrument for the economic freedom indices using the number of campaign contributions (per 10,000 people) made to statewide candidates, parties, or other political organizations that are classified by the National Institute for Money in Politics (NIMP) as pro-school choice by residents of the MSA. The NIMP have compiled individual contribution records from state cam-

[33]We also ignored the boundary redefinitions of the Census BDS variables and re-estimated our models using all 381 MSAs for which we have complete data. The estimated coefficients and magnitudes for our variables of interest do not change in any meaningful way.

paign finance reports since 2000 and they classify donors into more than 450 distinct categories such as police and firefighter unions, trucking, lodging and tourism, and pro-school choice advocates to name a few. If the rate of pro-school choice contributions from residents of an MSA reflects the intensity of a region's collective preference for the size and scope of government, then we would expect metro areas that have a higher average rate of pro-school choice contributions to also have higher average levels of economic freedom. The first-stage regressions, which are shown in Appendix Table A.1, confirm this as a region's 1972 economic freedom scores and average rate of pro-school campaign contributions are both positively and strongly related to an MSA's current economic freedom score.

4 Empirical Results

Our second-stage benchmark results are given in Tables 3 through Table 6. We also report the corresponding OLS results along side these instrumental variable regressions for the overall economic freedom index only. All regressions include state-fixed effects with standard errors clustered at the state-level. First-stage F-Statistics are given in each table, along with the Sargan over-identification test statistic.[34] Moran's I p-values are also reported in each IV specification, and there is no evidence of residual spatial autocorrelation. As can be seen across all specifications: our instruments are strongly correlated with current economic freedom, with no evidence of endogeneity. Thus, we have reason to believe our instruments are valid. Given the possibility of endogeneity in the OLS results, we therefore choose to focus on these instrumental variable estimates throughout the remainder of this section.

For each patent variable, we regress its value on each component of the economic freedom index, as well as the aggregate (or overall) index. For patent intensity (Table 3), we first present results for overall intensity (patents per 100,000 residents) in specifications (1) through (5). We then subsequently present results for individual intensity (individually owned patents per 100,000 residents) in specifications (6) through (9) and for firm intensity (firm owned patents per 100,000 residents) in specifications (10) through (13). For the narrow and broad patent concentration measures, we present results for individuals (specifications (1) to (5)) and firms (specifications (6) through (10)) in Tables 4, 5, and 6. Recall that all measures of economic freedom are scaled such

[34] The first-stage results are shown in Appendix Table A.1.

that a higher number implies more freedom.

Focusing on the economic freedom measures first, we find some evidence that reduced government spending (represented by an increase in the index score) can stimulate the rate of patented innovation. These results suggest that a standard deviation increase in the government spending score (1.140) increases patent intensity for individuals by 1.180 patents per 100,000 residents. It also implies that firm intensity increases by 11.802 patents per 100,000 residents. This is a substantial increase in firm intensity, though this latter effect is only significant at the 10% level. We also find some evidence that a reduction in taxation results in reductions in patent intensity. However, this effect is specific to individuals and is insignificant when examining patent intensity overall. It is possible that more ares with a lower general tax burden tend to have less in terms of innovation specific R&D policies, resulting in this negative correlation.

In terms of the controls, the findings are consistent with our expectations. The strongest results in Table 3 show that patent intensity is significantly higher in metro areas with a larger share of STEM employment and in regions with more university R&D expenditures. Specifically, a 1 percentage point increase in STEM employment (as a share of total employment) is correlated with an increase of roughly 5-7 patents per 100,000 people by firms and nearly 1 patent by individuals.[35] Similarly, a $1,000 increase in per capita university R&D spending correlates with an increase of 10-11 patents per 100,000 residents by firms and an increase of 1 in the patent rate for individual inventors. In addition, competition among inventors (Table 4) and technologies (Tables 5 and 6) is significantly stronger in metro areas with more R&D spending (both university and federally-funded), more STEM employment, and in regions with greater dynamism (job reallocation rate and net job creation rate). Consistent with Breschi and Lenzi (2016), we find that patent intensity is also strongly correlated with internal social proximity and inventor density, highlighting the importance of network connections. Our results also show that a more closely connected external network of co-inventors is more strongly linked to boosting individual patented innovation than firm innovation.

While the results in Table 3 imply that local government policies may have little effect on the

[35] Similar to Kang and Dall'erba (2016a), we also spatially lagged the university R&D spending, STEM employment, percent of the population holding graduate degrees, and net job creation rate covariates to explore the possibility of spillover effects in our control variables. We found no evidence that these spatially lagged covariates are significantly correlated with our patent outcomes.

rate of innovation, our results in Tables 4, 5, and 6 strongly suggest that regions with greater economic freedom have innovation environments that are significantly more competitive. In terms of inventor concentration for example (Table 4), we find that greater economic freedom in labor market policies results in significantly more competitive innovation for both firms and individual inventors. Specifically, a one standard deviation increase in an MSA's labor market score (1.060) reduces the patent ownership concentration HHI for individuals by 845 and firms by 718 (using columns 5 and 10 from Table 4). This explains about 52 percent of a one standard deviation change in ownership concentration for both individuals and firms. The results for the labor market scores are very similar for our patent product concentration HHI indices (columns 5 and 10 in Tables 5 and 6). In addition, our results also suggest that greater tax freedom leads to more diffuse innovation in terms of ownership and product technologies, but this effect appears to be limited to firms.

The strong effect of labor market freedoms across firms, individuals, and product technologies is particularly interesting. It seems that individuals located within areas that have high levels of labor market freedom are more innovative. Because we are focusing on long-run estimates, perhaps individuals in these areas are less reliant on government employment and become more innovative as a result. It could also be that areas with a significant share of employment generated income coming from minimum wage jobs have individuals that are restricted by their income. This is consistent with Simonen and McCann (2010)'s finding that greater local labor market mobility is correlated with more innovation. However, because our results are robust to the inclusion of GDP per-capita, this latter explanation is likely. Taken together, our benchmark results suggest that reduced government spending, increased labor market freedom, and increased tax freedom leads to more diverse and diffused regional innovation.

The empirical results presented in Tables 3 through 6 characterize the conditional mean of the distribution of patent outcomes so they inform us about the effects of economic freedom on patent activity and concentration in the average metropolitan area in our sample. However, because there is considerable dispersion across MSAs, a natural question is whether or not the estimated effects we uncovered also apply to metro areas in the tails of the distribution. In other words, should we expect expansions of economic freedom in metro areas like Dover, DE and Boulder, CO to be similar to an "average" MSA? Dover is a region with modest patent intensity and very concentrated innovation, while Boulder has both high intensity and relatively competitive innovation, so it would not be unreasonable to expect heterogeneous effects across these MSAs.

Since formal theory in this area remains underdeveloped, we can bring empirical evidence to bear on such a question. To accomplish this, we re-estimate the models with statistically significant results from our concentration measures (Tables 4, 5, and 6) using the instrumental variables quantile regression (hereafter IVQR) model proposed by Chernozhukov and Hansen (2005) and Chernozhukov and Hansen (2006). The IVQR estimator is given by:

$$(\hat{\beta}(\alpha,\tau), \hat{\gamma}(\alpha,\tau)) := \arg\min_{\beta,\gamma} Q_{\bar{p}}(\tau,\alpha,\beta,\gamma), \tag{3}$$

where $Q_{\bar{p}}$ is the conditional linear quantile function of the form $Q_{\bar{p}} = (1/n)\sum_{j=1}^{n}(\bar{p}_j - \alpha(\tau)\bar{EF}_j - \beta(\tau)X_j - \gamma(\tau)Z_j)$. $\bar{EF}$ denotes the economic freedom measure of interest, $\bar{p}$ is the patent outcome of interest, Z denotes the instruments, X denotes all of the exogenous regressors from equation 1, and τ denotes the quantile. We estimate equation 3 following the two-step procedure outlined in Chernozhukov and Hansen (2005) and Chernozhukov and Hansen (2006).[36]

Because our primary interest is on the economic freedom measures, we summarize the results of the quantile regressions in Appendix Figure A.1 and Table 7. Appendix Figure A.1 plots the quantile process of the economic freedom measure of interest for the 25th, 50th, 75th quartiles. The results of formal hypothesis tests from each quantile regression are reported in each row of Table 7. The column labeled "H0: No effect" in Table 7 shows the Kolmogorov-Smirnov test statistic proposed by Chernozhukov and Hansen (2006) to test null hypothesis that economic freedom has no effect on the patent outcome of interest (e.g. $\alpha(\tau) = 0, \forall\, \tau \in (0,1)$). We are able to reject the null hypothesis of no effect in 8 of the 11 specifications. This is generally consistent with the results from Tables 3, 4, and 5 and provides additional evidence that greater local economic freedom seems to lead to more competitive and diverse regional innovation.

Table 7 also shows a column titled "H0: Constant effect". This column shows the Kolmogorov-Smirnov test statistic calculated under the null hypothesis that economic freedom has a constant

[36] As Chernozhukov and Hansen (2006) note, the first estimation step involves defining a grid of values for α, α_i, k=1, ...K, and estimating the conventional τ-quantile regression of $\bar{p}_j - \alpha_k \bar{EF}_j$ on X_j and Z_j to obtain the coefficients $\hat{\beta}(\alpha_k,\tau)$ and $\hat{\gamma}(\alpha_k,\tau)$. The second step involves selecting the specific value of α, $\hat{\alpha}(\tau)$, that makes $\|\hat{\gamma}(\alpha_k,\tau)\|$ as close to zero as possible. $\hat{\beta}(\tau)$ is then given by $\hat{\beta}(\hat{\alpha}(\tau),\tau)$. We focus on the diffusion/concentration estimates (Tables 4, 5, and 6) since those results revealed the most consistent effects of economic freedom on innovation. In the diffusion quantile regressions, α ranges from -3000 to 2000 in increments of 1. We summarize the results from our IVQR estimation in Figure A.1 and Table 7 but will provide complete results upon request.

effect on patenting outcomes across the different quantiles (e.g. $\alpha(\tau) = \alpha, \forall\, \tau \in (0,1)$. This test is often referred to a location-shift test. As the results show, we are unable to reject the null hypothesis of a different effect across quantiles in 10 of the 11 extended regressions. This suggests that expansions in economic freedom lead to less concentrated innovation in terms of inventors and product technologies for regions with existing high- and low-levels of patented innovation.

