Innovation and Housing Costs

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Abstract

I examine the link between housing costs within a region and patent applications emanating from the region. For small entrepreneurs self-funding R&D, higher spending on housing could reduce the resources available for innovative investments. For larger firms, higher housing costs may make it more difficult to attract the human resources necessary to fuel innovation (scientists, engineers, technicians, programmers, etc.). Conversely, however, housing cost growth tracks with growth in home values, and higher home values can support innovation and risk-taking for entrepreneurs who borrow against home equity. I examine the net effects of these pressures using a sample of Florida counties from 2005 to 2019. Within counties over my time period, housing cost growth predicts fewer patent filings. Specifically, my tests suggest that shifting county-wide rents for a one-bedroom apartment upwards by $100 (15%) predicts 8% fewer patent applications emanating from the county. I confirm this result in an instrumental variables test that exploits county-level tourist tax policy changes that induce otherwise exogenous variation in housing costs. Overall, my findings support a causal relation wherein higher housing costs discourage innovation.

1. Introduction

In this paper, I investigate the relation between two stylized facts that loom large in Western economies. The first of these facts is that technological innovation is responsible for much, perhaps most, of the economic development witnessed since World War II (Boskin and Lau 1992). The second, that in recent decades housing cost growth has outstripped growth in the real earnings of households and individuals (Airgood-Obryck, Hermann, and Wedeen 2021; Gabriel and Painter 2020).

Given this importance of innovation in economic development, and the prevalence of rapidly growing housing costs, my goal is to explore whether a causal relationship runs from housing cost growth to innovative activity within a region. The relevant literatures in economics, regional science, and finance suggest potential avenues for such a relation, as does simple observation. For example, the U.S. cities with the highest housing costs, like San Francisco and Seattle, are responsible for the bulk of U.S. innovation. Beracha et al. (2021) identify that much of this is due to innovation spurring economic growth that drives housing costs higher. Cross-sectionally, this results in housing being more expensive in areas with innovative, vibrant economies.[1]

This result is well-established, but my analysis explores within-area effects to determine if a relation also runs *from* housing costs *to* innovation. As an example, I am more interested in the question of whether more or less innovation would have emanated from Seattle *if* housing costs in Seattle had grown at a slower rate in recent years. In this light, my question is quite intuitive. For a self-funded Seattle entrepreneur facing a rent hike, paying higher housing costs

[1] Other contributing factors that support this relation include spillovers, learning, and other network effects and externalities that result from having a concentration of innovative companies in one place, as well as urban amenities attracting high quality workers and employers (e.g., Almeida and Kogut 1999; Carlino, Chatterjee, and Hunt 2007; Lööf and Johansson 2014).

may translate to less cash being available for R&D. For larger businesses in Seattle, higher housing costs similarly may make it more difficult to attract the scientists, engineers, researchers, and technicians that fuel innovation, given that housing cost growth has outpaced real wage growth in the U.S. in recent decades (e.g., Airgood-Obryck, Hermann, and Wedeen 2021; Brooks 2021; Quigley and Raphael 2004). If higher housing costs systematically reduce R&D in this manner, then housing cost growth could (negatively) predict innovation outputs like patents.

My conjecture related to entrepreneurs, that those who self-fund R&D may cut back on R&D spending in the face of higher housing costs, is based on a long stream of research in economics and finance that finds firms often respond to financial constraints by cutting back on R&D (Aghion et al. 2012; Brown, Martinsson, and Petersen 2012; Czarnitzki and Hottenrott 2011; Ouyang 2011). These papers build on the premise that the benefits of R&D are uncertain and only realized in the future, which relative to more immediate resource demands (labor, supplies, utilities, taxes, etc.) makes it popular choice to curtail in the face of financial constraints.

My conjecture related to larger businesses, that higher housing costs make it more difficult for these firms to hire R&D workers, builds off of the much broader intuition of Glaeser and Gyourko (2018) and Hsieh and Moretti (2019). Both studies suggest that high housing costs in an area discourage the in-migration of productive workers, which slows economic development. These two papers take a macro-view when describing how higher housing costs can disrupt the efficient allocation of human resources across an economy, and my analysis can be viewed as examining a channel, innovation, through which this inefficient allocation of labor could operate to reduce economic growth.

These twin pressures predicting that higher housing costs reduce innovation, through discouraging either entrepreneurial innovation or the in-migration of innovation workers, are not without tension. Schmalz, Sraer, and Thesmar (2017), for example, use administrative data from France to find that increasing housing prices boost entrepreneurship, as entrepreneurs who own homes can borrow against the upswing in their home's equity. Corradin and Popov (2015) provide similar evidence in a U.S. setting, as do Connolly, La Cava, and Read (2015) in Australia. If this housing collateral effect dominates, on net, then higher housing costs could well increase local innovative activity and patent applications by providing innovative entrepreneurs easier access to financing.

All of these potential channels, through which housing cost growth could either increase or decrease regional innovation, have support in the literature and are likely at play in my setting. Instead of trying to gauge the individual magnitudes of these competing pressures, however, I focus on the *net* effects. That is, on net, does housing cost growth tend to encourage or discourage innovation? While this "on net" approach does not provide much insight on the magnitudes of the specific competing pressures driving the result, its benefit is in offering a relatively straightforward prediction about how we should expect continued housing cost growth to affect innovation.

To analyze these net effects of housing cost growth on innovation, I model patent applications made by inventors to the U.S. Patent and Trademark Office (USPTO) at the county-year level using Florida's 67 counties over a recent 15-year period (2005-2019). My primary independent variable is a measure of residential fair market rent estimated on the county-year level by the U.S. Department of Housing and Urban Development (HUD). After controlling for other local economic covariates like income, unemployment, number of business establishments, population, education, and county and year fixed effects, my models predict that a $100 (15%) increase in the fair market rent for a one-bedroom unit predicts 8% fewer patents on a county-year basis. Robustness checks confirm this result with rental price estimates for other unit sizes (two-bedroom, three-bedroom, etc.) and when using an index of county-year house prices instead of measures of rent.

Importantly, I also confirm this result in a two-stage least squares test where I exploit tourist tax policy changes that introduce reasonably exogenous variation in county-year housing costs. Relative to other states, Florida's popularity as a tourist destination translates to a sizable portion of housing units being held out of long-term use and instead being used as short-term transient rentals for tourists and travelers. I collect data on a series of county-level changes to taxes on short term overnight stays (tourist taxes) that affect housing costs by changing the attractiveness of holding housing units for short-term transient use. Briefly, when these tax policy changes favor holding housing units for short-term use as vacation rentals, more housing units in the county are shifted from long-term use to short-term use, and this reduction in the supply of long-term residential housing units subsequently boosts the market prices for long-term housing in the county (and vice versa).

