

# **Economic Diversification and The Resiliency Hypothesis: Evidence from the Impact of Natural Disasters on Regional Housing Values**

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**Abstract.** We estimate the effect regional economic diversification has on the resiliency of the U.S. housing market treating the spatial and temporal variation in natural disasters as exogenous shocks to regional economies. Our study demonstrates that diversity dampens both the magnitude and the duration of the effects of a disaster on local real estate values. Implications of our findings for the potential benefits of diversification in regional economies are discussed.

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## 1 Introduction

The extraordinary behavior of residential real estate markets over the housing boom and bust of the early part of this century has heightened awareness of the connections between local real estate markets and the overall health of metropolitan economies. Not only is there an impact running from the labor market to the strength of housing market demand, but the state of the housing market has a direct effect on local labor markets and production. There is an interest, on that account, in those characteristics of local economies that might mitigate large swings in housing prices.

Much of this focus has been on the characteristics of the local housing market. It has long been recognized that markets that can be characterized as having fewer topographical or political barriers to construction may have milder cyclical variation in housing prices, although there is also a recognition that negative shocks to housing markets will have larger cyclical implications because of the fixity of housing supply (Glaeser and Gyourko 2005). Less work has been directed to understanding the interplay between local labor markets and housing market dynamics. One natural link is the relationship between the industrial diversity of a local economy and the cyclical variation in housing markets. As noted in Coulson, Liu and Villupurim (2013), the relationship between housing prices and the important industries in an area is taken as commonplace (see e.g. Norman (2018) for San Francisco and McGeal (2010) for Detroit). The idea that a major concentration in a particular sector can have an outsized influence on home values naturally leads to the consideration whether a diverse economic base can dampen the cyclical variation in the real estate market. However, little research exists that considers the roles that regional economic diversity – or “the extent to which the economic activity of a region is distributed among a number of categories” – plays in the U.S. housing market (Parr 1965 p. 21).

It has been long argued that economic diversity plays a key role in promoting both regional economic growth as well as regional economic stability (Parr 1965, Kort 1991, Siegel et al. 1994, Siegel et al. 1995, Attaran 1986, Wagner and Deller 1988). Commonly, stability is defined in terms of the “absence of variation in economic activity over time” (Malizia and Ke 1993 p. 222). Along these lines and recognizing the inexorable link between the demand for housing and local labor market conditions,

Coulson et al. (2013) provided the first empirical evidence demonstrating that increases in economic diversification effectively leads to decreases in home price volatility. In a related work, Barth et al. (2015) show that home prices in Metropolitan Statistical Areas (MSAs) starting with a relatively lower degree of diversification tend to rise as these MSAs become less diversified. Conspicuously absent from this literature is any formal empirical examination of the role that regional economic diversity plays in promoting housing market resiliency. We address this shortcoming here.

Formally defined, resilience refers to “the ability or capacity of a system to absorb or cushion against damage or loss” (Rose and Liao 2005 p. 78; Holling 1973). Henceforth, in economics, resilience<sup>1</sup> is often defined as “the ability of a regional economy to maintain or return to a pre-existing state (typically assumed to be an equilibrium state) in the presence of some type of plausibly exogenous (i.e. externally generated) shock” (Hill et al. 2012). The fundamental empirical challenge to identifying the link between diversity and resilience is that regional housing market downturns are rarely ever exogenous to local labor market conditions. Economic diversification is no exception. To circumvent this difficulty, we investigate the link between diversity and resilience by estimating the effect economic diversification has on explaining real estate price dynamics to natural disasters.

Natural disasters provide a useful context for studying the effect of diversification on resiliency for several reasons. First, the exogenous nature of disasters gives us a unique setting to study housing market responses to shocks net of concerns stemming from potential endogeneity between real estate market performance and regional business cycles. Second, with the frequency and severity of natural disasters on the rise, studying the economic impacts of disasters is an economically meaningful pursuit in its own right. Through this lens, our paper contributes to broader research efforts in the environmental economics literature on climate change and human adaption by adding a complementary discussion centered on steps local policymakers might take to improve the economic resilience of their locality to climate-induced shocks.

The emphasis on housing prices is appropriate for many reasons beyond its

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<sup>1</sup> Martin and Sunley (2015) contain a more detailed discussion of the conceptualization and explanations of regional economic resilience.

importance to the local economy. The compensating differentials literature (Roback 1979; Albouy 2017) suggests that home (more specifically, land) prices are the most important statistic for gauging the quality of life.<sup>2</sup> More than home rents, or even wages, they are, given their role as asset valuations, the single best indicator of the present and future streams of quality of life available. The measurement of the long-term impact of natural disasters can best, and perhaps only, be measured through house price changes.

We focus our empirical work on housing market responses to hurricanes and typhoons using a panel dataset of purchase-only house price indices at the MSA level which are maintained by the Federal Housing Finance Agency (FHFA). We link these data to FEMA's National Emergency Management System (NEMIS) which indicates the month, day, year and impacted MSA for the universe of federally declared disasters. Finally, we compute the usual measure of economic diversification for each MSA – a fractionalization index of labor market income across NAICS supersectors – using industry level data from the Quarterly Census of Employment and Wages (QCEW).

We estimate the impact of a disaster using a difference-in-differences (DID) fixed effects estimator. This approach allows us to identify the average price effect due to a shock by estimating changes in home prices before and after a disaster hits impacted MSAs relative to home price dynamics across non-impacted MSAs. To test the hypothesis that regional economic diversification is a catalyst for resiliency, we estimate the effect regional economic diversity has on attenuating the impacts of natural disasters on local home prices.

To preface our main findings, our empirical results show that the impact of a disaster depends both on the level of diversity and the time elapsed since a shock. Highly concentrated regions experience price declines as large as -4.7% in the year immediately following a disaster. These initial impacts persist for as long as two years. Economic diversity has the effect of dampening the immediate price response due to a shock as well as the persistence of these initial price declines. We estimate that a one-standard deviation increase in diversification (relative to the mean level of diversification in the U.S. economy) offsets the immediate (one to two year) price effects of a disaster as much as 1.96% to 2.3%.

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<sup>2</sup> See also Coulson, Liu and Villupurim (2013).