To summarize, we find limited evidence that shifts in local government spending, tax, or labor market policies will lead to more regional innovation. To the extent that it occurs, our results suggest that any such increase will be modest and limited to individual inventors. However, we find credible evidence that greater economic freedom, particularly labor market policies, results in both more competitive and diverse innovation. These findings are also robust across metro areas with both high and low rates of existing competition for inventors and product technologies. This suggests that while local economic policies may have little effect on the *rate* of regional innovation, metro areas that expand economic freedom can expect to experience a greater diversity of production innovation that is undertaken by a broader range of firms and individuals. Policies that promote greater economic freedom, particularly with regard to labor market and tax freedom, appear to be a viable long-term alternative to place-based economic development strategies.

5 Conclusion and Policy Discussion

Understanding the causes of local development is paramount to the creation of local policies aimed at spurring growth. Innovation is often cited as a driver of economic growth and has also been cited as an indicator of economic dynamism (Decker et al. 2014). An important driver of innovative activity is economic freedom (e.g. Kreft and Sobel 2005). Economically free institutions can be defined as those that "...provide an infrastructure for voluntary exchange, and protect individuals and their property from aggressors seeking to use violence, coercion, and fraud to seize things that do not belong to them" (p. 406 Gwartney and Lawson 2003). The goal of this paper is to understand how patented innovation, a predominately-local phenomena, is affected by economic freedom at the metropolitan statistical area level. By doing so, we hope to provide local policy suggestions aimed at spurring innovation and growth.

To estimate the effect of economic freedom on metro level patent activity, we combine Stansel (2019)'s MSA level economic freedom data with Li et al. (2014)'s detailed patent data. We utilize a between regression and regress averaged patent measures on averaged economic freedom. Our regressions all include state fixed effects so that we are able to focus on differences in local policy. Given the potential for simultaneity, we also instrument economic freedom with its (at least) 20-year lag and the rate of pro-school choice campaign contributions in all regressions. We also test the robustness of our findings using quantile regression.

We find some evidence of government crowd out in that less government spending (as indicated by a higher score in that component of the index) is associated with increases in patent intensity. However, this effect is relatively modest. Our strongest results suggest that economic freedom (and its components) significantly decreases the concentration of innovation ownership across both firms and individuals. Similarly, economic freedom is also associated with significant decreases in the concentration of innovation across product types for both firms and individuals. Thus, not only do we see more patent activity and a wider variety of firms and individuals that are doing the innovating, those that are innovating are producing a wider variety of products.

Given the long-run nature of our study, this suggests that increased economic freedom is a non-temporary viable alternative to traditional place-based policies. Traditional place-based policies are accompanied with eligibility restrictions and eventually expire. For example, in the United States, R&D tax credits are limited to "qualified research" according to the Internal Revenue Service (IRS) (Wilson 2009). Even if these restrictions are minimal, it requires effort on the part of the company to verify that their research is qualified. Perhaps more importantly, R&D tax credits do not guarantee that the government will not be burdensome via alternative channels (e.g. costly regulatory environment). Economic freedom, and institutional quality more generally, is a long-run concept that has no eligibility requirements and is broad in scope. It incorporates not only tax burden, but also regulatory burden and government size. It facilitates an environment conducive to entrepreneurial activity and innovation that persists through time.

There are several interesting avenues for future research that result from this analysis. First, a further exploration of the relationship between innovation concentration and economic growth, as well as stability, is warranted. Patent ownership is an underutilized measure of market power (Watson and Holman 1970) and its effects are consequently understudied. Second, it would be interesting to see if the effect of patent activity on economic growth depends on the level of economic freedom in the area. Some researchers argue that the benefits of patents outweigh the political costs of rent-seeking (Boldrin and Levine 2013), explaining the mixed results in the literature. However, because rent-seeking in general tends to be lower in economically free areas (Sobel 2008) we may expect the effect of patents to increase (or become positive) when economic freedom is high. Lastly, while we incorporate a measure of patent interconnectivity between regions, we do not distinguish between origin and destination ideas. An interesting question is whether more economically free areas generate more ideas than their less economically free counterparts.

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Figure 1: Overall Mean Patent Intensity by MSA: 1992-2007