Intuition and post-estimation tests suggest that these tourist tax policy instruments are both relevant predictors of housing costs *and* unrelated to county-level patenting activity *except* through housing costs. Accordingly, this instrumental variables test permits me to endorse a causal interpretation of my findings. Overall, my results suggest that housing cost growth depresses regional innovation.

This result furthers the literature in two fields of finance and economics. First, while there has been considerable research into the predictors of high housing costs, there has been surprisingly little work on the consequences of unaffordable housing (e.g., Addison, Zhang, and Coomes 2013; Li 2015; Linneman and Megbolugbe 1992). The repercussions of high housing costs that have been studied to date focus primarily on microeconomic tests of health, inequality, migration, and other household-level outcomes (e.g., Berger and Blomquist 1992; Gabriel and Painter 2020; Gordon 2016; Matlack and Vigdor 2008; Nobari et al. 2019; Plantinga et al. 2013),[2] with only a few high-level macroeconomic analyses of total productivity (Glaeser and Gyourko 2018; Hsieh and Moretti 2019).

This paper is also tangentially related to the stream of finance literature connecting mortgage debt to entrepreneurship. In line with my own findings, Bracke, Hilber, and Silva (2018) and Szumilo and Vanino (2021) document that high mortgage debt discourages entrepreneurship, as homeowners with less debt are more willing to pursue risky business endeavors, as they have lower mortgage-related cash flow demands. My investigation is related in that I similarly find that lower housing-related cash flow demands encourage the pursuit of a risky business endeavor, innovation. I provide an incremental contribution to this existing research in documenting that (1) general housing costs, not just mortgage debt, predicts risky business endeavors, and that (2) innovation (i.e., patent applications), and not just small business formation, suffers when housing-related resource demands increase.

This latter point relates to this paper's second contribution, one to the literature on innovation, which has long been a focus of finance and economics research given its importance in powering the U.S. and world economy (Gordon 2016; Romer 1990; Schumpeter 1934; Solow 1957; Wong, Ho, and Autio 2005). Boskin and Lau (1992), for example, estimate that in the post-war period over half of the economic growth in Western economies is attributable to

[2] Brooks (2021) provides a thorough, recent survey of this literature.

technological development and innovation. Accordingly, there is significant interest in explaining the variation between low innovation and high innovation regions, and predictors in the literature include political corruption (Ayyagari, Demirgüç-Kunt, and Maksimovic 2014; Ellis, Smith, and White 2020; Huang and Yuan 2021), financial market sophistication (Brown, Martinsson, and Petersen 2013; Cornaggia et al. 2015; Hsu, Tian, and Xu 2014), religion (Adhikari and Agrawal 2016), taxes (Mukherjee, Singh, and Zaldokas 2017), and education (Varsakelis 2006). I add to this list in documenting that housing costs also play a meaningful role in explaining the regional variation in innovation.

Beyond contributing to the literatures in housing costs and innovation, I hope that connecting these two topics will inform policymakers as to the importance of housing affordability in supporting long run economic development. Addressing this issue at a national level is complicated by the tangle of municipal, county, and state regulations affecting housing, but policymakers at these subnational levels should view my results as suggesting that affordable housing does more than improve health, inequality, and educational outcomes. It also directly improves innovation, which is an important driver of regional economic development.

In the following sections I describe my empirical approach, present results, and briefly conclude.

2. Data and Methods

Higher housing costs could reduce innovation by limiting the resources small entrepreneurs have to spend pursuing innovation or by making it more difficult for larger businesses to obtain the human resources necessary to drive innovation. Alternatively, higher housing costs could spur innovation by providing innovative entrepreneurs more home equity collateral to borrow against. In identifying and analyzing these potential channels, researchers tend to focus on a per-firm basis (using public company data) or a per-inventor/per-entrepreneur basis (using census or other administrative data) (e.g., He and Tian 2013; Schmalz, Sraer, and Thesmar 2017). This approach has the benefit of being able to explicitly measure innovation inputs, like R&D spending, as well as innovation outputs, like patents. One downside of this micro-focused approach is that R&D spending and firm-level patent data is only widely available for the subset of publicly traded firms. Another downside specific to my research question: most public U.S. firms are geographically dispersed (García and Norli 2012), which limits my ability to measure the housing costs affecting specific firms. Using administrative data that offers detailed insight on smaller firms or entrepreneurs can overcome some of these problems, but necessarily restricts tests to a limited sample of typically small enterprises.

Most importantly, however, channel-specific analyses identifying individual mechanisms through which housing costs could affect innovation have, by and large, been examined in detail in the prior literature. Accordingly, I have little interest in rehashing how higher housing values allow for entrepreneurs to borrow against home equity to fund innovation (e.g., Corradin and Popov 2015; Schmalz, Sraer, and Thesmar 2017), or how cash constraints, like those spurred by higher spending on housing, push entrepreneurs to slash R&D (e.g., Aghion et al. 2012; Brown, Martinsson, and Petersen 2012; Czarnitzki and Hottenrott 2011; Ouyang 2011). Rather, my interest is in identifying the *net* effect of these (and all other) combined channels through which housing costs could affect innovation.

On-net studies, rather than using per-firm or per-inventor level models, are usually analyzed on a per-region basis, such as Cowan and Zinovyeva (2013)'s examination of how new universities boost innovation in the nearby areas. I use a similar setup, and I measure regional innovation using patent applications, as patent applicants (i.e., inventors) list their current town of residence on the patent application. This is an admittedly coarse measure, but Acs, Anselin, and Varga (2002) establish that on a regional level, patent counts are a reliable proxy for overall innovative activity. I follow the approach of Acs, Anselin, and Varga (2002) and others (Aryal et al. 2018, 2021) in focusing on the count of utility patent filings/applications on a county-year basis, as focusing on the patent application year as opposed to the patent grant year allows me to avoid having to adjust for the varying lag time between patent applications and patent grants (Hall, Jaffe, and Trajtenberg 2001).[3,4]

I use data on patent filings from the Patent Examination Research Dataset data series provided by the USPTO (Graham, Marco, and Miller 2018).[5] This data series provides downloadable bulk files for all patent applications filed in recent decades. Also included in this data series is a detailed file on the inventors listed on each patent application, including their city and state of residence. After matching the inventors' data to filings, I follow Aryal et al. (2018) and match inventors' city/state data to counties. I then aggregate this data on a county-year level. That is, for each county-year, I generate the count of patent applications that list a county

[3] Utility patents cover products and processes. Design patents, also in the data set I use, are excluded in most other similar studies as well, as design patents cover aesthetic instead of functional dimensions (e.g., newly designed computer fonts are covered by design patents, whereas newly designed computer chips are covered by utility patents).