We position our empirical findings into broader discussions in the literature centered on the potential “dual effects” of diversifying a regional economy. Researchers and policymakers often debate the value of diversification in terms of the direct effect of diversification on growth. In part, the tension in the literature exists given the competing views about the role diversity plays in influencing economic growth. For example, some view diversification as a movement away from potential efficiency gains resulting from specialization and, perhaps, mitigating economic growth (see e.g. Izraeli and Murphy, 2003). Others argue that diversification moves the economy towards an environment where knowledge spillovers can occur between industries, thus catalyzing economic growth (see e.g. Glaeser et al., 1992). Further complicating this matter, there exists a fundamental empirical challenge to estimating the direct effect of diversification on market outcomes. To identify a causal link, one would have to acknowledge the possibility that unobserved determinants of the market outcome of interest may also be correlated with diversity. Motivated by this observation, we build off the earlier work of Bartik (1991), Card (2001), and Ottoviano and Perri (2006) and propose an instrumental variables estimation strategy capable of controlling for this level of endogeneity. We then show that the benefits of diversification expressed in terms of resiliency do not appear to be offset by any potential costs stemming from a corresponding departure from industrial specialization.

We proceed by providing a background on related works in Section (2). We summarize our study area and data in Section (3). We present our empirical methodology in Section (4) and our findings in Section (5). In Section (6) we discuss potential threats to the identifying assumptions of our model. We summarize and conclude in Section (7).

## **2 Background**

The argument that industrial diversification may lead to reduced volatility and resilience in metropolitan economies is long-standing. Barth et al. (1975) note that, as would be suggested by standard portfolio theory, a diversified portfolio of industry employment yields lower overall volatility in metro employment. The emphasis on the use of portfolio theory as a lens through which to view employment volatility led to the

insight that what mattered was not simply diversity as such, but the covariances of sectoral employments. Diversity is simply a means to tamp down the effect of these covariances on aggregate employment variability. The portfolio approach was pursued in much of the subsequent literature, including Malizia and Ke (1993) and Izraeli and Murphy (2003) with respect to unemployment changes and Siegel et al. (1998) and Wagner and Deller (1998) in the context of an input-output model. Hammond and Thompson (2004) also note that greater industrial specialization yields greater employment volatility but also emphasized the role of local demographic characteristics.

Interestingly, Carvalho (2014) notes the idea that disaggregating the economy into smaller sectors will serve to dampen the overall effects of a disturbance to any one sector was perpetuated by the earlier work of Lucas (1977, page 20) who writes:

“In a complex modern economy, there will be a large number of such shifts in any given period, each small in importance relative to total output. There will be much ‘averaging out’ of such effects across markets.”

Inspired by the lessons of the 2011 earthquake in Japan, Carvalho (2014) provides a new and more sophisticated perspective on the role of diversification in the national economy by advancing a multisector general equilibrium model. The key insight of Carvalho (2014) is that whether or not diversity catalyzes resiliency may ultimately depend on the complexity of the input-output linkages between sectors in an economy. In effect, Carvalho (2014) argues that cyclical fluctuations may arise from small shocks working their way through or across input linkages. In a diversified but horizontal economy, disaggregation leads to decreases in aggregate volatility. In contrast, once Carvalho (2014) relaxes the assumption that intermediate producers work in isolation from each other, shocks to one sector may propagate through other sectors. In this paper we abstract away from modeling input-output linkages across sectors within our small *regional* economies, but instead focus our efforts on modeling the degree to which labor market activity is fractionalized across sectors.

We note here that there exists a separate debate on the role that diversity plays in promoting productivity. On this front, the empirical analyses by Frenken et al. (2007) takes up an additional reason that diversity may enhance economic growth: a broad

variety of industries increases the possibility of Jacobs (inter-industry) productivity spillovers (Glaeser et al. 1992). Note, however, that our focus on resilience to shocks has little to do with productivity spillovers and much more to do with the ability of a broader based economy to handle stress. Reliance on a small set of industries for economic health can be detrimental when shocks are specific to those sectors.

Estimating the causal effect of diversification on growth presents an entirely different set of challenges that originate from the presence of endogeneity stemming from latent confounders that are both correlated with the outcome of interest and diversity. Drawing on a recent study by Nizalova and Murtazashvili (2016), we revisit this issue and formally demonstrate that even if diversity and the economic outcome of interest are both related to unobservables, the assumption that natural disasters are conditionally random is sufficient to recover the causal effects of diversity on resilience using our estimation strategy. Of course, our baseline empirical specification is ultimately limited in its ability to identify the causal, direct effect of diversity on growth.

A formal examination of the relationship between diversity and growth is beyond the scope of what we are trying to achieve with this paper; nonetheless, in section (6) we present a solution to the identification problem we describe above by re-tooling the shift-share instrumental variable advanced by Ottaviano and Perri (2006) – which these authors initially formulated to study the economic value of cultural diversity – in order to instrument for economic diversity. This strategy, which has not been utilized in the extant literature on economic diversity identifies fruitful avenues for future research on the broader economic implications of diversification.

More closely related to our work, Feyrer, Sacerdote, and Stern (2007) study the impacts of the Rust Belt shock. More specifically, these authors examine the role that 1977 diversity levels played in explaining 1977 to 2000 population growth rates between shocked and non-shocked counties. However, as noted in the published comment associated with this manuscript, a potential threat to identification stems from concerns regarding the extent to which shocks considered by the authors are plausibly exogenous<sup>3</sup>. Hill et al. (2012) investigate drivers of resilience with quantitative case studies of

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<sup>3</sup>Please refer to the comment section associated with this manuscript by Albert Saiz available on Page 90 of Feyrer, Sacerdote, and Stern (2007).

metropolitan areas and show that diversity may attenuate an economic downturn.

The study most like ours is Xiao and Drucker (2013). Xiao and Drucker (2013) examine the relationship between economic diversity and employment and income dynamics following the 1993 U.S. Midwest flood. These authors' empirical work represents a significant advance over previous studies to the extent that the authors analyze the effects of a plausibly exogenous shock. Xiao and Drucker (2013) show that more diverse counties witnessed relatively larger increases in employment following the flood than less diverse counties; a finding which is consistent with the hypothesis that diversity is a driver of economic resiliency.