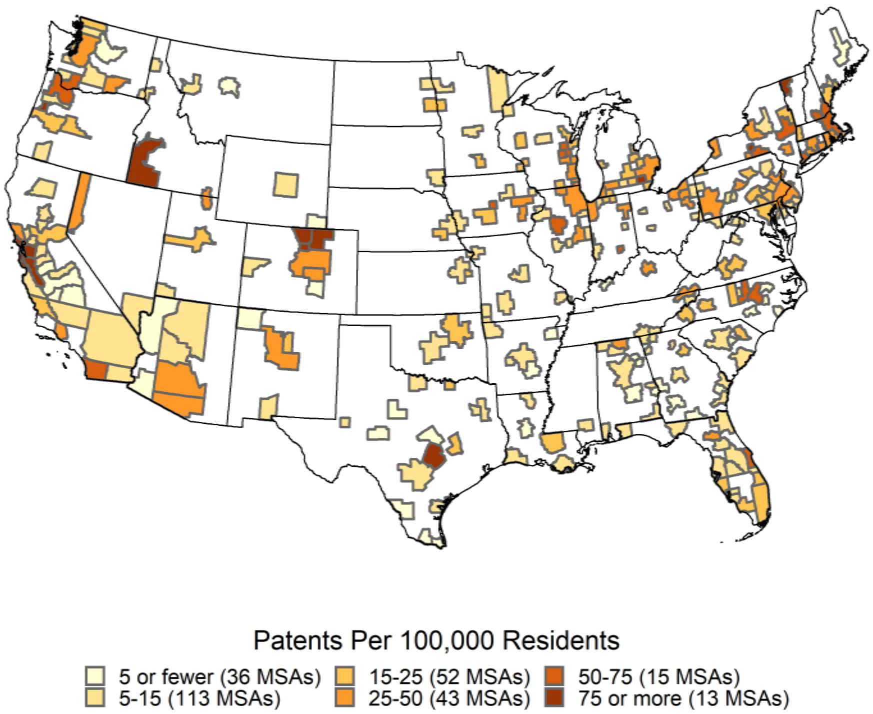


Figure 2: Mean Patent Concentration by MSA: 1992-2007

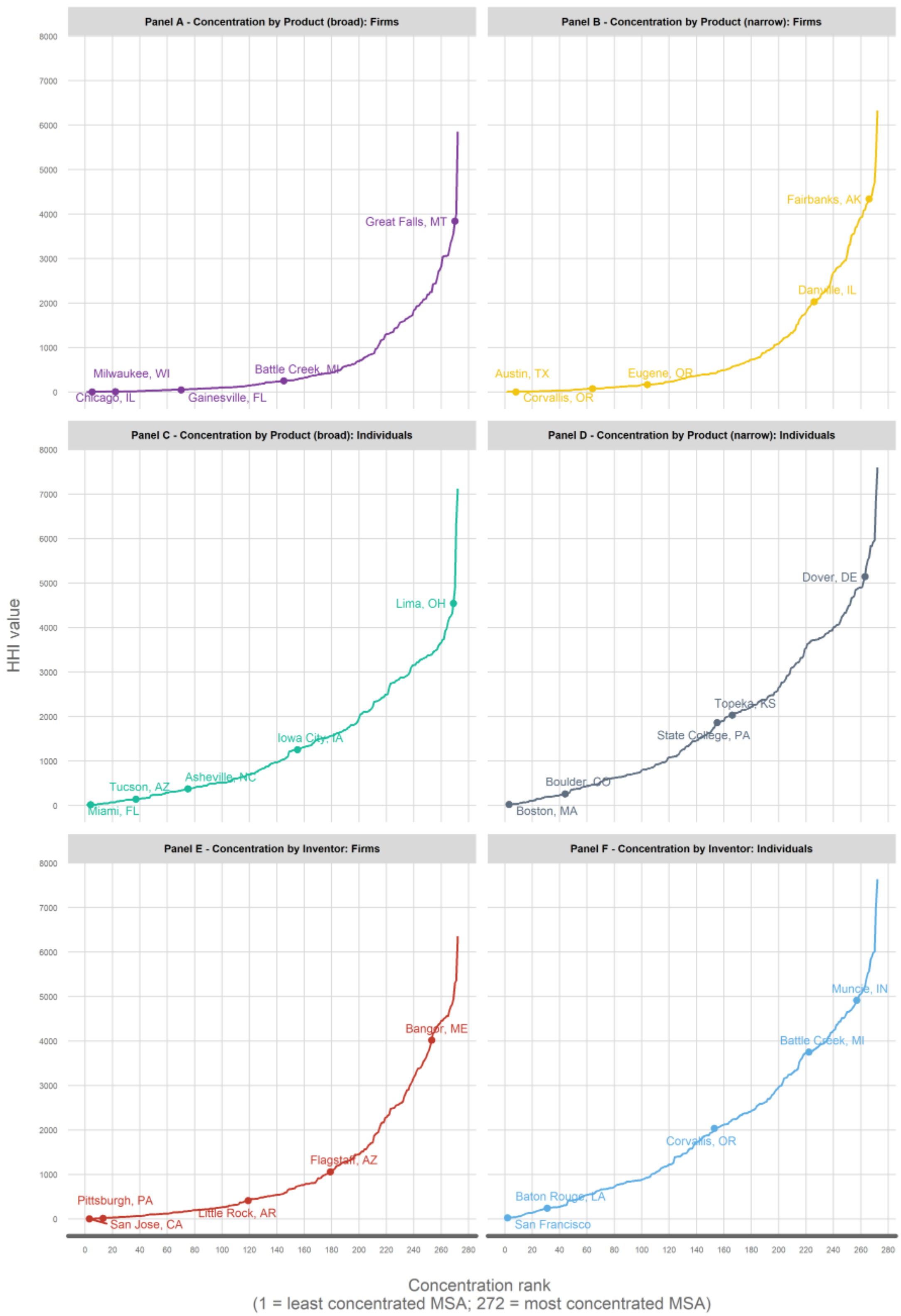


Figure 3: MSA Economic Freedom Scores: 2012

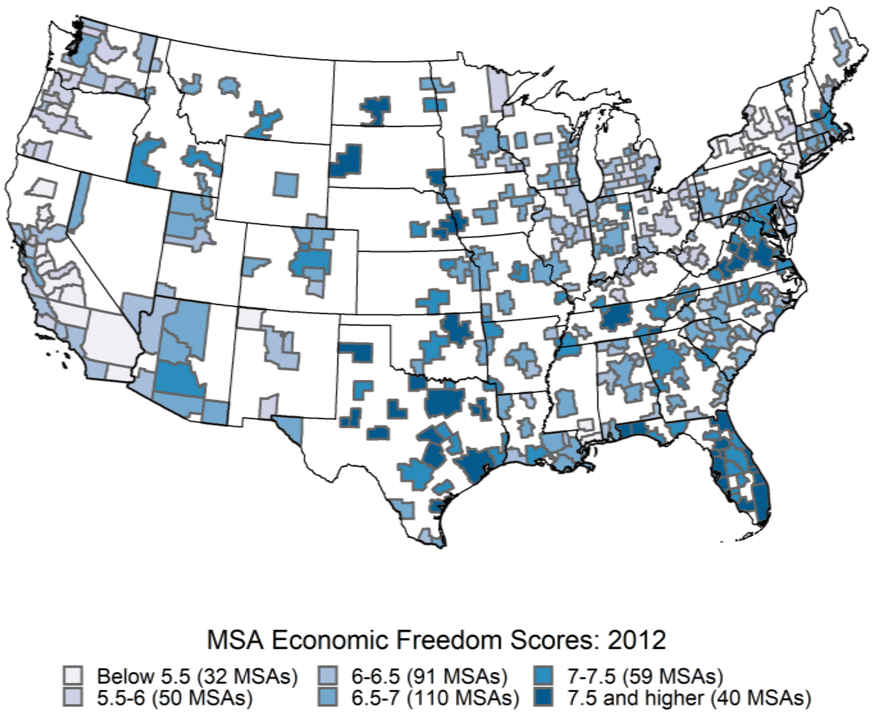


Table 1: Top 5% of MSAs for Overall and Individual Patent Intensity

CBSA Code	Area Name	overall intensity	individual intensity
11180	Ames, IA	72.5	
11460	Ann Arbor, MI	100.5	10.7
12420	Austin-Round Rock, TX	119.8	
14260	Boise City, ID	264.1	9.9
14500	Boulder, CO	119.2	11.9
14860	Bridgeport-Stamford-Norwalk, CT		10.5
15540	Burlington-South Burlington, VT	135.9	
18700	Corvallis, OR	179.8	8.7
22660	Fort Collins, CO	113.8	
24540	Greeley, CO	76.6	
27060	Ithaca, NY	82.4	
34940	Naples-Immokalee-Marco Island, FL		9.6
37100	Oxnard-Thousand Oaks-Ventura, CA		10.5
37340	Palm Bay-Melbourne-Titusville, FL		11.3
39900	Reno, NV		11.9
41740	San Diego-Carlsbad, CA		9.7
41860	San Francisco-Oakland-Hayward, CA	82.1	10.3
41940	San Jose-Sunnyvale-Santa Clara, CA	299.3	17.1
42020	San Luis Obispo-Paso Robles-Arroyo Grande, CA		9.1
42100	Santa Cruz-Watsonville, CA	77.6	9.8
45940	Trenton, NJ	89.8	

A missing value indicates that an MSA is not ranked in the top 5%. For instance, Ames, IA is one of the top 5% of MSAs in terms of overall patent intensity but the region is not ranked in the top 5% for individual patent intensity. Boulder, CO is an MSA that is ranked in the top 5% for both overall and individual patent intensity.

Table 2: Summary Statistics

Variable	Mean	Standard Deviation	Maximum	Minimum
overall intensity	23.27	32.69	299.28	0.11
individual intensity	4.17	2.42	17.13	0.11
firm intensity	19.09	31.17	282.16	0.00
innovation concentration firms	1143.47	1379.83	6353.14	0.00
innovation concentration individuals	1990.80	1637.85	7635.61	22.19
product concentration narrow firms	906.04	1236.54	6330.95	0.00
product concentration narrow individuals	1839.30	1608.33	7595.29	16.50
product concentration broad firms	632.42	923.15	5853.69	0.00
product concentration broad individuals	1343.08	1263.51	7117.27	11.24
economic freedom: spending	6.91	1.14	9.09	2.17
economic freedom: taxation	5.80	0.66	7.89	3.12
economic freedom: labor	6.70	1.06	9.27	3.65
economic freedom: overall	6.47	0.78	8.33	3.72
establishment density	20.25	5.41	95.09	11.28
university R and D	0.16	0.48	4.54	0.00
federal R and D	0.01	0.09	1.21	0.00
net migration rate	-191.73	63.19	-102.46	-577.21
STEM employment	2.77	0.97	7.95	0.84
HHI employment	1110.02	284.42	2953.43	435.69
job reallocation rate	26.90	3.35	35.76	16.43
net job creation rate	2.31	1.41	8.06	-1.81
graduate degree	6.71	5.26	27.86	0.00
per capita GDP	35.78	9.58	79.44	16.68
MSA population	5.11	9.51	91.03	0.51
loans per establishment	34.86	66.42	761.74	0.00
export share	9.63	4.74	38.38	1.54
top 1 percent income share	0.11	0.04	0.29	0.05
absolute upward mobility	42.26	3.72	53.51	34.22
inventor density	0.14	0.34	3.03	0.00
internal social proximity	3.00	6.63	101.37	0.00
external social proximity	1.85	0.83	12.25	0.13
economic freedom: overall (1972 score)	5.56	0.94	7.78	3.25
economic freedom: spending (1972 score)	7.58	1.31	9.68	3.61
economic freedom: taxation (1972 score)	5.80	0.94	8.07	2.90
economic freedom: labor (1972 score)	3.30	1.14	7.35	1.02
school choice campaign contributions	0.02	0.08	0.88	0.00

Our sample includes all 272 metropolitan statistical areas (MSAs) in the U.S. whose geographical definitions did not change between 2009 and 2015 because the Census Business Dynamic Statistics data are only available for MSAs under the 2009 area definitions. Values shown are the averages of annual MSA observations for most variables from 1992 to 2007. School choice contributions, available from the National Institute for Money in Politics, are the annual averages from 2000 to 2007 because these data do not begin until 2000. The net migration rate figures, constructed from the IRS Statistics of Income county-to-county flows, are the annual averages from 1997 to 2007. Per capita GDP figures from the Bureau of Economic Analysis are the annual averages (in thousands of dollars) from 2001 to 2007. The percentage of the population ages 25 and older with a graduate degree was constructed using data from IPUMS for 2005-2007. MSA exports as a share of GDP are from the Brookings Institution and have coverage from 2003 to 2007. Loans per establishment are the mean dollar amount of commercial and industrial loans outstanding in an MSA per year per establishment. The outstanding loan data was constructed from individual bank call reports provided by the Federal Reserve Bank of Chicago. All patent variables were constructed from the raw disambiguated data of Li et al. (2014) available at Harvard Dataverse. Inventor density, internal social proximity, and external social proximity were also constructed from the disambiguated patent data following Breschi and Lenzi (2016). The share of income earned by the top 1 percent and absolute upward mobility are a single data point based on data from 1996-2012 as estimated by Chetty et al. (2014). Economic freedom variables are from Stansel (2019). University R&D and federal R&D spending are from the National Science Foundation. MSA establishment density, STEM employment, and HHI employment were constructed using the Quarterly Census of Earnings and Wages data from the Bureau of Labor Statistics. The job reallocation rate and net job creation rate are from the Census's Business Dynamic Statistics program. The economic freedom score from 1972 is used to instrument for the average value from 1992 to 2007 along with school choice campaign contributions.