[4] My focus on regional versus firm innovation also precludes me from focusing on only private sector innovation, which may be more interesting for some readers, as patents from universities and government labs are also included in the USPTO data I use. My conjecture for large firms, based on Glaeser and Gyourko (2018) and Hsieh and Moretti (2019), that higher housing costs make it more difficult to hire R&D workers, could operate similarly for public sector innovators. However, about 94% of all U.S. patents are issued to private sector filers, so while I can only measure innovation at the regional level, almost all of this activity occurs in the private sector (Robbins, Boroush, and Hill 2018).

[5] https://developer.uspto.gov/product/patent-examination-research-dataset-public-pair-stata-dta-and-ms-excel-csv#product-files

resident as an inventor. Note that many patent applications list multiple inventors. In these cases, I attribute the patent to every county in which one of the inventors resides.[6]

The USPTO Patent Examination Research Dataset contains patent application data from inventors all over the world, but I focus my analysis on patent filings emanating from Florida inventors. I focus my analysis on Florida for two reasons. First, Florida's major cities do not cross county lines, so I can more accurately match inventors to counties by town in Florida than in most other states. New York City, for example, spans five counties (one for each borough), Atlanta spans two, and Houston spans three. By comparison, Florida's largest cities (Miami, Orlando, Jacksonville, and Tampa) are all completely contained in single counties. As my housing cost data is measured at the county level, this convenient alignment of Florida's city and county borders permits much more accurate matching of inventors' towns to counties. Secondly, as I detail in a later section, two separate county-level tax policies in Florida introduce largely exogenous variation into county-year housing costs. In later tests, I am able to exploit these policies as instruments in a two-stage least squares test to better identify a causal effect of housing costs on innovation. Florida tax policy is relatively unique in that unlike most states, local tax policy is set at the county and not municipal level. Accordingly, the policy changes I use as instruments induce county-wide changes, which allow for more powerful instruments. Using data from other states where local tax policy is set at the municipal level would not align as closely with my county-level data on patent applications and housing costs.

Fortunately, Florida has 67 counties, so even restricting my analysis to this single state still allows for a large panel. I collect housing costs data for these counties from the Fair Market

[6] In a robustness check I confirm that my results hold when only attributing a patent to the county of the first named inventor on the application, as lead inventors are customarily listed first on patent filings.

Rent data series maintained by the U.S. Department of Housing and Urban Development (HUD). HUD's public housing programs, like Section 8, typically pay recipients a stipend for housing that is adjusted by the housing costs of the area. Section 8, for example, requires recipients to pay 30% of their income towards housing, and then the Section 8 program contributes the difference between this 30% contribution and the 40th percentile rent for the county-year for the size of the unit (one-bedroom, two-bedroom, etc.). Managing this program requires HUD administrators to calculate this 40th percentile rent figure for every county-year for common housing unit sizes, and they do so using data from U.S. census records and surveys of apartment management companies.

HUD makes this fair market rent data available at the county-year, and I use it as my primary measure of county-year housing costs.[7] Prior economics research using this HUD data on Fair Market Rent to proxy for regional housing costs includes Monras (2019), Saiz (2007), and Sharpe (2019), who examine how immigrants' demand for housing affects housing costs.

This Fair Market Rent data series is available at the county level only beginning in the mid-2000s, so I begin my sample period in 2005 and end it in 2019 (to avoid the effects of the Covid-19 pandemic in 2020). This 15-year sample period for all 67 counties in Florida generates a sample of 1,005 county-years (1,005 county-years = 15 years x 67 counties).

I use this sample to estimate the following generalized difference-in-differences model to predict patent filings by county-year:

$$Ln(1 + \#\ Patent\ Applications_{c,t}) = \alpha + \beta_1\ x\ Rent_{c,t} + \Sigma\ Controls_{c,t} \qquad (1)$$

Subscript c indexes county (n = 67), and subscript t indexes year (2005-2019). I primarily use log-linear regression to account for the skewness in patent applications per county-year,

[7] https://www.huduser.gov/portal/datasets/fmr.html

where the median is 14 and the maximum is 1,059 (but in robustness checks I also use count models and linear-linear models). As I mention in the introduction, I am interested in within-county tests, as my focus is on how increasing housing costs affects innovation within a county, as opposed to between county tests that would capture the effect of urban areas having both higher rents and more patents. To estimate within-county models, I include county-level fixed effects. I likewise include year fixed effects to adjust for Florida-wide time series variation.

To ensure that my β_1 treatment effect coefficient is isolating the effect of housing costs, I also control for a host of potentially correlated control variables. Population and the number of workers per county-year likely predicts both housing costs and patents, so I include both as control variables. I draw county-year population data from the U.S. Census Bureau estimates, and my measure for the county-year number of workers comes from the Quarterly Census of Earnings and Wages (QCEW) data series published by the U.S. Bureau of Labor Statistics (BLS). I also control for the county-year number of business establishments from the QCEW data, as more businesses could predict more innovation.

The QCEW data also contains average salary by county-year, which I likewise include, as workers earning higher pay are likely to be higher quality and more likely to innovate. I similarly control for worker quality using data on the percentage of adults over 25 who have a high school diploma and bachelor’s degree. This education data is drawn from the decennial census, so county-year measures are matched to the latest census estimates (2000 or 2010).

Next, to control for county-level trends in innovation and regional trends in innovation, I control for lagged county-level innovation (same-county patent filings in year *t-1*) and concurrent year patent filings in neighboring counties (patent filings for adjacent counties in year *t*). I identify neighboring counties using the NBER County Adjacency file.[8] Finally, to adjust for correlated error terms across years for the same county, I cluster standard errors at the county level (n = 67).

3. Results

3.1 Summary Statistics

The summary statistics for these control variables, as well as county-year measures of rent and patent filings, are reported in Table 1. As previously mentioned, county-year patent filings have a long right tail, as urban counties have many more patents relative to sparsely populated rural counties. The average county-year has 99.6 patent filings, but the median is only 14. Average and median county-year fair market rent for a one-bedroom unit is about $660. Average and median annual salaries are also similar, at about $35,000.

[Table 1 about here]

I report a correlation table for these and other variables in Table 2. As expected, the county-year number of patent applications is strongly positively correlated with measures of housing costs, in keeping with innovation and rents being high in urban areas (e.g., Beracha et al. 2021). Patent filings per county-year is also strongly correlated with education, salaries, and number of residents, as well as the number of businesses.