Our study further contributes to various strands of the environmental economics literature centered on real estate market responses to natural disasters (Harrison et al. 2001, Bin and Polasky 2004, Hallstrom and Smith 2005, Morgan 2007, Bin et al. 2008, Daniel et al. 2009, Kousky 2010, Bin and Landry 2013, Atreya et al. 2013, Atreya and Ferreira 2015, Boustan et al. 2017, McCoy and Walsh 2018, and Dillon-Merrill et al. 2018). Apart from Boustan et al. (2017) and Dillon-Merrill et al. (2018), these studies focus on the micro-level (e.g. within MSA) impacts of a shock. For instance, Bin and Landry (2013) estimate relative changes in housing prices between properties inside and outside statutorily designated flood-risk zones before and after two major hurricanes in Pitt County, North Carolina. Likewise, McCoy and Walsh (2018) study the impacts of wildfire on housing values by comparing home prices before and after fire across various dimensions of treatment including view of fire, proximity to fire, and latent fire risk.

Unlike these studies, Boustan et al. (2017) study the effect of natural disasters on migration rates, home prices, and local poverty rates in U.S. counties from 1920 to 2010. These authors show that a natural disaster may result in a 6% decrease in housing prices and a 3% decrease in rents. Dillon-Merrill et al. (2018) study the impacts of natural disasters on U.S. housing prices and rents using a national dataset on disasters for 242 MSAs. These authors find that natural disasters lead to permanent increases in housing rents but have an ambiguous effect on housing values.

### **3 Study area and data**

The primary dataset utilized in this paper is the quarterly, purchase-only house price



index (HPI) database developed by the Federal Housing Finance Agency (FHFA).<sup>4</sup> The HPI is a weighted, repeat-sales index constructed from repeat mortgage transactions of single-family properties for the 100 largest MSAs in the U.S. as defined by the Office of Management and Budget (OMB). In cases for which the population in any given MSA exceeds 2.5 million, the FHFA divides said MSA into a subset of Metropolitan Divisions.<sup>5</sup> In these cases, the FHFA computes HPIs for each Metropolitan Division, instead of the MSA each division resides within. For the sake of exposition, we refer to our geographic unit of observation throughout the paper as an “MSA” included in the FHFA database. The purchase-only HPI is available for each of these MSAs from the first quarter of 2001 to the fourth quarter of 2016.

In order to construct a measure of economic diversity, we obtained industry level wage data from the Bureau of Labor Statistics’ Quarterly Census of Employment and Wages (QCEW).<sup>6</sup> Of particular interest to us are total wages, which track total compensation paid during the calendar quarter to employees within each NAICS supersector of each U.S. county.<sup>7</sup> NAICS supersectors which are synonymous with two digit NAICS codes represent the twenty, top-level industry groupings in the United States<sup>8</sup>. We measure economic diversity by first aggregating total wages within each NAICS supersector,  $s$ , across counties residing within the same MSA,  $i$ , at each year-quarter time-step,  $t$ . We employ the usual measure of economic diversification that is based on the fractionalization index of labor market income across NAICS supersectors,

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<sup>4</sup> Link to data: <https://www.fhfa.gov/>.

<sup>5</sup> The FHFA divides the following MSAs into Metropolitan Divisions: Boston-Cambridge-Newton, MA-NH; Chicago-Naperville-Elgin, IL-IN-WI; Dallas-Fort Worth-Arlington, TX; Detroit-Warren-Dearborn, MI; Los Angeles- Long Beach-Anaheim, CA; Miami-Fort Lauderdale-West Palm Beach, FL; New York- Newark-Jersey City, NY-NJ-PA; Philadelphia-Camden-Wilmington, PA-NJ-DE-MD; San Francisco-Oakland-Hayward, CA; Seattle-Tacoma-Bellevue, WA; Washington-Arlington-Alexandria, DC-VA-MD-WV. Additional information on MSA and division titles may be found here: <http://www.whitehouse.gov/sites/default/files/omb/bulletins/2015/15-01.pdf>.

<sup>6</sup> Link to data: <https://www.bls.gov/cew/datatoc.htm>.

<sup>7</sup> In cases where total county level wages for a particular industry are suppressed by the BEA, we impute wages by multiplying the share of total state level establishments located in the given county of interest by total state quarterly wages of said industry.

<sup>8</sup> The set of NAICS Supersectors includes: Sector 11: Agriculture, Forestry, Fishing and Hunting; Sector 21: Mining, Quarrying, and Oil and Gas Extraction; Sector 22: Utilities; Sector 23: Construction; Sector 31-33: Manufacturing; Sector 42: Wholesale Trade; Sector 44-45: Retail Trade; Sector 48-49: Transportation and Warehousing; Sector 51: Information; Sector 52: Finance and Insurance; Sector 53: Real Estate and Rental and Leasing; Sector 54: Professional, Scientific, and Technical Services; Sector 55: Management of Companies and Enterprises; Sector 56: Administrative and Support and Waste Management and Remediation Services; Sector 61: Educational Services; Sector 62: Health Care and Social Assistance; Sector 71: Arts, Entertainment, and Recreation; Sector 72: Accommodation and Food Services; Sector 81: Other Services (except Public Administration); Sector 92: Public Administration.

$$DIV_{it} = 1 - \sum_{s \in S} [Share_{st}^i]^2, \quad (1)$$

where  $Share_{st}^i$  denotes the share of labor market income for industry  $s$  within MSA  $i$  at time  $t$ .

We treat the universe of federally declared hurricanes and typhoons as exogenous shocks to local real estate markets. Data describing these events are maintained by FEMA's<sup>9</sup> National Emergency Management Information System (NEMIS). NEMIS tracks all disasters beginning with the first declared disaster in 1953 and ending with the most recent disaster as of August 26, 2016. For each federally declared disaster, NEMIS indicates the impacted county and records the month, day, and year each disaster began. We use the County to MSA crosswalk provided by the United States Census Bureau to map impacted counties into impacted MSAs. Using these data, we can effectively identify the entire history of natural disasters impacting each MSA in our study area.

We provide a graphical illustration of the 100 MSAs included in our sample in Figure (1). To visualize differences in the degree of diversification across MSAs, Figure (1) illustrates the average level diversification within each MSA over the study period standardized to have a mean of zero and standard deviation equal to one. Henceforth, MSAs in dark green represent the least diversified regions (e.g. those with long-run average diversity levels 3.95 to 2.14 standard deviations below the mean MSA). Likewise, MSAs in bright red represent the most diversified regions; those with long-run average diversity levels .98 to 1.45 standard deviations above the mean MSA. Lastly, we provide a list of every MSA in our sample in appendix Table A1 along with each MSAs home price and diversity rank in 2001 and 2016.