Table 3: Effects of Economic Freedom on MSA Patent Intensity

	Dependent variable:												
	overall intensity					individual intensity				firm intensity			
	(1.OLS)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	OLS	IV	IV	IV	IV	IV	IV	IV	IV	IV	IV	IV	IV
(Intercept)	-61.098**	-42.459	-130.327**	2.916	22.652	-4.306	-12.631***	11.981	-3.648	-38.153	-117.696**	-9.065	26.300
	(26.050)	(37.383)	(53.447)	(46.302)	(46.647)	(5.246)	(3.729)	(9.611)	(5.928)	(35.687)	(51.234)	(45.336)	(42.358)
establishment density	0.002	-0.022	0.201	0.032	-0.181	-0.053	-0.033	-0.038	-0.057	0.031	0.234	0.070	-0.124
	(0.129)	(0.144)	(0.231)	(0.114)	(0.273)	(0.050)	(0.034)	(0.045)	(0.055)	(0.136)	(0.252)	(0.120)	(0.230)
university R and D	10.656***	10.411***	12.631***	9.944***	10.437***	0.583***	0.782***	0.410*	0.604***	9.828***	11.849***	9.534***	9.832***
	(2.955)	(2.929)	(3.295)	(2.972)	(3.072)	(0.187)	(0.192)	(0.225)	(0.191)	(2.830)	(3.186)	(2.872)	(2.956)
federal R and D	-1.499	-2.303	7.985	-1.281	-3.527	0.232	1.137	0.477	0.258	-2.535	6.849	-1.758	-3.784
	(22.629)	(22.546)	(27.383)	(21.745)	(20.895)	(0.799)	(1.076)	(0.699)	(0.869)	(22.135)	(26.568)	(21.437)	(20.354)
net migration rate	-0.035	-0.041	0.002	-0.042*	-0.064	-0.001	0.003	-0.002	-0.001	-0.040	-0.001	-0.040*	-0.063*
	(0.028)	(0.030)	(0.025)	(0.025)	(0.040)	(0.002)	(0.002)	(0.002)	(0.003)	(0.029)	(0.024)	(0.024)	(0.037)
STEM employment	6.147*	6.386**	5.263	6.491**	8.046*	0.711***	0.604**	0.768***	0.747**	5.675*	4.659	5.723*	7.299*
	(3.257)	(3.142)	(3.336)	(3.213)	(4.146)	(0.224)	(0.235)	(0.251)	(0.288)	(2.997)	(3.172)	(3.042)	(3.908)
HHI employment	-0.002	-0.002	-0.002	-0.004	-0.003	0.000	0.000	0.000	0.000	-0.003	-0.003	-0.003	-0.003
	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.001)	(0.001)	(0.001)	(0.001)	(0.005)	(0.005)	(0.005)	(0.005)
job reallocation rate	0.109	-0.013	0.749	-0.152	-0.515	-0.001	0.070	-0.057	-0.007	-0.012	0.679	-0.095	-0.507
	(0.318)	(0.406)	(0.568)	(0.390)	(0.568)	(0.062)	(0.058)	(0.071)	(0.074)	(0.386)	(0.546)	(0.375)	(0.516)
net job creation rate	0.847	0.751	1.217	0.522	0.419	-0.035	0.009	-0.118	-0.039	0.786	1.209	0.640	0.457
	(1.615)	(1.655)	(1.588)	(1.639)	(1.793)	(0.160)	(0.131)	(0.156)	(0.179)	(1.589)	(1.551)	(1.597)	(1.682)
graduate degree	-0.072	-0.028	-0.332	-0.028	0.202	0.101***	0.073**	0.105***	0.105**	-0.129	-0.405*	-0.133	0.097
	(0.286)	(0.281)	(0.244)	(0.288)	(0.432)	(0.036)	(0.036)	(0.034)	(0.041)	(0.272)	(0.234)	(0.277)	(0.408)
per capita GDP	0.189	0.242	0.013	0.155	0.829	0.034*	0.012	0.011	0.049	0.209	0.002	0.144	0.780
	(0.190)	(0.257)	(0.272)	(0.194)	(0.527)	(0.020)	(0.015)	(0.025)	(0.056)	(0.248)	(0.266)	(0.188)	(0.485)
MSA population	-0.499**	-0.503**	-0.462*	-0.522***	-0.469**	-0.002	0.002	-0.008	0.000	-0.501**	-0.463*	-0.514***	-0.468**
	(0.219)	(0.209)	(0.251)	(0.193)	(0.191)	(0.010)	(0.011)	(0.012)	(0.011)	(0.207)	(0.246)	(0.196)	(0.189)
export share	0.829	0.790	1.067*	0.841	0.495	-0.042	-0.017	-0.030	-0.049	0.832	1.084*	0.871	0.544
	(0.620)	(0.611)	(0.627)	(0.614)	(0.684)	(0.036)	(0.032)	(0.036)	(0.042)	(0.599)	(0.616)	(0.601)	(0.662)
loans per establishment	-0.025	-0.025	-0.024	-0.025	-0.024	-0.003***	-0.003*	-0.003*	-0.003***	-0.022	-0.021	-0.022	-0.021
	(0.025)	(0.025)	(0.023)	(0.024)	(0.026)	(0.001)	(0.001)	(0.002)	(0.001)	(0.026)	(0.023)	(0.024)	(0.026)
top 1 percent income share	-42.181	-39.226	-75.211	-46.162	-27.411	3.855	0.684	1.945	4.010	-43.081	-75.896	-48.107	-31.421
	(48.019)	(47.844)	(55.296)	(43.882)	(46.007)	(3.466)	(2.936)	(4.189)	(4.187)	(48.721)	(55.267)	(45.417)	(45.423)
absolute upward mobility	0.669	0.681	0.317	0.607	0.580	0.142***	0.111**	0.120**	0.137***	0.539	0.206	0.488	0.443
	(0.463)	(0.478)	(0.406)	(0.455)	(0.541)	(0.051)	(0.047)	(0.054)	(0.053)	(0.452)	(0.392)	(0.434)	(0.516)
inventor density	46.659***	46.787***	44.831***	47.747***	44.712***	1.989***	1.819***	2.308***	1.909**	44.797***	43.012***	45.440***	42.804***
	(9.551)	(9.178)	(10.855)	(8.510)	(7.935)	(0.622)	(0.536)	(0.729)	(0.739)	(9.234)	(10.836)	(8.706)	(7.819)
internal social proximity	2.583***	2.598***	2.506***	2.596***	2.695***	0.041***	0.032***	0.041***	0.043***	2.557***	2.474***	2.554***	2.652***
	(0.292)	(0.300)	(0.292)	(0.290)	(0.318)	(0.011)	(0.010)	(0.010)	(0.012)	(0.292)	(0.285)	(0.283)	(0.310)
external social proximity	-0.338	-0.260	-0.743	-0.283	0.267	0.305***	0.260**	0.305***	0.316***	-0.564	-1.003	-0.588	-0.049
	(1.063)	(1.123)	(1.126)	(1.092)	(1.280)	(0.111)	(0.101)	(0.101)	(0.115)	(1.073)	(1.090)	(1.054)	(1.220)
economic freedom: spending			12.388*				1.040**				11.348*		
			(6.576)				(0.445)				(6.302)		
economic freedom: taxation				-7.448				-2.368*				-5.080	
				(5.847)				(1.233)				(5.728)	
economic freedom: labor					-12.795				-0.434				-12.361
					(8.542)				(0.870)				(7.885)
economic freedom: overall	1.001	-1.815				-0.296				-1.519			
	(2.754)	(5.194)				(0.593)				(5.076)			
N	272	272	272	272	272	272	272	272	272	272	272	272	272
Moran's I p-value		0.262	0.129	0.189	0.698	0.953	0.393	0.773	0.968	0.256	0.155	0.203	0.667
State fixed effects	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
First-stage F		27.871	22.716	20.328	21.192	27.871	22.716	20.328	21.192	27.871	22.716	20.328	21.192
Sargan test statistic		0.076	0.098	0.248	0.989	0.132	0.032	1.254	0.246	0.060	0.094	0.149	0.979
R^2	0.874	0.874	0.860	0.879	0.847	0.722	0.750	0.728	0.708	0.872	0.857	0.876	0.847

Standard errors are clustered by state. MSAs are assigned to the state where its most populous county is located. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