[Table 2 about here]

[8] https://www.nber.org/research/data/county-adjacency

3.2 OLS Models

I first examine whether housing costs predict patent filings within-county in Table 3, which presents two fixed-effects OLS models. In Column 1 I estimate a baseline regression, which includes all of the control variables but omits a housing cost proxy. Significant predictors of county-year patent filings include lagged same-county patent filings, concurrent-year patent filings in neighboring counties, and the number of business establishments in the county. These control variables, along with the county and year fixed effects, account for almost all of the variation in county-year patent filings, as the model's R^2 exceeds 97%.

In Column 2 I re-estimate this model but include my variable of interest, *Rent (Monthly Rent for 1-bedroom Unit in \$100s)*$_{c,t}$ (I report this measure in units of \$100 for easier interpretation in the tables). This treatment effect loads with a negative and statistically significant coefficient (t = -2.46), indicating that higher housing costs predict fewer patent filings on a county-year basis. The -0.08 coefficient on *Rent (Monthly Rent for 1-bedroom Unit in \$100s)*$_{c,t}$ suggests that a one unit increase in housing costs, or a \$100 increase in typical rents for a 1-bedroom unit, predicts an 8% decrease in patent filings per county-year.[9]

[Table 3 about here]

For comparison, a \$100 increase in rent for a 1-bedroom unit is nearly equivalent to shifting rents from the first quartile to the median, or from the median to the third quartile.[10] To help relate this treatment effect magnitude to other predictors of innovation, Ellis, Smith, and White (2020) similarly find that a one quartile increase in public corruption predicts regional

[9] This treatment effect is also interpretable in increments, such that a \$50 increase in monthly rent predicts a 4% decrease in patent filings, etc.

[10] A \$100 increase in one-bedroom unit rents is similarly about 15% of the sample mean (\$668) and about two-thirds of a standard deviation (\$156).

innovation being lower by about 8%. Likewise, Varsakelis (2006) predicts that regional standardized test scores in math or science decreasing by about one-sixth of a standard deviation would also map to patent filings being about 8% lower.

3.3 Instrumental Variables Test

This first result suggests that higher spending on housing corresponds to fewer patent filings within a county, and at levels that are consistent with other established predictors of patent activity highlighted in the prior literature. However, attributing causality in this OLS analysis is complicated by potential endogeneity problems. For example, a correlated omitted variable problem could arise if the hurricanes that routinely strike coastal Florida both destroy housing (reducing housing supply and driving equilibrium housing prices upwards) and disrupt business activity (reducing patent filings). Similarly, reverse causality could generate my result if real estate is a relatively more attractive investment class when and where innovation is low. In such a case, the low expected returns to entrepreneurship or investment in local firms could induce the marginal investor to invest in real estate, which could push up local real estate values (see Heaton and Lucas 2000 and Hong, Kubik, and Stein 2008).

To rule out these and other endogeneity threats, I use instrumental variables that introduce variation into Florida housing costs that is reasonably exogenous to underlying economic conditions, innovation, and the like. My two instruments exploit county-level changes to Florida tourist taxes, which are sales taxes on short term overnight stays in hotels, vacation rentals, campgrounds, and other short-term accommodations. These county-level tourist taxes make up only a very small piece of county government revenue (about $15 per year per capita for the median county, much lower than comparable revenue figures for property taxes and general sales taxes), but given the prominence of tourism in Florida’s economy, county-level tourist tax policy *does* affect housing costs (Wenner 2019). Most stand-alone rental units, like one-off condos or beach houses rented by owners, avoid paying these county level tourist taxes by keeping a low regulatory profile, whereas hotels are unable to avoid these taxes as they are easy for tax collectors to identify (via zoning records, advertising, health and safety inspections, etc.). Accordingly, county-level tourist tax hikes make one-off vacation rentals *more* attractive than hotels, as hotels are subject to paying this higher tax (Bibler, Teltser, and Tremblay 2021; Wilking 2020). Accordingly, I predict that tourist tax hikes motivate property owners in affected counties to shift housing from long-term rental use (for residents) to short-term rental use (for travelers). If this shift appreciably reduces the supply of housing units available for long-term rental use, then long-term housing costs could rise (in response to reduced supply).

Relatedly, beginning in late 2015 a number of Florida counties, frustrated by small-time landlords evading tourist taxes on their short-term rental units, began establishing tax collection agreements with Airbnb wherein Airbnb collects county-level tourist taxes automatically via the platform and then remits these taxes directly to the county government. These tax collection agreements make holding housing units as short-term rentals *less* profitable for owners, as owners are less able to evade taxes after these agreements are established (given the primacy of the Airbnb platform in the short-term rental market). Bibler, Teltser, and Tremblay (2021) and Wilking (2020) both find that these tax collection agreements spur property owners to move away from Airbnb, and Ellis et al. (2021) document that as a result these Airbnb tax collection agreements reduce housing costs in affected areas by about 2%, which the authors attribute to an increase in the supply of long-term housing units as the marginal property owners shift units from short-term use to long-term rental use (in the face of stronger tax enforcement for short-term rentals).

I use these tourist tax policy changes to instrument for housing costs in Florida counties in Table 4. In Column 1 I present the first stage model, where both instruments load in the expected direction at statistically significant levels. My first instrument, *Tourist Tax Rate (%)*$_{c,t}$, loads with a positive coefficient, which corroborates my prediction that vacation rentals in homes and apartments are more attractive than hotels after increases in local tourist tax rates, as vacation rentals can easily evade these taxes whereas hotels cannot (Bibler, Teltser, and Tremblay 2021). Accordingly, tourist tax hikes spur property owners to shift housing units from long term residential use to short term vacation rentals, which pushes housing costs upwards by reducing the supply of housing units available for long term residents. Similarly, my second instrument, *Airbnb Tax Collection Agreement*$_{c,t}$, loads with a negative coefficient, consistent with Ellis et al. (2021)'s finding that enforcing tourist tax compliance makes using homes as vacation rentals less appealing for property owners (inducing the marginal property owner to shift their unit from the short-term vacation rental market to the long-term rental housing market, which reduces housing costs by boosting the supply of housing units in the residential market).

[Table 4 about here]

I provide the necessary post-estimation tests at the bottom of Table 4. The first such test estimates the weak identification F-statistic at 10.43, which exceeds the rule of thumb cutoff at 10, below which instruments are assumed to be weak. This test suggests that my instruments satisfy the relevance restriction by rejecting the null hypothesis that these tourist tax instruments are only weakly related to housing costs. Reported next is the overidentification J-statistic, which at 0.10 (p-value = 0.75) suggests that my instruments are not correlated with innovation *except* through housing costs, therefore satisfying the exclusion restriction. Together, these post-estimation tests suggest that my instruments are valid (i.e., satisfy both the relevance restriction and exclusion restriction).