[Figure (1): About Here]

[Figure (2): About Here]

Figure (2) plots the trend in home prices for every MSA in our sample. Specifically, panel (a) of Figure (2) plots the growth rate in the HPI for each MSA using 2001 as the base. Overall prices increased steadily between 2001 and 2006 and declined precipitously after 2007. To further illustrate the degree to which the bubble burst, in panel (b) we plot

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<sup>9</sup> Link to data: <https://www.fema.gov/media-library/assets/documents/28318>. The version of this dataset that we utilize in this paper was retrieved from fema.gov on August 26, 2016. "FEMA and the Federal Government cannot vouch for the data or analyses derived from these data after the data have been retrieved from the Agency's websites(s) and/or Data.gov."

the growth rate in home prices for every MSA relative to 2006. Panel (a) of figure (3) plots standardized diversity indices for every MSA; this figure indicates that there does exist a systematic trend across MSAs, but seems to suggest that MSAs that were relatively less diverse in 2001 grew increasingly more diverse by 2016. However, further inspection of the data indicates the slight upward trend common to MSAs beginning with relatively low levels of diversity at the beginning of the study period reflects a broader trend across all MSAs. To see this, in panel (b) we compute the average level diversity across all MSAs within each year; inspection of the average trend across all MSAs provides a more detailed perspective. During the housing boom, the average MSA grew increasingly more diverse; following the housing bust, the trend reverted.

Despite these overall trends in diversity, we learn that there exists an immense amount of heterogeneity in the trajectory of our small regional economies. To further illustrate the variation in the data, we compute the growth rate,  $g_{i,01-16}$ , in economic diversification between 2001 and 2016 for each individual MSA  $i$  in our sample. Panel (a) of figure (3), which plots the growth rate for every MSA over time shows while the majority of MSAs experienced positive overall growth in diversity, many MSAs exhibited negative overall growth to further quantify this level of variation, panel (b) plots the distribution of growth rates among all MSAs in the data using a kernel density estimator to approximate the density of  $f(g_{i,01-16})$  from observations on  $g_{i,01-16}$ . While the average MSA became more diverse between 2001 and 2016, 31% of MSAs experienced negative overall growth.

[Figure (3): About Here]

[Figure (4): About Here]

## 4 Methods

To study the impact of regional growth shocks on residential housing prices, we estimate a difference-in-differences model exploiting the random nature of regional disasters. More specifically, we employ the fixed effects estimator,

$$\ln(HPI)_{it} = \sum_{\tau=-T}^T \{\beta_{\tau} \cdot W_{i\tau} + \delta_{\tau} \cdot (W_{i\tau} \times DIV_{it})\} + \gamma \cdot DIV_{it} + \alpha_i + \lambda_{it} + \varepsilon_{it}, \quad (2)$$

where  $\ln(HPI)_{it}$  is the log transformed housing price index for MSA  $i$  in time  $t$ ,  $DIV_{it}$  is

the fractionalization index for regional economic activity for MSA  $i$  in time  $t$ , and  $W_{i\tau}$  is a treatment-indicator  $\tau$  years prior to or after a disaster-related event. To fix ideas,  $W_{i(2)}$  is equal to one if at time  $t$  MSA  $i$  is within 1 to 2 years of a disaster. Likewise,  $W_{i(-2)}$  is equal to one if at time  $t$  MSA  $i$  is within -1 to -2 years of a disaster. Additionally,  $\alpha_i$  captures MSA-specific, time-invariant unobserved heterogeneity. Finally,  $\lambda_{it}$  includes an exhaustive set of year-quarter fixed effects and MSA specific, fixed effects and linear time trends. Note, the causal interpretation of  $\beta_\tau$  and  $\delta_\tau$  stems from the assumption that whether or not a region is hit by a natural disaster is random conditional on MSA and year-quarter fixed effects.

We specify equation (2) with a series of three pre-disaster and three post-disaster event indicators and, similar to Gallagher (2014), bin each  $W_{i\tau}$  for any time period  $\tau < -3$  and for any time period  $\tau > 3$  by creating single event indicator variables for the end periods of the event study,  $W_{i(-T)}$  and  $W_{i(T)}$ . The inclusion of  $W_{i(-T)}$  and  $W_{i(T)}$  simply serve the practical purpose of allowing us to study how home prices evolve in the years shortly after a disaster (e.g.  $\tau \in [1,3]$ ) as well as in the years shortly before a disaster all estimates taken relative to the year immediately before a disaster ( $\tau = -1$ ).

The classical difference-in-differences estimator is typically operationalized by excluding the interaction terms  $W_{i\tau} \times DIV_{it}$  from the model. In this case the researcher relies on estimates of  $\beta_\tau$  to identify the average impact of the event of interest. However, the inclusion of  $W_{i\tau} \times DIV_{it}$  allows us to estimate how the average effect of a disaster is influenced by economic diversity. Letting  $DIV^j$  denote a particular value of  $DIV_{it}$ , the relevant parameter of interest to us is,

$$\theta(\tau, DIV^j) = \beta_\tau + \delta_\tau \cdot DIV^j. \quad (3)$$

For the sake of clarity, with  $DIV^j$  set at the mean  $\mu_{DIV}$ , parameter estimates of  $\theta(\tau, \mu_{DIV}) = \beta_\tau + \delta_\tau \cdot \mu_{DIV}$  represent the average impact of a disaster in the  $\tau^{th}$  year following a shock. Thus, the interpretation of  $\theta(\tau, \mu_{DIV})$  parallels what is typically reported in related works focused more exclusively on estimating the average impact associated with an event.