Table 4: Effects of Economic Freedom on MSA Patent Inventor Concentration

	Dependent variable:									
	innovation concentration individuals					innovation concentration firms				
	(1.OLS) OLS	(1) IV	(2) IV	(3) IV	(4) IV	(5.OLS) OLS	(5) IV	(6) IV	(7) IV	(8) IV
(Intercept)	11708.960***	9473.581**	7652.233*	2069.176	10260.870***	12560.441***	13034.738***	8728.885**	14212.018***	8993.709***
	(3041.244)	(3943.465)	(3953.674)	(6193.362)	(2698.593)	(2904.022)	(3667.639)	(3608.317)	(4894.844)	(3138.478)
establishment density	-15.966*	-13.129	-14.049	-10.301	-18.898**	-13.993*	-14.595*	-14.750	1.998	-13.525
	(9.277)	(12.146)	(15.035)	(15.829)	(7.853)	(7.826)	(8.325)	(12.724)	(16.249)	(8.529)
university R and D	-186.891	-157.538	-164.550	-67.870	-112.970	-315.508*	-321.736*	-318.972*	-316.384*	-221.958
	(190.178)	(199.871)	(210.213)	(211.103)	(192.261)	(164.733)	(170.691)	(188.405)	(178.823)	(162.516)
federal R and D	-1662.202***	-1565.700***	-1675.578***	-1421.720***	-1500.681***	-1868.631***	-1889.106***	-2030.989***	-1456.251***	-1630.416***
	(213.965)	(343.207)	(483.553)	(509.414)	(208.850)	(193.263)	(215.377)	(453.900)	(386.879)	(229.057)
net migration rate	-4.315	-3.654	-3.592	-2.180	-4.133	-3.277	-3.418	-2.973	-1.790	-2.431
	(2.689)	(3.128)	(3.438)	(2.769)	(2.877)	(2.839)	(3.175)	(3.732)	(2.868)	(2.877)
STEM employment	-638.562***	-667.240***	-690.745***	-734.117***	-605.708***	-571.434***	-565.349***	-620.831***	-627.659***	-573.433***
	(186.376)	(206.157)	(212.544)	(197.455)	(168.963)	(162.005)	(169.993)	(180.331)	(160.214)	(153.123)
HHI employment	0.444	0.469	0.522	0.601	0.480	0.651*	0.646*	0.750**	0.490	0.707**
	(0.420)	(0.436)	(0.424)	(0.487)	(0.381)	(0.374)	(0.373)	(0.367)	(0.462)	(0.356)
job reallocation rate	-82.115	-67.520	-61.080	-28.457	-77.433	-84.976*	-88.073*	-69.438	-70.212	-65.750
	(55.681)	(62.005)	(62.582)	(64.205)	(58.131)	(49.497)	(47.368)	(48.196)	(49.221)	(53.557)
net job creation rate	-217.030**	-205.493**	-196.465**	-167.599*	-209.313**	-229.963***	-232.411***	-210.836**	-237.602***	-211.347**
	(92.062)	(90.891)	(94.951)	(97.683)	(87.234)	(87.537)	(87.784)	(90.295)	(87.309)	(84.950)
graduate degree	-52.186**	-57.383**	-58.733**	-68.383***	-50.655**	-46.457*	-45.354*	-50.351*	-59.724**	-50.582**
	(23.080)	(23.441)	(23.722)	(23.937)	(24.457)	(23.628)	(24.993)	(27.852)	(26.286)	(24.645)
per capita GDP	-12.278	-18.709	-24.634*	-27.143*	8.475	1.849	3.214	-10.365	-28.830*	12.790
	(12.254)	(13.669)	(14.089)	(13.857)	(18.181)	(13.608)	(14.684)	(16.344)	(16.028)	(19.346)
MSA population	-12.893	-12.493	-12.903	-10.499	-9.784	-6.535	-6.620	-7.130	-8.668	-3.472
	(8.358)	(9.157)	(9.874)	(12.023)	(8.693)	(7.027)	(6.926)	(8.212)	(7.935)	(8.052)
export share	51.197*	55.908*	57.071*	62.843**	44.422	-38.652*	-39.651*	-35.228	-18.262	-39.495*
	(28.372)	(31.063)	(32.487)	(29.555)	(28.187)	(20.196)	(21.013)	(22.581)	(24.504)	(21.540)
loans per establishment	-0.797	-0.799	-0.850	-0.844	-0.755	0.135	0.136	0.046	0.234	0.167
	(0.905)	(0.938)	(0.902)	(1.007)	(0.836)	(1.286)	(1.277)	(1.181)	(1.733)	(1.284)
top 1 percent income share	6878.182**	6523.808**	6875.157*	6182.590*	6741.730***	3541.222	3616.413	4046.767	1510.637	3055.013
	(2723.940)	(3060.169)	(3727.679)	(3454.179)	(2511.832)	(2270.918)	(2335.085)	(3757.087)	(2856.541)	(2249.274)
absolute upward mobility	12.690	11.263	19.031	12.570	2.911	9.708	10.010	22.790	-5.848	-0.102
	(38.804)	(37.984)	(35.905)	(38.494)	(39.019)	(38.109)	(38.268)	(41.697)	(43.256)	(38.630)
inventor density	766.160*	750.898*	777.814*	661.984	599.175	1015.201***	1018.439***	1057.463***	1132.092***	857.184***
	(406.702)	(438.806)	(450.987)	(543.367)	(373.228)	(299.549)	(290.400)	(333.184)	(360.430)	(318.298)
internal social proximity	-9.097	-10.901*	-11.776*	-14.607**	-7.461	-3.472	-3.089	-5.529	-8.386	-3.963
	(6.279)	(6.416)	(6.415)	(7.063)	(6.578)	(5.031)	(5.239)	(5.240)	(6.009)	(6.346)
external social proximity	-41.235	-50.671	-55.094	-69.298	-31.633	-56.878	-54.876	-67.374	-84.676	-58.564
	(68.528)	(68.913)	(70.801)	(71.573)	(67.469)	(53.149)	(54.273)	(55.708)	(57.616)	(53.279)
economic freedom: spending			-359.504					-625.093		
			(480.624)					(621.855)		
economic freedom: taxation				438.867					-1208.340**	
				(723.985)					(564.589)	
economic freedom: labor					-797.997**					-678.961**
					(333.576)					(339.119)
economic freedom: overall	-945.502***	-607.771				-1157.191***	-1228.850**			
	(243.795)	(466.717)				(337.187)	(569.406)			
N	272	272	272	272	272	272	272	272	272	272
Moran's I p-value		0.183	0.181	0.275	0.291		0.652	0.671	0.628	0.397
State fixed effects	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
First-stage F		27.871	22.716	20.328	21.192		27.871	22.716	20.328	21.192
Sargan test statistic		0.004	0.058	0.402	0.064		0.024	0.118	0.001	0.003
R^2	0.651	0.648	0.642	0.632	0.669	0.647	0.647	0.630	0.566	0.657

Standard errors are clustered by state. MSAs are assigned to the state where its most populous county is located. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

Table 5: Effects of Economic Freedom on MSA Patent Production Concentration (Primary Class/Narrow)

	Dependent variable:									
	product concentration narrow individuals					product concentration narrow firms				
	(1.OLS) OLS	(1) IV	(2) IV	(3) IV	(4) IV	(5.OLS) OLS	(5) IV	(6) IV	(7) IV	(8) IV
(Intercept)	10860.364***	7528.082*	6595.825*	-508.814	9191.535***	11547.027***	12144.968***	7982.135**	13415.045***	8318.706**
	(2969.503)	(3980.814)	(3707.415)	(6735.545)	(2800.309)	(2870.096)	(3499.128)	(3343.628)	(4840.491)	(3236.709)
establishment density	-14.351	-10.122	-11.117	-10.841	-16.279*	-10.356	-11.115	-11.001	4.666	-10.085
	(10.124)	(14.079)	(16.001)	(15.997)	(9.446)	(7.337)	(7.814)	(10.766)	(14.708)	(8.531)
university R and D	-239.958	-196.202	-204.807	-103.234	-171.478	-263.142*	-270.993*	-265.795	-267.657*	-176.720
	(188.055)	(198.642)	(207.751)	(212.675)	(188.120)	(148.608)	(152.325)	(167.978)	(161.105)	(145.592)
federal R and D	-1514.144***	-1370.288***	-1457.099***	-1315.325***	-1358.131***	-1643.226***	-1669.039***	-1790.813***	-1258.744***	-1424.461***
	(204.606)	(367.129)	(468.138)	(485.489)	(214.974)	(205.316)	(212.341)	(425.592)	(412.532)	(256.213)
net migration rate	-4.609*	-3.623	-3.669	-2.437	-4.324	-3.058	-3.235	-2.766	-1.710	-2.299
	(2.559)	(3.054)	(3.305)	(2.737)	(2.728)	(2.410)	(2.665)	(3.191)	(2.433)	(2.434)
STEM employment	-588.935***	-631.685***	-643.739***	-688.059***	-566.724***	-501.942***	-494.271***	-547.899***	-552.420***	-502.114***
	(189.118)	(209.157)	(212.434)	(203.754)	(174.365)	(145.057)	(149.573)	(159.648)	(144.052)	(139.492)
HHI employment	0.372	0.408	0.440	0.582	0.407	0.522	0.515	0.614*	0.364	0.573*
	(0.428)	(0.444)	(0.432)	(0.488)	(0.400)	(0.346)	(0.342)	(0.340)	(0.419)	(0.326)
job reallocation rate	-83.762	-62.006	-59.593	-24.957	-76.914	-68.319	-72.223	-53.762	-55.947	-51.069
	(58.419)	(64.949)	(64.317)	(68.442)	(60.391)	(46.626)	(44.686)	(44.626)	(46.689)	(51.651)
net job creation rate	-214.808**	-197.610**	-193.050*	-156.664	-205.989**	-189.105**	-192.191**	-171.302**	-197.895**	-172.248**
	(94.714)	(94.400)	(97.973)	(100.233)	(91.101)	(80.543)	(81.121)	(82.608)	(81.739)	(78.328)
graduate degree	-52.138**	-59.885**	-60.109**	-68.242***	-51.864**	-41.707*	-40.317*	-45.383*	-53.815**	-45.285**
	(23.341)	(23.745)	(24.239)	(24.181)	(24.648)	(21.234)	(21.957)	(24.916)	(23.706)	(21.874)
per capita GDP	-14.863	-24.450	-27.593*	-26.182*	1.470	1.842	3.562	-9.509	-26.855*	12.538
	(12.595)	(14.825)	(14.596)	(14.554)	(18.150)	(12.785)	(13.929)	(14.887)	(14.652)	(20.488)
MSA population	-10.587	-9.990	-10.319	-7.440	-7.871	-4.284	-4.391	-4.824	-6.385	-1.420
	(7.892)	(9.166)	(9.589)	(11.981)	(8.279)	(6.448)	(6.384)	(7.559)	(7.318)	(7.172)
export share	47.718	54.740*	54.902	57.268*	42.901	-34.141*	-35.401*	-30.906	-15.123	-35.217*
	(28.951)	(32.082)	(33.623)	(30.541)	(28.421)	(18.652)	(19.530)	(20.897)	(22.764)	(20.968)
loans per establishment	-0.458	-0.462	-0.496	-0.531	-0.424	0.239	0.239	0.157	0.334	0.269
	(0.866)	(0.903)	(0.876)	(0.980)	(0.818)	(1.241)	(1.230)	(1.151)	(1.662)	(1.237)
top 1 percent income share	6931.889**	6403.623**	6687.263*	6513.446*	6746.302***	3860.336*	3955.127*	4318.907	1951.999	3423.222*
	(2733.454)	(3179.804)	(3668.249)	(3631.544)	(2524.872)	(2099.664)	(2070.981)	(3512.884)	(2731.328)	(1991.736)
absolute upward mobility	10.041	7.915	13.339	12.813	1.467	-3.789	-3.407	8.219	-18.569	-12.949
	(39.149)	(37.719)	(36.711)	(39.715)	(39.349)	(34.215)	(34.182)	(37.414)	(38.032)	(35.648)
inventor density	727.855*	705.103	725.262	586.471	583.222	936.615***	940.697***	975.211***	1050.933***	788.590***
	(402.758)	(457.101)	(457.069)	(559.012)	(379.603)	(263.463)	(256.352)	(294.254)	(318.975)	(275.694)
internal social proximity	-10.799	-13.488*	-13.839**	-16.202**	-9.767	-5.837	-5.355	-7.762	-10.337*	-6.193
	(6.738)	(7.038)	(6.983)	(7.492)	(6.999)	(4.659)	(4.916)	(4.894)	(5.338)	(5.997)
external social proximity	-34.255	-48.322	-50.056	-61.257	-27.972	-56.319	-53.795	-66.145	-81.870	-57.344
	(66.613)	(66.477)	(68.452)	(69.181)	(64.746)	(47.560)	(47.735)	(49.142)	(52.050)	(47.561)
economic freedom: spending			-242.312					-574.967		
			(448.681)					(574.921)		
economic freedom: taxation				729.465					-1161.989**	
				(777.043)					(567.533)	
economic freedom: labor					-676.799**					-639.942*
					(322.629)					(342.927)
economic freedom: overall	-868.479***	-365.024				-1070.529***	-1160.868**			
	(221.267)	(458.716)				(352.579)	(516.168)			
N	272	272	272	272	272	272	272	272	272	272
Moran's I p-value		0.194	0.197	0.33	0.278		0.533	0.593	0.536	0.34
State fixed effects	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
First-stage F		27.871	22.716	20.328	21.192		27.871	22.716	20.328	21.192
Sargan test statistic		0.004	0.001	0.249	0.179		0.197	0.009	0.053	0.053
R^2	0.629	0.623	0.619	0.609	0.645	0.628	0.627	0.609	0.539	0.640