Next, after instrumenting rent with *Tourist Tax Rate (%)*$_{c,t}$ and *Airbnb Tax Collection Agreement*$_{c,t}$ in the first stage (Column 1), I use the instrumented measure of housing costs in the second stage model in Column 2. This instrumented variable, *Rent (Monthly Rent for 1-bedroom Unit in $100s)*$_{c,t}$, loads with a negative and statistically significant coefficient in Column 2. This further suggests that higher housing costs predict fewer patents, and by exploiting exogenous variation in housing costs this model both reduces endogeneity concerns and supports a causal interpretation of my results.

3.4 Alternate Measures of Housing Costs

For simplicity, until this point I have measured housing costs using the HUD Fair Market Rent for one-bedroom units at the county-year level. In Table 5, I demonstrate that my results are consistent when using other measures of housing costs. Column 1 in Table 5 replicates the one-bedroom unit result, and in Columns 2, 3, and 4 I use as a housing cost proxy the HUD Fair Market Rent for two-bedroom, three-bedroom, and four-bedroom units, respectively. All three of these rent measures load with a negative coefficient, and only the Column 4 result is not statistically significant. In Columns 2 and 3, the -0.04 coefficient suggests that shifting county-level rents upwards by $100 for two-bedroom or three-bedroom housing units predicts 4% fewer patents originating from the county.

[Table 5 about here]

In Column 5 I employ a different proxy for housing costs, one based on house prices as opposed to rent. The house price measure I use is the county-year House Price Index constructed by the U.S. Federal Housing Finance Agency (FHFA). Briefly, this index is built to track single-family home price changes on a county-year level using repeated property assessments associated with Freddie Mac or Fannie Mae loans. For example, consider a home that sells in Collier County Florida in 2010 for $100,000 and when being refinanced in 2012 is assessed at $108,000. Assuming the home is financed via an FHFA program, FHFA economists observe these repeated assessments for the same property and can use the 8% increase in the home's value over two years to, when combined with all other repeat assessments in Collier County, estimate how home prices change on a county-year level. This measure is described in detail by Bogin, Doerner, and Larson (2019a, 2019b, 2019c) and is used similarly in other studies to proxy for region-year house prices, such as the Berger, Turner, and Zwick (2020) analysis of how tax credits affect housing prices.

The baseline year index value of the FHFA House Price Index (HPI) is one, but baseline years vary by county (larger counties have index values dating back to the 1970s, whereas smaller counties only have index values beginning in the 1990s or early 2000s). To control for this difference, I normalize all HPI measures to the 2004 value, which is the year prior to the beginning of my sample period. I use this normalized HPI measure to proxy for housing prices and housing price growth in my sample counties, but note that I lose some county-years from my sample in my associated tests, as some years a few of the smaller counties in my sample do not have enough repeat assessment-type transactions for the FHFA to accurately estimate an HPI (which is represented as blank or missing data in the underlying index).

This normalized house price measure, *FHFA House Price Index (normalized to 2004)*$_{c,t}$, loads with a negative and statistically significant coefficient in Column 5. The -0.53 coefficient suggests that a unit (100%) increase in home prices would predict a 53% decrease in patent applications, or, alternatively, that a 1% increase in home prices in a county predicts 0.53%

fewer patents emanating from that county. Importantly, the consistency of my result to this alternate measure indicates that my finding is neither an artifact of the HUD Fair Market Rent data nor strictly limited to measuring housing costs via rent.

3.5 Alternate Regression Specifications

I next test the robustness of my result to alternative regression specifications. As mentioned previously, my primary models (Tables 3, 4, and 5) use a log-linear form to adjust for the skewness in county-year patent filing counts. In Table 6 I confirm the consistency of my result to other regression specifications, namely linear OLS, negative binomial count models, and Poisson pseudo-likelihood models. Column 1 reports the linear OLS model and sees the rent covariate (*Rent (Monthly Rent for 1-bedroom Unit in $100s)*$_{c,t}$) load with a negative and significant coefficient of -15.3. This coefficient indicates that a $100 increase in county-wide rents for one-bedroom units predicts about 15 fewer patent applications originating from the county. In alternative terms, this maps to a 15% increase in rent predicting a 15% decrease in patents at the county level. A smaller treatment effect emerges in Column 2, the negative binomial count model, where the -0.05 coefficient (two-tailed p-value = 0.04) on *Rent (Monthly Rent for 1-bedroom Unit in $100s)*$_{c,t}$ maps to a $100 increase in countywide rents predicting a 4.8% decrease in patents.

I report a similar count-type model in Column 3 using Poisson pseudo-likelihood regression. Briefly, Santos Silva and Tenreyro (2006) find that heteroskedasticity can lead to biased, inconsistent estimators in log-linear models. Correia, Guimarães, and Zylkin (2020) suggest that a generalized case of Poisson regression, termed Poisson pseudo-likelihood regression, provides more consistent estimators in these cases. I report such a regression in Column 3, where the treatment effect suggests that a $100 increase in county-wide rents for one-bedroom units predicts an 4.6% decline in county-wide patent applications (two-tailed p-value < 0.001). Together, these three regressions confirm across alternate specifications that higher housing costs predict fewer patents in within-county tests.

[Table 6 about here]

3.6 Lead Inventors Only

My prior robustness checks focus on different measures of housing costs and different types of regression models. Next, I test the robustness of my result to measuring patent applications in different ways. In my prior tests I attribute patents to all listed inventors (and their counties of residence), but in Table 7 I only attribute patents to the county of the lead inventor listed on the patent application. The lead inventor, or first listed inventor on a patent application, holds no special legal or ownership status, but the slot is traditionally reserved for the inventor who contributed the most to the patent in question.

I confirm my findings to this alternative measure of patent applications in Table 7, where I report models using all four types of rental housing costs (one-bedroom to four-bedroom) as well as the FHFA HPI measure of single-family home prices. Briefly, all of these covariates load with a negative coefficient that is at least marginally statistically significant. The economic magnitude of these results is analogous to that of the prior models as well. In Column 1, for example, a $100 increase in county-level rents for one-bedroom units predicts a 6% reduction in patent applications from a lead inventor. For comparison, the Table 3 result using all inventors generates a corresponding treatment effect size of 8%.

[Table 7 about here]

3.7 Inventor Team Size

Next, I examine whether solo inventors, small inventor teams (two or three inventors), or large inventor teams (four or more inventors) are differentially affected by housing cost pressures. My data on patent filings only includes inventors' names, city of residence, and patent application number, so identifying which filings come from small entrepreneurs and which come from larger businesses is not perfectly clear. However, I can estimate tests by the number of inventors associated with each patent filing. My ad hoc intuition is that patents with a single named inventor are more likely to emanate from small entrepreneurs, whereas patents with large teams of listed inventors are more likely to originate from larger businesses. In my sample of Florida patent applications from 2005 to 2019, patent filings by solo inventors, small inventor teams (two or three inventors), and large inventor teams (four or more inventors) each account for about one third of patent filings. In Table 8, I model how housing costs predict patent filings for each of these inventor team classifications.