In our empirical work we first present parameter estimates of  $\theta(\tau, DIV^j)$  evaluated across the distribution of  $DIV_{it}$ . We use the superscript “j” to refer to the “j<sup>th</sup>” percentile of

$DIV_{it}$ . This approach also allows us to evaluate the economic significance of diversification on resiliency by reporting the magnitude of the estimated impact of a shock at different values of diversity,  $j$  and  $j'$  (e.g.  $\theta(\tau, DIV^j)$  vs.  $\theta(\tau, DIV^{j'})$ ). We formally test the hypothesis that economic diversification is a catalyst for resiliency by examining whether or not the impact of a disaster on home prices are is affected by changes in diversity. More precisely, if economic diversity catalyzes price resiliency to disasters then,

$$\frac{\partial \theta(\tau, DIV^j)}{\partial DIV^j} > 0. \quad (4)$$

Finally, one of the underlying identifying assumptions of our model is that the average change in home values across impacted MSAs would have been proportional to the average change in prices in non-impacted MSAs in the absence of treatment. While we cannot directly test whether or not this assumption holds, we provide evidence supporting parallel trends by investigating estimates of  $\theta(\tau, DIV^j)$  in the periods leading up to a disaster (e.g.  $\tau < -1$ ).

## 5 Results

Table (1) presents parameter estimates of  $\theta(\tau, DIV^j)$  obtained from estimating equation (2). Each column of Table (1) reports estimates evaluated at various values of economic diversity starting with the 5<sup>th</sup> percentile of diversity in column (1) and ending with the 95<sup>th</sup> percentile of diversity in column (7). Standard errors, which are reported in parenthesis, are clustered at the MSA level.

[Table (1): About Here]

As noted above, the underlying identifying assumption of our empirical model is that the average change in housing prices across impacted MSAs would have been proportional to the average change in prices across non-impacted MSAs in the absence of treatment. To assess the validity of this assumption, we first focus our attention on coefficient estimates in the time periods leading up to a disaster. For instance, focusing on the 5<sup>th</sup> percentile of diversity, model estimates for  $\theta(-3, DIV^5)$  and  $\theta(-2, DIV^5)$  are small in magnitude and statistically insignificant. Turning attention to columns (2) through (7), parameter estimates for  $\theta(-3, DIV^j)$  and  $\theta(-2, DIV^j)$  are also statistically

insignificant and close to zero in magnitude. Independent of the level of diversification, we find no statistical evidence suggesting that home price trends among impacted regions differ from home price trends in non-impacted regions in the years leading up to a shock; an empirical finding that lends credence to the underlying identifying assumption of the model.

Next, we turn our attention to coefficient estimates of the post-disaster treatment indicators. As indicated in column (1), at the 5<sup>th</sup> percentile of diversity, we estimate that disasters induced a statistically significant reduction in housing prices of 4.8% and 5.2% in the first two years following a shock, respectively. After two years, we do not detect a statistically significant impact of a disaster on housing prices, which suggests that the immediate market impacts of a disaster are economically relevant but nonetheless transitory.

Next, we focus our attention to parameter estimates of  $\theta(+1, DIV^j)$ , which capture the immediate, first year impact of a shock. Table (1) shows that as we move from the 5<sup>th</sup> to the 10<sup>th</sup> percentile of diversity, the first-year impact of a disaster decreases in magnitude from -4.8% to -2.8%. Estimates further decline as we move to the 25<sup>th</sup> percentile but remain statistically significant. At the average level of diversity in the data (column 4), model estimates indicate a 0.8% reduction in home prices. Coefficient estimates reported in columns (2) and (3), which reveal the market impacts of a hurricane at the 10<sup>th</sup> and 25<sup>th</sup> percentiles of diversity, are not suggestive of a statistically meaningful reduction in prices in the second year following a shock. In contrast, we do estimate a statistically significant price effect two years after a shock when evaluated at the 5<sup>th</sup> percentile of diversity. We visualize these findings in Figure (5). Specifically, panel (a) of Figure 5 plots coefficient estimates on the y-axis against years since a shock on the x-axis for non-diversified MSAs. Panel (b) plots coefficient estimates for the diversified MSAs.

To summarize these findings, recall that the parameter  $\theta(\tau, DIV_{it})$  represents the price impact of a disaster in the  $\tau^{th}$  year after a shock conditioning the level of diversity  $DIV_{it}$ . Estimates of  $\theta(\tau, DIV_{it})$  allow us to evaluate differences in the degree to which housing prices change in response to a disaster at any point in time and at any level of regional diversity. Model results reported in Table (1) show that highly concentrated

regions (e.g. those lying below the 25<sup>th</sup> percentile of diversity) experience negative and statistically significant price declines in the first two years following a shock. However, as diversity increases, these immediate price responses attenuate towards zero. Collectively, these findings indicate that diversification attenuates both the magnitude and the duration of the impacts of a disaster on regional housing values.

### 5.1 The resiliency hypothesis

The empirical findings presented in the preceding section lend credence to the resiliency hypothesis. To the extent that economic diversification attenuates the immediate impact and the persistence of a shock, our estimates suggest that diversification has an economically meaningful impact on an MSAs level of resiliency. Here, we formally test if diversification has a statistically significant effect on resiliency.

We formalize a test of the resiliency hypothesis by first recalling that the estimated price effect of a disaster  $\tau$  years after a disaster hits expressed as a function of diversity is given by,

$$\theta(\tau, DIV_{it}) = \beta_{\tau} + \delta_{\tau} \cdot DIV_{it}. \quad (5)$$

This expression allows us to derive the direct effect that a unit increase in diversity has on attenuating home price responses due to a disaster,

$$\frac{\partial \theta(\tau, DIV_{it})}{\partial DIV_{it}} = \delta_{\tau}. \quad (6)$$

Note that  $DIV_{it}$  is bounded above by one. As such, it is useful to consider estimates of  $\delta_{\tau} \cdot s_{DIV} = \tilde{\delta}_{\tau}$ . Scaling parameter estimates of  $\delta_{\tau}$  by the standard deviation of diversity in the data ( $s_{DIV}$ ) has no impact on statistical inference, but does serve the practical purpose of allowing us to interpret estimates of  $\tilde{\delta}_{\tau}$  as the effect diversification has on dampening the price effects of a shock due to a one standard deviation increase in diversity. Along these lines, we evaluate the resiliency hypothesis by testing if the signs on coefficient estimates of  $\tilde{\delta}_{\tau}$  are positive in years in which we estimate statistically significant reductions in housing values due to a disaster. We express the resiliency hypothesis more formally below:

$$\begin{aligned} H_0: \tilde{\delta}_{\tau} &= 0 \\ H_A: \tilde{\delta}_{\tau} &\neq 0 \end{aligned}$$

Table (2) reports estimates of  $\tilde{\delta}_{\tau}$  derived from coefficient estimates of equation (2).