Standard errors are clustered by state. MSAs are assigned to the state where its most populous county is located. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

Table 6: Effects of Economic Freedom on MSA Patent Production Concentration (All Classes/Broad)

	Dependent variable:									
	product concentration broad individuals					product concentration broad firms				
	(1.OLS) OLS	(1) IV	(2) IV	(3) IV	(4) IV	(5.OLS) OLS	(5) IV	(6) IV	(7) IV	(8) IV
(Intercept)	8437.861***	5066.811	4986.290	-1483.960	6468.711***	8213.312***	9627.623***	6004.590**	11053.289***	6436.218**
	(2432.319)	(3163.400)	(3078.839)	(5855.290)	(2157.292)	(2419.934)	(2917.011)	(2661.516)	(4039.953)	(2596.147)
establishment density	-9.175	-4.897	-6.492	-6.908	-9.293	-9.421*	-11.216*	-10.729	2.223	-10.371
	(8.269)	(12.194)	(13.138)	(12.665)	(8.357)	(5.500)	(6.479)	(8.370)	(10.238)	(6.578)
university R and D	-181.356	-137.091	-152.270	-62.952	-125.384	-192.426*	-210.998*	-202.766	-212.174*	-132.199
	(136.732)	(143.955)	(149.929)	(154.953)	(137.114)	(108.728)	(111.509)	(124.566)	(122.753)	(105.873)
federal R and D	-1206.034***	-1060.505***	-1155.995***	-1053.784***	-1066.723***	-1169.001***	-1230.058***	-1313.445***	-883.863***	-1025.759***
	(141.214)	(267.421)	(351.730)	(330.749)	(159.814)	(157.189)	(144.055)	(322.813)	(298.020)	(169.145)
net migration rate	-3.293*	-2.295	-2.522	-1.485	-2.845	-2.286	-2.704	-2.239	-1.460	-1.925
	(1.937)	(2.339)	(2.560)	(2.126)	(2.032)	(1.856)	(2.024)	(2.454)	(1.903)	(1.847)
STEM employment	-479.488***	-522.736***	-523.842***	-562.591***	-476.542***	-361.371***	-343.227***	-389.884***	-390.195***	-349.612***
	(160.591)	(179.649)	(179.554)	(176.302)	(152.037)	(113.980)	(117.989)	(126.617)	(114.917)	(110.916)
HHI employment	0.168	0.205	0.223	0.358	0.201	0.344	0.328	0.410*	0.192	0.377
	(0.330)	(0.344)	(0.334)	(0.387)	(0.315)	(0.254)	(0.250)	(0.247)	(0.323)	(0.238)
job reallocation rate	-67.569	-45.560	-47.896	-17.373	-57.331	-50.809	-60.043*	-43.322	-47.814	-42.413
	(45.606)	(50.254)	(50.341)	(54.309)	(46.484)	(34.598)	(33.709)	(33.641)	(34.965)	(38.405)
net job creation rate	-166.284**	-148.885**	-148.665*	-115.580	-155.987**	-136.912**	-144.212**	-125.987**	-150.824**	-127.577**
	(75.006)	(75.149)	(78.460)	(79.689)	(71.079)	(61.271)	(61.562)	(61.322)	(59.093)	(60.408)
graduate degree	-38.164**	-46.001**	-44.675**	-51.466***	-40.056**	-29.522*	-26.234	-30.989*	-37.341**	-30.363*
	(19.148)	(19.390)	(19.695)	(19.556)	(20.262)	(15.819)	(16.121)	(18.689)	(17.754)	(16.154)
per capita GDP	-11.282	-20.980*	-21.571*	-19.603	-3.280	1.237	5.305	-5.989	-20.461*	12.868
	(9.416)	(11.286)	(11.539)	(12.614)	(13.013)	(9.575)	(10.475)	(10.818)	(10.920)	(16.354)
MSA population	-5.187	-4.583	-4.956	-2.361	-3.272	-1.745	-1.999	-2.287	-3.803	0.488
	(5.921)	(7.295)	(7.321)	(9.501)	(6.451)	(4.552)	(4.419)	(5.243)	(4.787)	(4.974)
export share	38.529	45.634	44.399	45.814*	37.290	-22.745	-25.725*	-21.493	-8.607	-25.602
	(25.788)	(28.865)	(30.154)	(27.224)	(24.848)	(13.998)	(14.608)	(15.743)	(17.441)	(15.602)
loans per establishment	-0.577	-0.581	-0.607	-0.645	-0.556	0.286	0.288	0.222	0.372	0.313
	(0.737)	(0.778)	(0.747)	(0.838)	(0.716)	(0.777)	(0.748)	(0.701)	(1.109)	(0.756)
top 1 percent income share	4860.021**	4325.610*	4648.891	4595.602	4598.923**	2360.556	2584.766*	2824.647	878.273	2141.399*
	(2132.848)	(2581.522)	(2930.272)	(2883.873)	(2004.728)	(1491.463)	(1371.176)	(2519.295)	(1887.204)	(1288.316)
absolute upward mobility	17.608	15.457	20.094	20.757	11.495	-5.080	-4.178	4.870	-17.270	-12.164
	(30.713)	(29.428)	(28.688)	(31.415)	(29.644)	(26.369)	(26.508)	(29.720)	(29.868)	(27.566)
inventor density	630.074**	607.058	627.168*	502.047	530.466*	693.066***	702.722***	728.044***	801.490***	575.374***
	(312.408)	(369.415)	(355.755)	(446.254)	(309.791)	(200.217)	(188.521)	(216.837)	(231.060)	(195.986)
internal social proximity	-4.464	-7.184	-6.937	-8.904	-4.515	-4.745	-3.604	-5.770	-7.719*	-4.294
	(5.686)	(5.965)	(5.929)	(6.301)	(5.852)	(3.754)	(3.949)	(3.844)	(4.098)	(4.592)
external social proximity	-20.755	-34.985	-33.610	-42.791	-20.448	-31.133	-25.163	-36.303	-48.456	-28.076
	(51.910)	(52.451)	(53.825)	(53.463)	(50.104)	(34.859)	(35.388)	(36.282)	(38.075)	(35.237)
economic freedom: spending			-188.740					-457.317		
			(368.225)					(450.039)		
economic freedom: taxation				689.708					-1018.632**	
				(685.343)					(460.192)	
economic freedom: labor					-437.677*					-536.192**
					(234.951)					(271.270)
economic freedom: overall	-696.090***	-186.778				-756.789***	-970.469**			
	(178.754)	(363.669)				(278.191)	(416.045)			
N	272	272	272	272	272	272	272	272	272	272
Moran's I p-value		0.17	0.16	0.289	0.215		0.593	0.64	0.537	0.38
State fixed effects	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
First-stage F		27.871	22.716	20.328	21.192		27.871	22.716	20.328	21.192
Sargan test statistic		0.025	0.030	0.477	0.025		0.283	0.005	0.110	0.094
R^2	0.601	0.591	0.590	0.578	0.616	0.604	0.600	0.584	0.506	0.618

Standard errors are clustered by state. MSAs are assigned to the state where its most populous county is located. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

Table 7: Hypothesis Tests from Quantile IV Regressions

Regression	Outcome	Freedom Index	H0: No effect	H0: Constant effect
Table 4: 5	innovation concentration individuals	spending	2.626**	1.990*
Table 4: 7	innovation concentration firms	ecfr_overall	2.870***	1.329
Table 4: 9	innovation concentration firms	taxation	0.765	0.754
Table 4: 10	innovation concentration firms	labor	2.255**	1.003
Table 5: 5	product concentration narrow individuals	labor	3.849***	0.506
Table 5: 7	product concentration narrow firms	ecfr_overall	2.371**	0.833
Table 5: 9	product concentration narrow firms	taxation	0.707	0.899
Table 5: 10	product concentration narrow firms	labor	2.308**	1.014
Table 6: 7	product concentration broad firms	ecfr_overall	2.221**	0.893
Table 6: 9	product concentration broad firms	taxation	1.138	1.177
Table 6: 10	product concentration broad firms	labor	3.392***	0.576

This table shows the results from individual instrumental variables quantile regression results using the method of Chernozhukov and Hansen (2006). All models were estimated using the 25th, 50th, and 75th quantiles. The no effect and constant effect test statistics are the Kolmogorov-Smirnov statistics described in Chernozhukov and Hansen (2006). *** denotes rejection of the null hypothesis at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