Columns 1 through 4 report county-year panel regressions predicting how HUD Fair Market Rent for different apartment unit sizes predict patent filings in the county-year by solo inventors, and Column 5 reports a similar model using the FHFA Home Price Index. All of these different measures of housing costs load with negative coefficients, and four do so at statistically significant levels. Similar results emerge from Columns 6 through 10 that analogously estimate patent filings by small teams of inventors, where two or three inventors are listed on the patent filing. The results for large inventor teams in Columns 11 through 15 are less strong, but still indicative of higher housing costs reducing patent filings.

[Table 8 about here]

F-tests do not uncover any systematic differences in magnitudes in these treatment effects by inventor team size. Overall, I interpret this admittedly ad hoc evidence as suggesting that higher housing costs map to fewer patent filings for all types of inventor teams, including solo inventors, small inventor teams, and large inventor teams. This effect does not seem, for example, to be limited only to small entrepreneurs, where patent filings by solo inventors are likely more common, or to large businesses, where patent filings by teams are likely more common.

4. Conclusion

Innovation has been perhaps the most important driver of economic growth in Western economies in recent decades (Boskin and Lau 1992). Accordingly, understanding the pressures that encourage and inhibit innovation is a topic of interest for researchers in economics, finance, public policy, law, regional science, and sociology, among others. I extend this literature by examining whether housing cost growth affects innovation. This analysis is predicated on a simple conjecture that higher housing costs could (1) reduce the financial resources that small entrepreneurs have available to invest in R&D, (2) make it more difficult for larger businesses to attract and hire the scientists, researchers, programmers, engineers, and technicians necessary to generate innovation, or conversely (3) make it easier for entrepreneurs to finance innovation by borrowing against rising home equity.

Using a county-year panel covering Florida’s 67 counties from 2005 to 2019, I find that on net, the former pressures dominate, in that housing cost growth predicts fewer patent applications. I estimate within-county models using county and year fixed effects, and I consistently document that shifting area rents upward by 1% predicts patent filings by resident inventors falling by about 0.5%. Mean and median rents for one-bedroom apartments in this sample are about $660, which suggests that shifting county-level rents for these units upward by $100 (15%) predicts 8% fewer patents originating from the county in question (on an annual basis). In robustness checks I confirm that this relation is consistent using alternate regression specifications, different rules to assign patent filings to counties, and for different sizes of inventor teams.

Most importantly, I confirm the county-level relation between higher housing costs and fewer patent applications in a two-stage least squares test that instruments for housing costs with two tax policy measures. Briefly, this test exploits exogenous variation in county-level housing costs brought on by county-level tourist tax policies that increase or decrease the appeal of holding housing units for short-term vacation rentals instead of long-term residential rentals. Post-estimation tests suggest that these instruments satisfy both the relevance and exclusion restrictions, and the second stage model corroborates my prior findings by establishing that the tax policy-induced exogenous variation in housing costs predicts the number of patent filings at the county-year level.

I view this finding as linking two separate economics literatures, as to date prior research has established that higher housing cost burdens reduce entrepreneurial risk-taking (Bracke, Hilber, and Silva 2018) and discourage the in-migration of workers (e.g., Plantinga et al. 2013), as well as stymie overall regional economic productivity (Glaeser and Gyourko 2018; Hsieh and Moretti 2019). My analysis highlights one channel, innovation, via which the former pressures (i.e., housing cost growth spurring a reduction in entrepreneurial risk-taking and creating an impediment to attracting human resources) contribute to the latter outcome (i.e., a reduction in regional economic productivity).

Finally, for policymakers, this finding could be of interest in further highlighting the importance of affordable housing. Policies that restrict land use and drive up housing costs, like single-family only zoning, minimum lot sizes, and building height limits, are often popular with voters who own homes and have incentives to curb local housing supply or preserve local character (e.g., Glaeser, Gyourko, and Saks 2005; Glaeser and Ward 2009; Ihlanfeldt 2007). While often pursued by well-meaning regulators and politicians, my results suggest that these policies may curtail innovation, which is likely an unintended consequence, but one that could have measurable fallout by slowing economic growth in affected regions.

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Table 1: Summary Statistics

Summary statistics at the county-year level for all 67 Florida counties from 2005 to 2019. Subscript *c* indexes county, and subscript *t* indexes year.

Variable	n (county-years)	Mean	Std. Dev.	Minimum	1st Quartile	Median	3rd Quartile	Maximum
# Patent Applications$_{c,t}$	1,005	99.6	183.8	0.0	1.0	14.0	103.0	1,059.0
# Patent Applications by First Named Inventor$_{c,t}$	1,005	64.9	121.1	0.0	1.0	8.0	66.0	718.0
Monthly Rent for 1-bedroom Unit$_{c,t}$	1,005	668.3	156.5	315.0	545.0	659.0	766.0	1,266.0
Monthly Rent for 2-bedroom Unit$_{c,t}$	1,005	803.7	202.4	406.0	648.0	786.0	935.0	1,682.0
Monthly Rent for 3-bedroom Unit$_{c,t}$	1,005	1,067.9	282.6	488.0	865.0	1,046.0	1,237.0	2,157.0
Monthly Rent for 4-bedroom Unit$_{c,t}$	1,005	1,219.4	359.4	544.0	933.0	1,188.0	1,462.0	2,761.0
FHFA House Price Index (normalized to 2004)$_{c,t}$	929	1.1	0.2	0.6	1.0	1.1	1.3	1.6
# Adjacent County Patent Applications$_{c,t}$	1,005	462.4	507.6	0.0	45.0	286.0	741.0	2,314.0
% Adults with High School Dipolma$_{c,t}$	1,005	82.4	8.0	54.2	77.4	84.0	88.7	94.6
% Adults with Bachelors Degree$_{c,t}$	1,005	20.2	9.5	6.8	12.4	18.4	27.9	45.7
% Unemployed$_{c,t}$	1,005	6.3	2.8	2.1	3.9	5.6	8.2	14.7
Average Annual Salary$_{c,t}$	1,005	35,916.4	6,005.9	24,478.0	31,598.0	34,917.0	39,354.0	56,621.0
Population$_{c,t}$	1,005	290,000.0	460,000.0	7,581.0	27,642.0	110,000.0	330,000.0	2,800,000.0
# Workers$_{c,t}$	1,005	110,000.0	200,000.0	1,184.0	6,868.0	31,633.0	120,000.0	1,200,000.0
# Business Establishments$_{c,t}$	1,005	8,854.1	15,947.6	111.0	518.0	3,071.0	8,296.0	100,000.0
% Tourist Tax Rate$_{c,t}$	1,005	3.3	1.6	0.0	2.0	3.0	5.0	6.0
Airbnb Tax Collection Agreement$_{c,t}$	1,005	0.2	0.4	0.0	0.0	0.0	0.0	1.0

Table 2: Correlation Matrix

Pearson correlations of the pooled county-year data for all 67 Florida counties from 2005 to 2019. Subscript *c* indexes county, and subscript *t* indexes year.

	Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
(1)	# Patent Applications$_{c,t}$	1.00															
(2)	Monthly Rent for 1-bedroom Unit$_{c,t}$	0.52	1.00														
(3)	Monthly Rent for 2-bedroom Unit$_{c,t}$	0.51	0.98	1.00													
(4)	Monthly Rent for 3-bedroom Unit$_{c,t}$	0.51	0.96	0.98	1.00												
(5)	Monthly Rent for 4-bedroom Unit$_{c,t}$	0.51	0.93	0.95	0.96	1.00											
(6)	FHFA House Price Index (normalized to 2004)$_{c,t}$	-0.03	-0.19	-0.20	-0.20	-0.15	1.00										
(7)	# Adjacent County Patent Applications$_{c,t}$	0.40	0.41	0.41	0.37	0.37	-0.11	1.00									
(8)	% Adults with High School Dipolma$_{c,t}$	0.32	0.59	0.60	0.63	0.63	-0.30	0.09	1.00								
(9)	% Adults with Bachelors Degree$_{c,t}$	0.56	0.67	0.67	0.67	0.66	-0.12	0.20	0.79	1.00							
(10)	% Unemployed$_{c,t}$	-0.04	0.07	0.03	-0.01	-0.06	-0.69	0.13	-0.02	-0.10	1.00						
(11)	Average Annual Salary$_{c,t}$	0.71	0.68	0.69	0.70	0.72	0.03	0.33	0.53	0.69	-0.18	1.00					
(12)	Population$_{c,t}$	0.78	0.55	0.54	0.53	0.55	0.05	0.37	0.20	0.43	-0.05	0.68	1.00				
(13)	# Workers$_{c,t}$	0.79	0.52	0.51	0.49	0.51	0.09	0.35	0.19	0.43	-0.08	0.69	0.98	1.00			
(14)	# Business Establishments$_{c,t}$	0.78	0.56	0.55	0.54	0.55	0.06	0.34	0.18	0.42	-0.06	0.67	0.99	0.97	1.00		
(15)	% Tourist Tax Rate$_{c,t}$	0.44	0.53	0.52	0.53	0.55	-0.09	0.26	0.55	0.57	-0.07	0.62	0.37	0.39	0.35	1.00	
(16)	Airbnb Tax Collection Agreement$_{c,t}$	0.00	0.06	0.10	0.12	0.13	0.17	-0.01	0.06	-0.04	-0.31	0.23	0.02	0.03	0.02	0.08	1.00

Table 3: OLS Models with County and Year Fixed Effects

Log-linear OLS models predicting the number of patent applications emanating from Florida counties on a county-year basis over the 2005-2019 window. Fixed effects for county and year are included. Subscript *c* indexes county, and subscript *t* indexes year. T-statistics are reported in brackets beneath coefficients. Standard errors are clustered at the county level. Two-tailed statistical significance at the $p < 0.10$, $p < 0.05$, and $p < 0.01$ level is denoted by *, **, and ***, respectively.

$\text{Ln}(1 + \#\ \text{Patent Applications}_{c,t}) = \alpha + \beta_1 \times \text{Rent}_{c,t} + \Sigma\ \text{Controls}_{c,t}$	1	2
Rent (Monthly Rent for 1-bedroom Unit in \$100s)$_{c,t}$		-0.08**
		[-2.46]
Ln(1 + # Patent Applications$_{c,t-1}$)	0.17***	0.17***
	[3.42]	[3.50]
Ln(1 + # Adjacent County Patent Applications$_{c,t}$)	0.12*	0.12*
	[1.69]	[1.69]
% Adults with High School Dipolma$_{c,t}$	0.01	0.01
	[0.54]	[0.48]
% Adults with Bachelors Degree$_{c,t}$	0.01	0.02*
	[1.48]	[1.73]
% Unemployed$_{c,t}$	-0.01	-0.01
	[-0.51]	[-0.21]
Average Annual Salary (\$1,000s)$_{c,t}$	0.02	0.01
	[1.15]	[1.00]
Ln(1+Population$_{c,t}$)	-0.31	-0.42
	[-0.55]	[-0.74]
Ln(1+ # Workers$_{c,t}$)	0.25	0.32
	[0.47]	[0.61]
Ln(1+ # Business Establishments$_{c,t}$)	1.10**	1.09**
	[2.06]	[2.03]
County and Year Fixed Effects	Yes	Yes
Observations	1,005	1,005
R^2	97.13%	97.15%

Table 4: Two-Stage Least Squares Model

Two-stage lease squares model that in the first stage instruments county-year rent with the county-year tourist tax rate and an indicator for whether the county has a tax collection agreement in place with Airbnb. The second stage uses the instrumented rent from the first stage to predict county-year patent applications in a log-linear fixed effects OLS model. Data covers all 67 Florida counties on a county-year basis over the 2005-2019 window. Fixed effects for county and year are included. Subscript *c* indexes county, and subscript *t* indexes year. T-statistics are reported in brackets beneath coefficients. Standard errors are clustered at the county level. Two-tailed statistical significance at the p < 0.10, p < 0.05, and p < 0.01 level is denoted by *, **, and ***, respectively.

	First Stage DV: $Rent_{c,t}$	Second Stage DV: Ln(1 + # Patent $Applications_{c,t}$)
	1	2
Instrument: Tourist Tax Rate $(\%)_{c,t}$	0.08*	
	[1.82]	
Instrument: Airbnb Tax Collection $Agreement_{c,t}$	-0.19**	
	[-2.16]	
Instrumented: Rent (Monthly Rent for 1-bedroom Unit in $100s)$_{c,t}$		-0.64*
		[-1.93]
Weak Instrument F-statistic	10.43	
Overidentification J-statistic	0.10 (p-value = 0.75)	
Other Controls Included but Suppressed from Output	Yes	Yes
County and Year Fixed Effects	Yes	Yes
Observations	1,005	1,005
R^2	94.55%	97.16%

Table 5: OLS Models with County and Year Fixed Effects and Alternate Measures of Housing Costs

Log-linear OLS models predicting the number of patent applications emanating from Florida counties on a county-year basis over the 2005-2019 window. Fixed effects for county and year are included. Subscript *c* indexes county, and subscript *t* indexes year. T-statistics are reported in brackets beneath coefficients. Standard errors are clustered at the county level. Two-tailed statistical significance at the $p < 0.10$, $p < 0.05$, and $p < 0.01$ level is denoted by *, **, and ***, respectively.