For time periods in which we estimate statistically significant reductions in housing values due to a disaster (e.g. periods +1 and +2) we reject the null hypothesis in favor of the alternative that  $\tilde{\delta}_1$  and  $\tilde{\delta}_2$  are statistically different from zero. Likewise, in time periods where the coefficient estimates of  $\theta(\tau, DIV_{it})$  are insignificant (e.g. periods -3, -2, 3, and 4) we fail to reject the null hypotheses that  $\tilde{\delta}_\tau$  equal zero.

These findings provide statistical evidence allowing us to reject in the null hypothesis in favor of the resiliency hypothesis. Yet, whether or not these tests are valid ultimately depends on the underlying identifying assumptions of our empirical model. We proceed by discussing the potential threats to the identifying assumptions of our modeling exercise.

## 5.2 Threats to identification

The first identifying assumption of our empirical model is that conditional on MSA and time fixed effects, the shocks we introduce to regional economies are random. This assumption cannot be explicitly tested; instead, we rely on the conditionally random nature of a natural disaster as one piece of evidence supporting.

The second identifying assumption of our empirical model is that non-impacted MSAs serve as valid control groups for impacted MSAs; that is, to interpret our estimates as causal requires one to assume that price trends in impacted MSAs would have been proportional to price trends in non-impacted MSAs in the absence of treatment. While this assumption cannot be explicitly tested, our empirical findings in section (5) provide evidence supporting it. More specifically, model estimates of equation (2) reported in Table (1) demonstrate that in the period of time leading up to a shock, there does not exist economically or statistically meaningful differences in pre-treatment price trends between impacted and non-impacted regions.

Lastly, we highlight that economic diversification ( $DIV_{it}$ ) appears in our empirical specification both by itself and in an interacted form with a suite of disaster indicators,  $DIV_{it} \times W_{i(\tau)}$ . As such, one might raise the concern that if economic diversity and housing values are both related to some latent confounder, since coefficient estimates on  $W_{i(\tau)}$  and  $DIV_{it} \times W_{i(\tau)}$  are both used to test the resiliency hypothesis, model estimates of the impact of diversity on resiliency (e.g. coefficient estimates of the interaction terms)



are potentially problematic due to the inconsistency of the estimator.

The key to addressing this criticism is to highlight that the variables  $W_{i(\tau)}$  capture conditionally random events: climate shocks. This feature of our model changes how we typically think about the interactions of  $W_{i(\tau)}$  with a potentially endogenous regressor. Most notably, as inferred from Nizalova and Murtazashvili (2016), if disasters are conditionally independent of both  $\varepsilon_{it}$  and  $DIV_{it}$ , then coefficients on the interaction terms  $DIV_{it} \times W_{i(\tau)}$  can still be consistently estimated whether  $DIV_{it}$  is independent of  $\varepsilon_{it}$ , or not. Henceforth, since we only rely on estimates of the coefficients on  $DIV_{it} \times W_{i(\tau)}$  and  $W_{i(\tau)}$ , the conditionally random nature of disasters allows us to consistently estimate the effect of diversification has on catalyzing resiliency.

### 5.3 Alternative model specifications

Next, we test the robustness of our model estimates to alternative model specifications. In the baseline log-linear specification described in equation (2), parameter estimates of  $\theta(\tau, DIV_{it})$  represent the *approximate* percent change in housing values  $\tau$  years after an event. The actual percent change is  $\exp[\theta(\tau, DIV_{it})] - 1$ . Table (3) replicates Table (2), but reports estimates of  $\exp[\theta(\tau, DIV_{it})] - 1$  instead of  $\theta(\tau, DIV_{it})$ . Across all time periods ( $\tau$ ) and all values of diversity, estimates of  $\exp[\theta(\tau, DIV_{it})] - 1$  in Table (3) are qualitatively similar to the estimates reported in Table (2).

We also consider the following variant of estimating equation (2) which allows diversity to enter the model in a non-linear fashion:

$$\ln(HPI)_{it} = \sum_{\tau=-T}^T \{\beta'_{\tau} \cdot W_{i\tau} + \delta'_{\tau} \cdot (W_{i\tau} \times \ln(DIV_{it}))\} + \gamma' \cdot \ln(DIV_{it}) + \dots$$

$$\dots + \alpha'_i + \lambda'_{it} + \varepsilon'_{it}. \quad (7)$$

Here, we superscript all model parameters to indicate we are estimating a different model. Given estimates of equation (7), the price effect of a disaster  $\tau$  years after a disaster impacts a region expressed as a function of diversity is,

$$\theta'(\tau, DIV_{it}) = \beta'_{\tau} + \delta'_{\tau} \cdot \ln(DIV_{it}). \quad (8)$$

Parameter estimates of  $\theta'(\tau, DIV_{it})$  which we report in Table (4) are also qualitatively

similar to parameter estimates of  $\theta(\tau, DIV_{it})$  in Table (2)<sup>10</sup>.

## 6 The direct effect of diversification on housing values

Our findings show that regional economic diversification tamps down the effects of a disaster on housing values. These findings indicate that there may exist meaningful benefits from enhancing local, urban variety as a means to mitigating housing price responses to externally generated shocks. However, resiliency is only one of the three main objectives policy makers often seek to achieve through diversification; price stability and price appreciation other relevant considerations. While Coulson et al. (2013) demonstrates that economic diversity effectively decreases housing price volatility, less work has been dedicated to understanding the direct effect of diversification on housing values. We proceed by addressing this shortcoming of the literature.

On the theoretical front, a priori, the relationship between diversity and housing values is ambiguous. Some researchers have noted that diversification necessarily implies a departure from specialization. From a pure quantitative perspective, this is true. Moreover, to the extent that there may exist efficiency advantages stemming from specialization, some have argued that diversification may be an impediment to economic growth and thus, leading to decreases in home values. Izraeli and Murphy (p.2, 2003) summarize this sentiment quite succinctly<sup>11</sup>:

“The theory of comparative advantage shows very clearly the gain from specialization and trade. In the context of a nation, the geographic concentration of production benefits sub-national units, i.e., regions. This rationale explains why regions specialize in one or few industries in which they enjoy a comparative advantage over their trade partners.”