Table A.1: First-Stage Regressions

	Dependent variable:			
	economic freedom: spending	economic freedom: taxation	economic freedom: labor	economic freedom: overall
	(1) OLS	(2) OLS	(3) OLS	(4) OLS
(Intercept)	3.652**	5.824***	5.084***	4.550***
	(1.467)	(0.771)	(0.815)	(0.617)
establishment density	-0.015	0.003*	-0.013	-0.009
	(0.017)	(0.002)	(0.014)	(0.011)
university R and D	-0.090	-0.045	0.083**	-0.010
	(0.059)	(0.043)	(0.033)	(0.033)
federal R and D	-0.548	0.027	-0.212	-0.261
	(0.417)	(0.104)	(0.339)	(0.256)
net migration rate	-0.001**	0.000	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.000)
STEM employment	0.050	0.053	0.136**	0.082**
	(0.080)	(0.037)	(0.059)	(0.040)
HHI employment	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
job reallocation rate	-0.052***	-0.024**	-0.038**	-0.037***
	(0.019)	(0.010)	(0.019)	(0.012)
net job creation rate	-0.027	-0.048***	-0.023	-0.034
	(0.029)	(0.015)	(0.037)	(0.023)
graduate degree	0.019*	0.001	0.013	0.010
	(0.010)	(0.004)	(0.010)	(0.007)
per capita GDP	0.010	-0.007**	0.037***	0.013***
	(0.007)	(0.004)	(0.009)	(0.005)
MSA population	-0.004	-0.001	-0.001	-0.002
	(0.004)	(0.002)	(0.004)	(0.003)
export share	-0.018**	0.005	-0.018**	-0.010*
	(0.008)	(0.007)	(0.009)	(0.006)
loans per establishment	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
top 1 percent income share	1.565	-0.260	1.152	0.924
	(1.063)	(0.629)	(2.098)	(1.105)
absolute upward mobility	0.017	-0.008	0.003	0.005
	(0.014)	(0.008)	(0.017)	(0.009)
inventor density	0.227***	0.099	-0.139	0.053
	(0.087)	(0.087)	(0.185)	(0.107)
internal social proximity	0.005**	0.000	0.004	0.003*
	(0.002)	(0.001)	(0.003)	(0.002)
external social proximity	0.022	0.018	0.030	0.025
	(0.026)	(0.013)	(0.035)	(0.021)
school choice campaign contributions	0.186	0.254**	0.234**	0.219**
	(0.133)	(0.104)	(0.110)	(0.087)
economic freedom: spending (1972 score)	0.456***			
	(0.154)			
economic freedom: taxation (1972 score)		0.266***		
		(0.088)		
economic freedom: labor (1972 score)			0.386***	
			(0.072)	
economic freedom: overall (1972 score)				0.419***
				(0.079)
N	272	272	272	272
State fixed effects	yes	yes	yes	yes
Joint F instruments	22.716***	20.328***	21.192***	27.871***
R^2	0.894	0.908	0.899	0.919

Standard errors are clustered by state. MSAs are assigned to the state where its most populous county is located. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level. Each economic freedom score is instrumented using the respective 1972 score and the rate of pro-school choice campaign contributions in the MSA (per 10,000 residents).

Table A.2: Change in Innovation Concentration (1976-1991)
Regressed on Change in Economic Freedom (1992-2007)

	Dependent variable:							
	Δ innovation concentration individuals				Δ innovation concentration firms			
	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) OLS	(7) OLS	(8) OLS
Δ economic freedom: spending	-245.757				411.556			
	(799.933)				(341.131)			
Δ economic freedom: taxation		368.959				462.104		
		(844.861)				(551.574)		
Δ economic freedom: labor			-549.487				-90.494	
			(876.445)				(556.715)	
Δ economic freedom: overall				-613.330				579.344
				(1457.520)				(690.670)
N	272	272	272	272	272	272	272	272
R^2	0.239	0.239	0.242	0.240	0.270	0.267	0.265	0.268
State fixed effects	yes	yes	yes	yes	yes	yes	yes	yes

Standard errors are clustered by state. MSAs are assigned to the state where its most populous county is located. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

Table A.3: Change in Product Concentration Narrow (1976-1991) Regressed on Change in Economic Freedom (1992-2007)

	Dependent variable:							
	Δ product concentration narrow individuals				Δ product concentration narrow firms			
	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) OLS	(7) OLS	(8) OLS
Δ economic freedom: spending	4.741				287.633			
	(975.973)				(304.695)			
Δ economic freedom: taxation		841.857				262.391		
		(916.089)				(437.037)		
Δ economic freedom: labor			-723.371				-16.150	
			(948.238)				(514.191)	
Δ economic freedom: overall				-289.082				421.920
				(1474.817)				(559.353)
N	272	272	272	272	272	272	272	272
R^2	0.239	0.239	0.242	0.240	0.270	0.267	0.265	0.268
State fixed effects	yes	yes	yes	yes	yes	yes	yes	yes

Standard errors are clustered by state. MSAs are assigned to the state where its most populous county is located. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

Table A.4: Change in Product Concentration Broad (1976-1991) Regressed on Change in Economic Freedom (1992-2007)

	Dependent variable:							
	Δ product concentration broad individuals				Δ product concentration broad firms			
	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) OLS	(7) OLS	(8) OLS
Δ economic freedom: spending	-4.895				106.823			
	(868.822)				(207.119)			
Δ economic freedom: taxation		867.927				168.014		
		(877.746)				(394.969)		
Δ economic freedom: labor			-345.483				-148.341	
			(829.877)				(357.714)	
Δ economic freedom: overall				28.256				63.054
				(1466.931)				(452.789)
N	272	272	272	272	272	272	272	272
R^2	0.239	0.239	0.242	0.240	0.270	0.267	0.265	0.268
State fixed effects	yes	yes	yes	yes	yes	yes	yes	yes

Standard errors are clustered by state. MSAs are assigned to the state where its most populous county is located. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

Table A.5: Long Difference Regression: Innovation Concentration
(All variables measured as difference between 1992 and 2007)

	Dependent variable:							
	innovation concentration individuals				innovation concentration firms			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
establishment density	-61.114	-98.625	0.891	-21.825	-25.394	-3.730	-28.249	-22.520
	(114.999)	(123.661)	(104.472)	(105.463)	(75.810)	(75.248)	(83.096)	(88.793)
university R and D	171.094	193.598	256.317	185.616	-301.862	-316.354	-315.640	-305.966
	(391.616)	(386.382)	(395.550)	(396.937)	(247.292)	(246.854)	(252.225)	(247.499)
federal R and D	-134.191	-211.822	-312.052**	-172.013	557.559*	567.112*	612.946**	598.080**
	(232.305)	(269.867)	(129.095)	(136.462)	(292.514)	(310.591)	(275.932)	(278.805)
STEM employment	207.555	172.937	202.937	225.399	-27.526	-5.426	-23.118	-24.663
	(269.245)	(277.270)	(279.138)	(276.637)	(202.740)	(193.341)	(204.488)	(202.377)
HHI employment	-3.325**	-3.188**	-2.723*	-3.214**	0.430	0.336	0.338	0.407
	(1.461)	(1.537)	(1.628)	(1.465)	(1.038)	(1.066)	(0.988)	(1.049)
job reallocation rate	57.833	56.615	36.016	51.519	-32.506	-31.797	-29.418	-31.739
	(48.190)	(48.577)	(48.862)	(46.514)	(39.338)	(39.477)	(36.932)	(37.782)
net job creation rate	-42.737	-40.416	-40.584	-43.774	-40.222	-42.404	-40.360	-39.953
	(39.852)	(40.078)	(39.030)	(38.695)	(50.653)	(52.394)	(50.366)	(50.798)
MSA population	-67.303	-66.796	-47.812	-60.775	55.270**	55.928**	52.043**	53.956**
	(56.332)	(55.416)	(56.998)	(57.496)	(23.533)	(22.613)	(23.246)	(22.557)
loans per establishment	-1.006	-1.150	-1.021	-0.946	0.832	0.898	0.864	0.862
	(2.685)	(2.747)	(2.696)	(2.704)	(0.790)	(0.835)	(0.767)	(0.765)
inventor density	-514.812	-522.781	-171.048	-369.731	120.285	176.235	45.835	73.843
	(493.326)	(385.925)	(526.629)	(465.034)	(299.969)	(316.785)	(265.519)	(292.131)
internal social proximity	-5.995	-6.861	-7.629	-6.135	12.842*	13.227*	13.252*	13.079*
	(5.910)	(5.975)	(6.211)	(6.207)	(6.856)	(7.268)	(6.813)	(6.731)
external social proximity	-357.466	-355.586	-486.431	-399.703	-164.493	-165.850	-147.378	-160.862
	(399.804)	(412.367)	(372.258)	(397.373)	(315.807)	(311.652)	(344.581)	(326.703)
economic freedom: spending	-461.987				179.207			
	(640.642)				(325.629)			
economic freedom: taxation		744.669				-616.539		
		(909.777)				(545.446)		
economic freedom: labor			-1574.801*				210.407	
			(837.915)				(561.588)	
economic freedom: overall				-1505.339				134.252
				(1120.947)				(838.564)
N	272	272	272	272	272	272	272	272
R^2	0.232	0.232	0.257	0.239	0.187	0.190	0.187	0.187

Standard errors are clustered by state. MSAs are assigned to the state where its most populous county is located. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

Table A.6: Long Difference Regression: Product Concentration Narrow
(All variables measured as difference between 1992 and 2007)