$Ln(1 + \# \text{ Patent Applications}_{c,t}) = \alpha + \beta_1 \times \text{Housing Costs}_{c,t} + \Sigma \text{ Controls}_{c,t}$	1	2	3	4	5
Rent (Monthly Rent for 1-bedroom Unit in $100s)$_{c,t}$	-0.08**				
	[-2.46]				
Rent (Monthly Rent for 2-bedroom Unit in $100s)$_{c,t}$		-0.04*			
		[-1.70]			
Rent (Monthly Rent for 3-bedroom Unit in $100s)$_{c,t}$			-0.04**		
			[-2.19]		
Rent (Monthly Rent for 4-bedroom Unit in $100s)$_{c,t}$				-0.01	
				[-0.62]	
FHFA House Price Index (normalized to 2004)$_{c,t}$					-0.53**
					[-2.25]
Other Controls Included but Suppressed from Output	Yes	Yes	Yes	Yes	Yes
County and Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	1,005	1,005	1,005	1,005	929
R^2	97.15%	97.14%	97.14%	97.13%	97.03%

Table 6: Alternate Model Specifications

Robustness checks using alternate regression specifications. Column 1 reports a linear OLS model, Column 2 reports a negative binomial (count) model, and Column 3 reports a Poisson pseudo-likelihood model. Each model predicts the number of patent applications emanating from Florida counties on a county-year basis over the 2005-2019 window. Fixed effects for county and year are included. Subscript *c* indexes county, and subscript *t* indexes year. T-statistics are reported in brackets beneath coefficients. Standard errors are clustered at the county level. Two-tailed statistical significance at the $p < 0.10$, $p < 0.05$, and $p < 0.01$ level is denoted by *, **, and ***, respectively.

	# Patent Applications$_{c,t}$ = $\alpha + \beta 1$ x Rent$_{c,t}$ + Σ Controls$_{c,t}$		
	1	2	3
Rent (Monthly Rent for 1-bedroom Unit in $100s)$_{c,t}$	-15.31***	-0.05**	-0.05**
	[-3.64]	[-2.06]	[-2.58]
Regression Model Type	Linear OLS	Negative Binomial	Poisson Pseudo-likelihood
Other Controls Included but Suppressed from Output	Yes	Yes	Yes
County and Year Fixed Effects	Yes	Yes	Yes
Observations	1,005	1,005	1,005
R^2	94.07%	39.35%	97.36%

Table 7: OLS Models with County and Year Fixed Effects for Lead Inventors Only

Log-linear OLS models predicting the number of patent applications emanating from Florida counties on a county-year basis over the 2005-2019 window. In this robustness check, counties are only credited as the source of a patent application if home to the first named (lead) inventor on the patent application. Fixed effects for county and year are included. Subscript *c* indexes county, and subscript *t* indexes year. T-statistics are reported in brackets beneath coefficients. Standard errors are clustered at the county level. Two-tailed statistical significance at the $p < 0.10$, $p < 0.05$, and $p < 0.01$ level is denoted by *, **, and ***, respectively.

$\text{Ln}(1 + \text{\# Patent Applications by First Named Inventor}_{c,t}) = \alpha + \beta_1 \text{ x Housing Costs}_{c,t} + \Sigma \text{ Controls}_{c,t}$	1	2	3	4	5
Rent (Monthly Rent for 1-bedroom Unit in \$100s)$_{c,t}$	-0.06*				
	[-1.86]				
Rent (Monthly Rent for 2-bedroom Unit in \$100s)$_{c,t}$		-0.05*			
		[-1.72]			
Rent (Monthly Rent for 3-bedroom Unit in \$100s)$_{c,t}$			-0.03		
			[-1.49]		
Rent (Monthly Rent for 4-bedroom Unit in \$100s)$_{c,t}$				-0.03*	
				[-1.68]	
FHFA House Price Index (normalized to 2004)$_{c,t}$					-0.71***
					[-2.90]
Other Controls Included but Suppressed from Output	Yes	Yes	Yes	Yes	Yes
County and Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	1,005	1,005	1,005	1,005	929
R^2	97.05%	97.05%	97.05%	97.06%	96.91%

Table 8: OLS Models with County and Year Fixed Effects by Inventor Team Size

Log-linear OLS models predicting the number of patent applications emanating from Florida counties on a county-year basis over the 2005-2019 window. In this robustness check, inventor teams are subdivided by size (solo inventors, small inventor teams, and large inventor teams). Counties are credited as the source of a patent application if home to any named inventor on the patent application. Fixed effects for county and year are included. Subscript *c* indexes county, and subscript *t* indexes year. T-statistics are reported in brackets beneath coefficients. Standard errors are clustered at the county level. Two-tailed statistical significance at the $p < 0.10$, $p < 0.05$, and $p < 0.01$ level is denoted by *, **, and ***, respectively.

	$Ln(1 + \# \text{ Patent Applications}_{c,t}) = \alpha + \beta_1 \times \text{Housing Costs}_{c,t} + \Sigma \text{ Controls}_{c,t}$														
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Rent (Monthly Rent for 1-bedroom Unit in $100s)$_{c,t}$	-0.05					-0.10***					-0.06				
	[-1.46]					[-2.92]					[-1.61]				
Rent (Monthly Rent for 2-bedroom Unit in $100s)$_{c,t}$		-0.05*					-0.06**					-0.03			
		[-1.80]					[-2.06]					[-0.70]			
Rent (Monthly Rent for 3-bedroom Unit in $100s)$_{c,t}$			-0.04**					-0.03*					-0.04*		
			[-2.24]					[-1.72]					[-1.91]		
Rent (Monthly Rent for 4-bedroom Unit in $100s)$_{c,t}$				-0.03**					-0.01					0.01	
				[-2.05]					[-0.94]					[0.63]	
FHFA House Price Index (normalized to 2004)$_{c,t}$					-0.87***					-0.39*					0.01
					[-3.71]					[-1.70]					[0.05]
Inventor Team Type			Solo Inventor					Small Inventor Team (Two or Three Inventors)					Large Inventor Team (Four or More Inventors)		
Other Controls Included but Suppressed from Output	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County and Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,005	1,005	1,005	1,005	929	1,005	1,005	1,005	1,005	929	1,005	1,005	1,005	1,005	929
R^2	96.16%	96.17%	96.17%	96.18%	96.03%	96.31%	96.28%	96.28%	96.27%	96.01%	95.43%	95.42%	95.43%	95.42%	95.25%