Taking a different view, Glaeser et al. (1992) emphasize the importance of knowledge spillovers that occur between industries. Their idea, which is consistent with the earlier work of Jacobs (1969), suggests that “variety and diversity of geographically proximate industries rather than geographical specialization promote innovation and growth.” (p.

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<sup>10</sup> Model estimates reported in Table (2) are also unchanged if we allow allowing diversity to enter the model in a quadratic form.

<sup>11</sup> As indicated by Izraeli and Murphy (2003), the dual effects of diversity on economic stability and growth are also considered by Gilchrist and St. Louis (1990), Attaran (1986), and Cutler and Hansz (1971).

1128). On this account, diversity may ultimately lead to increases in housing values.

On the empirical front, there exists inherent difficulties in estimating the direct effect of diversity on home prices. As we note earlier, to establish a causal link one would need to confront the possibility that diversification is an endogenous covariate. An ideal but impractical experimental setting is one in which economic diversity in an MSA changes randomly and without regard to local economic conditions. Given the lack of this ideal setting, alternative approaches must be considered. We advance one such approach here.

To do this, we adopt an instrumental variables approach and construct an instrumental variable that is correlated with changes in diversification in a given MSA, is otherwise exogenous to local economic conditions in said MSA, and is arguably excludable from the structural equation. We construct this instrument by adopting the shift-share methodology used by Ottaviano and Perri (2006), Card (2001), and Bartik (1991). The structure of the instrument we use parallels the instrument utilized by Ottaviano and Peri (2006) in their analysis of the economic value of cultural diversity. With the goal of re-tooling these authors' instrument for our empirical setting, we first recall that our measure of economic diversification is given by the fractionalization index:

$$DIV_{it} = 1 - \sum_{s \in S} [Share_{st}^i]^2, \quad (4)$$

where  $Share_{st}^i$  denotes the share of labor market income for industry  $s$  within MSA  $i$  at time  $t$ . Letting  $Share_{st}^{Nation/i}$  denote the national share of labor market income for industry  $s$  excluding the contribution of MSA  $i$  from the numerator and the denominator of this share.

Given  $Share_{st}^{Nation/i}$  we compute the national growth rate for each industry  $s$  between time  $t$  and  $t - 1$ ,

$$g_{ist,t-1} = \frac{Share_{st}^{Nation/i} - Share_{st-1}^{Nation/i}}{Share_{st-1}^{Nation/i}}. \quad (5)$$

The national growth rate for industry  $s$  is MSA-specific since it is computed net of the contribution of labor market income to industry  $s$  from MSA  $i$ . Like Ottaviano and Peri (2006), we use  $g_{ist,t-1}$  to calculate the 'attributed' share of labor market income in industry  $s$  in MSA  $i$  at time  $t$  based on the national growth rate in sector  $s$  between time  $t$

and  $t - 1$ ,

$$\widehat{Share}_{st}^l = Share_{st-1}^l \cdot (1 + g_{ist,t-1}). \quad (6)$$

The attributed shares of labor market income can then be evaluated to construct the attributed diversity index,

$$DIV_{it}^{IV} = 1 - \sum_{s \in S} [\widehat{Share}_{st}^l]^2, \quad (7)$$

which we use to instrument for the level of diversification in each MSA. Here, the identifying assumption is that changes in the national growth rate of sector  $s$  are exogenous to the local economic conditions of a specific region  $i$ . Finally, we consider variants of the following estimating equation,

$$\ln(HPI)_{it} = \alpha + f(DIV_{it}; \beta_1) + \alpha_i + \lambda_t + \varepsilon_{it}, \quad (9)$$

where  $\alpha_i$  a complete set of MSA fixed effects and  $\lambda_t$  an exhaustive set of year-quarter fixed effects.

We report OLS estimates of equation (9) in column (1) of Table (5). For completeness, in column (2) we present estimates of equation (9) allowing diversity to enter the model non-linearly. For the sake of interpretation, in the log-linear specifications (columns (1) and (3)) we present estimates of equation (9) after standardizing the diversity index mean zero standard deviation one. This allows us to interpret coefficient estimates as the effect of diversity on home prices due to a one standard deviation increase in diversity. Columns (2) and (4) report 2SLS estimates of columns (1) and (3) respectively letting diversity enter the model in logarithmic form. Additionally, relevant first-stage statistics are also reported.

[Table (5): About Here]

Column (1) suggests a one standard deviation increase in diversification may lead to 1.34% reduction in price. Column (2) indicates that a 1% increase in diversification may lead to a corresponding 0.6% decrease in housing values; however, both effects are statistically insignificant. Further, as shown in columns (3) and (4), the magnitudes of these estimated price decreases are meaningfully attenuated after we instrument for diversity suggesting there is no economically discernable relationship between diversification and housing values.

## 7 Conclusion

Diversification is often regarded as a positive policy objective for local real estate markets in terms of improving price resiliency; albeit, this conventional wisdom has persisted in the absence of any formal empirical evidence. Our findings demonstrate that economic diversification has the two-pronged effect of attenuating the immediate impact and the relative persistence of a shock in a small regional economy to local housing values. Our modeling exercise shows that diversity catalyzes the resiliency of the housing markets to climate shocks.

There exists a long-standing debate in the literature on the potential “dual-effects” of diversification on the regional economy in terms of the direct effect of diversification on regional market performance. Through the lens of the housing market, we show that the concerns issued in previous studies regarding the potential downsides of diversification stemming from the micro-economic foundations of comparative advantage do not appear to be warranted: After instrumenting for diversity, we find no economically meaningful or statistically relevant relationship between diversity and regional housing values. Considering these results, the policy goal of improving resiliency through diversification can likely be achieved net of ancillary concerns of impeding economic progress.