	Dependent variable:							
	product concentration narrow individuals				product concentration narrow firms			
	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) OLS	(7) OLS	(8) OLS
establishment density	-34.622	-79.495	23.666	1.734	-39.873	-19.985	-36.184	-25.882
	(113.115)	(121.604)	(95.803)	(100.811)	(66.587)	(67.815)	(77.455)	(80.539)
university R and D	72.431	99.620	158.946	88.523	-202.831	-218.161	-202.345	-202.766
	(393.776)	(385.061)	(402.009)	(401.473)	(202.114)	(202.834)	(196.721)	(199.973)
federal R and D	8.257	-78.260	-189.600	-48.971	460.443*	421.482*	471.825**	489.761*
	(277.152)	(320.414)	(148.654)	(167.520)	(244.621)	(244.010)	(231.780)	(255.885)
STEM employment	89.423	47.632	82.356	105.134	26.606	49.748	28.284	34.500
	(240.869)	(250.405)	(252.299)	(251.748)	(199.968)	(190.187)	(200.593)	(198.351)
HHI employment	-3.252**	-3.085*	-2.644	-3.133**	0.284	0.177	0.290	0.293
	(1.513)	(1.583)	(1.644)	(1.523)	(0.719)	(0.732)	(0.757)	(0.750)
job reallocation rate	63.487	62.029	41.625	57.014	-16.181	-15.523	-16.510	-17.216
	(46.554)	(46.885)	(47.463)	(45.194)	(35.364)	(35.625)	(33.917)	(34.361)
net job creation rate	-32.730	-29.803	-30.681	-33.867	-45.264	-48.405	-45.154	-45.293
	(35.383)	(34.956)	(34.549)	(34.665)	(47.617)	(49.140)	(47.923)	(48.522)
MSA population	-62.475	-62.040	-42.640	-55.515	63.188**	65.079**	63.264**	63.742**
	(57.611)	(56.458)	(57.566)	(59.123)	(25.997)	(26.244)	(25.130)	(24.949)
loans per establishment	-0.058	-0.228	-0.093	-0.016	0.207	0.246	0.221	0.254
	(2.299)	(2.283)	(2.242)	(2.332)	(0.573)	(0.668)	(0.557)	(0.591)
inventor density	-421.644	-440.417	-60.409	-258.095	33.851	154.686	27.025	29.124
	(427.954)	(351.782)	(485.761)	(420.054)	(266.452)	(277.273)	(233.628)	(252.403)
internal social proximity	-3.571	-4.586	-5.324	-3.828	7.530	7.728	7.588	7.725
	(5.603)	(5.614)	(5.663)	(5.803)	(6.590)	(7.002)	(6.614)	(6.738)
external social proximity	-245.421	-243.123	-373.915	-287.957	-377.678	-379.290	-380.150	-386.076
	(367.315)	(377.361)	(347.451)	(369.132)	(294.887)	(292.643)	(318.330)	(305.674)
economic freedom: spending	-536.882				46.013			
	(679.818)				(277.852)			
economic freedom: taxation		924.355				-818.324		
		(883.065)				(587.122)		
economic freedom: labor			-1569.969*				-29.536	
			(899.655)				(468.074)	
economic freedom: overall				-1518.453				-294.547
				(1106.859)				(774.550)
N	272	272	272	272	272	272	272	272
R^2	0.217	0.217	0.241	0.223	0.196	0.203	0.196	0.197

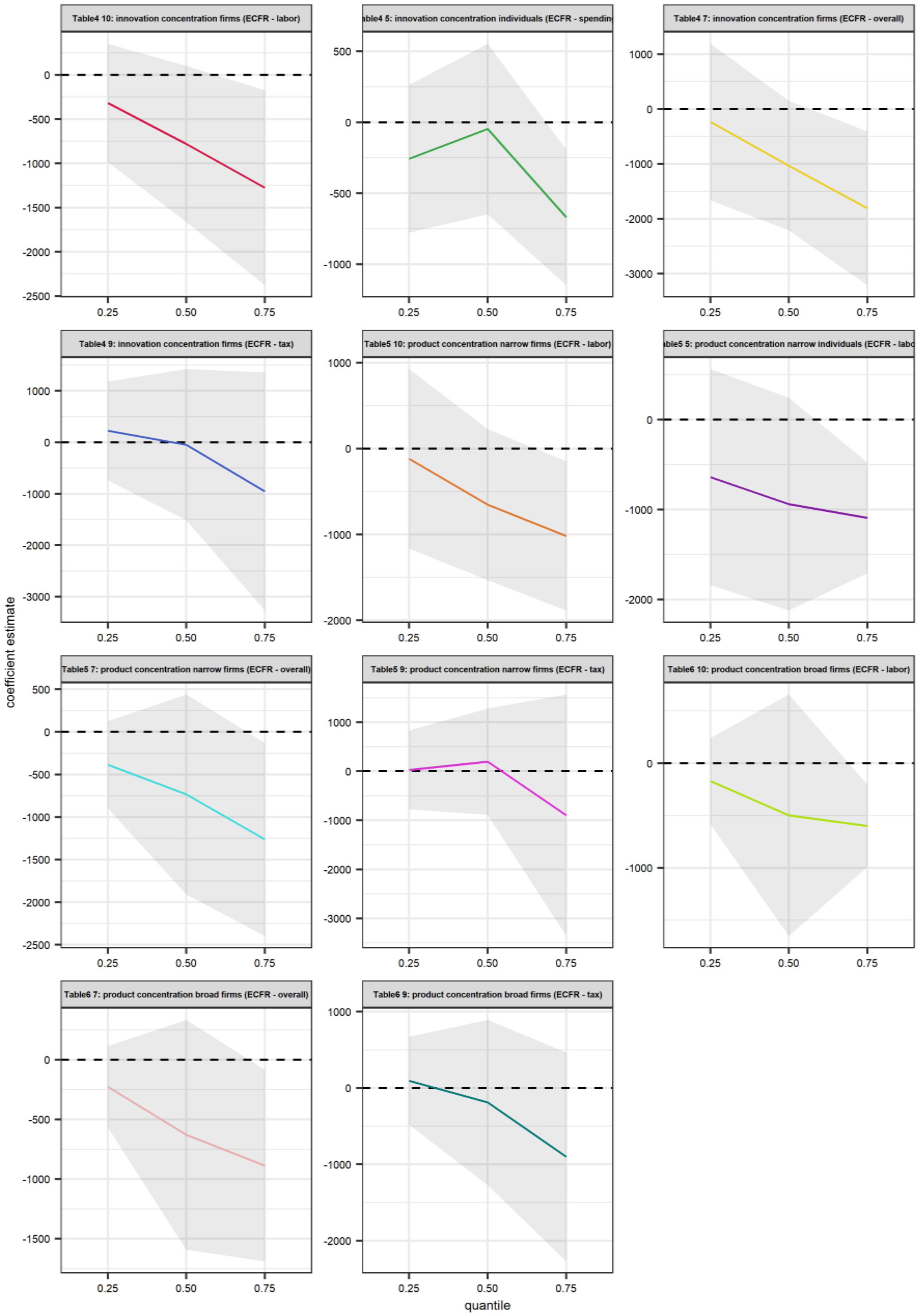
Standard errors are clustered by state. MSAs are assigned to the state where its most populous county is located. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

Table A.7: Long Difference Regression: Product Concentration Broad
(All variables measured as difference between 1992 and 2007)

	Dependent variable:							
	product concentration broad individuals				product concentration broad firms			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
establishment density	39.721	-4.393	90.802	94.126	25.868	44.195	45.474	54.465
	(110.408)	(111.047)	(101.336)	(110.722)	(53.791)	(56.784)	(62.377)	(59.170)
university R and D	239.214	259.902	340.665	265.184	-273.329	-289.035	-252.374	-269.702
	(422.801)	(430.157)	(437.200)	(432.748)	(194.705)	(188.079)	(192.614)	(190.209)
federal R and D	164.296	-63.153	-131.875	62.819	439.971**	366.840**	412.434**	470.614**
	(298.262)	(338.387)	(166.643)	(157.318)	(179.881)	(170.469)	(194.193)	(210.909)
STEM employment	27.564	-5.012	10.454	50.505	40.509	64.059	41.601	55.591
	(275.822)	(302.396)	(284.851)	(278.952)	(175.993)	(169.096)	(175.647)	(176.413)
HHI employment	-3.970***	-3.867**	-3.271**	-3.780**	0.502	0.388	0.654	0.541
	(1.497)	(1.565)	(1.589)	(1.541)	(0.661)	(0.670)	(0.674)	(0.699)
job reallocation rate	34.516	33.106	9.938	24.380	13.671	14.284	8.039	10.726
	(57.656)	(58.722)	(60.218)	(57.248)	(31.984)	(31.670)	(30.048)	(31.212)
net job creation rate	-25.718	-26.234	-23.822	-27.544	-11.829	-15.610	-11.172	-12.121
	(31.422)	(31.730)	(31.827)	(31.528)	(30.632)	(32.007)	(31.930)	(32.227)
MSA population	-73.496	-69.231	-50.054	-62.425	36.283	39.028	41.029*	38.627
	(56.437)	(56.797)	(59.580)	(61.112)	(23.701)	(26.381)	(23.744)	(24.071)
loans per establishment	0.595	0.362	0.482	0.649	0.566	0.584	0.580	0.644
	(1.686)	(1.674)	(1.838)	(1.806)	(0.544)	(0.671)	(0.543)	(0.612)
inventor density	-454.123	-265.335	14.940	-188.505	-18.143	147.389	54.907	10.787
	(384.392)	(372.372)	(435.648)	(422.910)	(275.394)	(282.728)	(248.577)	(261.098)
internal social proximity	-10.117	-11.578	-12.523	-10.591	8.540	8.602	8.227	8.772
	(8.993)	(8.427)	(9.861)	(10.025)	(5.873)	(6.362)	(6.259)	(6.312)
external social proximity	-463.225	-462.060	-604.904*	-529.336	-294.169	-295.941	-328.152	-315.881
	(357.604)	(376.658)	(363.879)	(364.525)	(269.885)	(265.767)	(298.573)	(279.153)
economic freedom: spending	-881.349				-50.032			
	(864.458)				(198.480)			
economic freedom: taxation		156.044				-950.867*		
		(891.919)				(487.100)		
economic freedom: labor			-1734.537**				-414.109	
			(799.445)				(449.005)	
economic freedom: overall				-2361.689*				-767.336
				(1316.328)				(634.314)
N	272	272	272	272	272	272	272	272
R^2	0.227	0.214	0.248	0.240	0.215	0.226	0.219	0.221

Standard errors are clustered by state. MSAs are assigned to the state where its most populous county is located. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

Figure A.1: IV Quantile Regression Coefficient Plots



Shading shows 95% confidence interval.