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## Figures

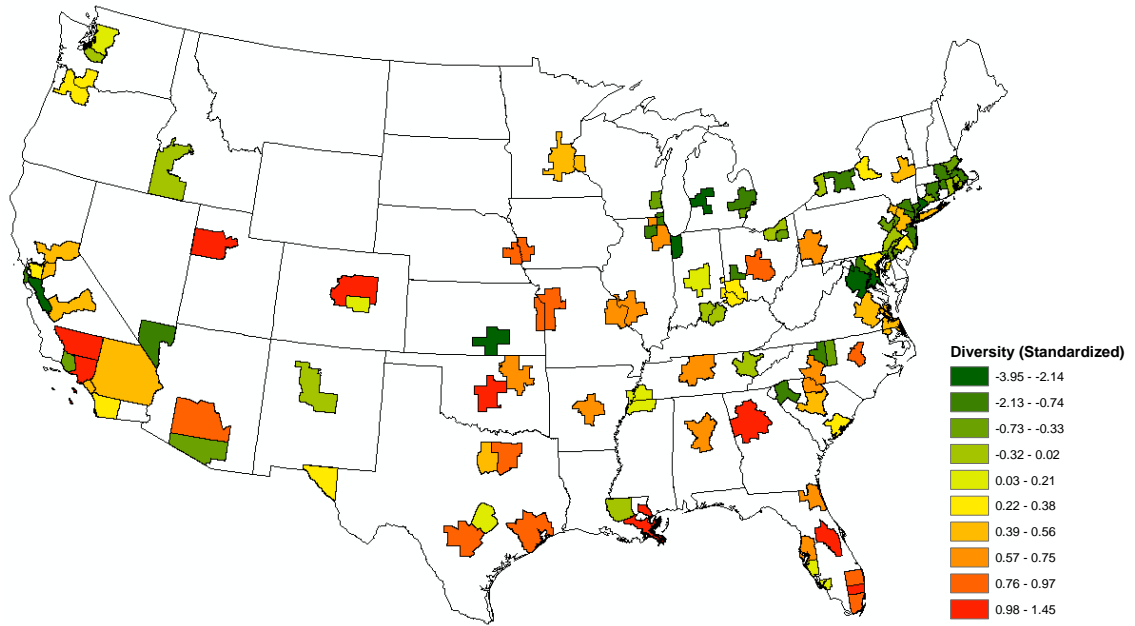


Figure (1): Study Area

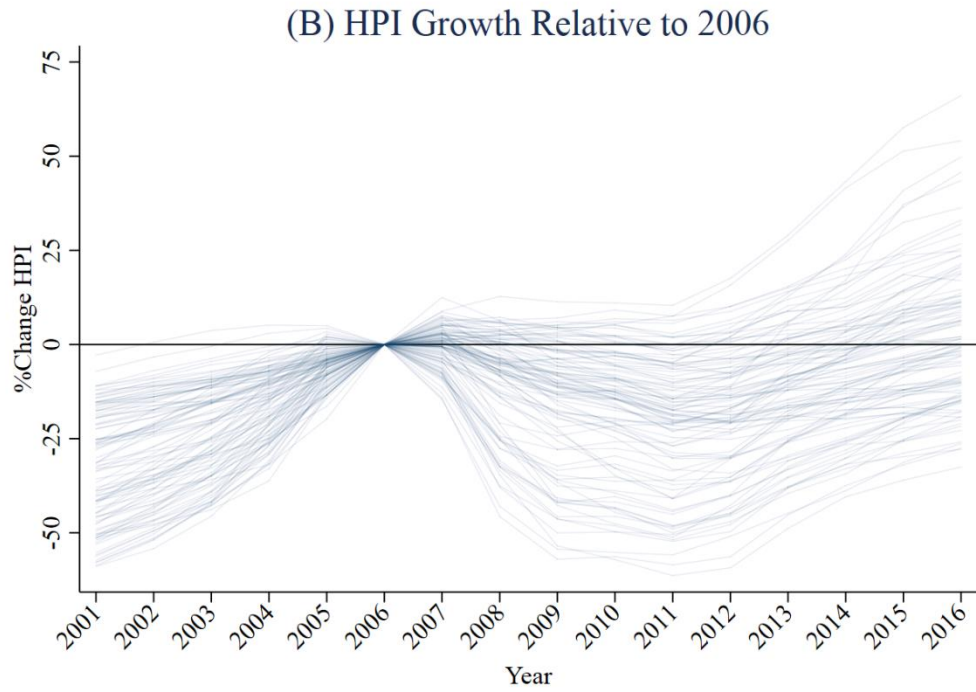
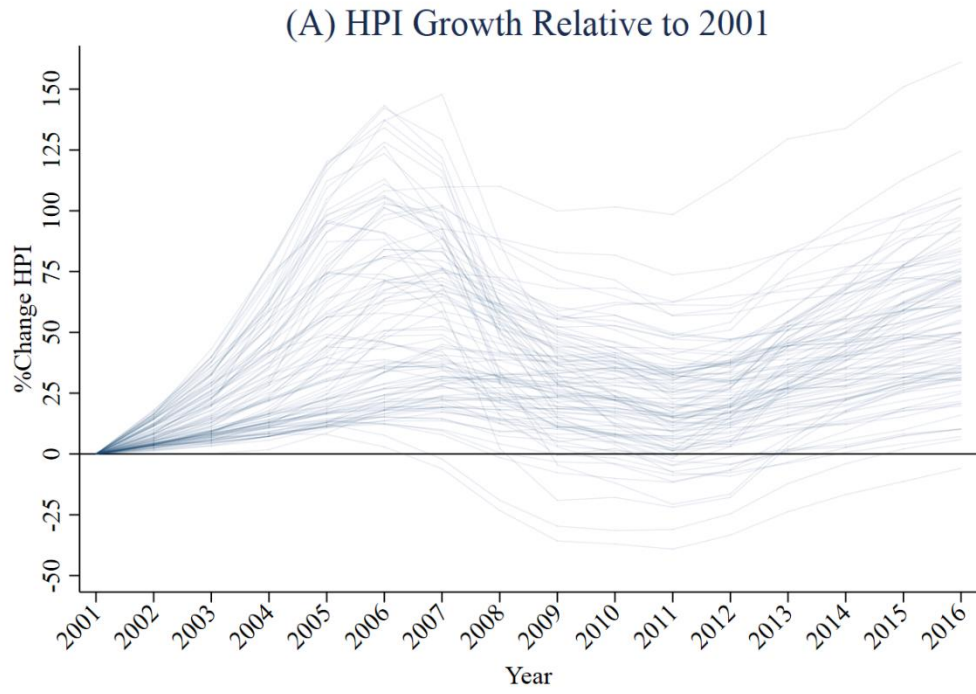


Figure (2): FHFA Purchase-Only House Price Index (HPI) by MSA for all MSAs

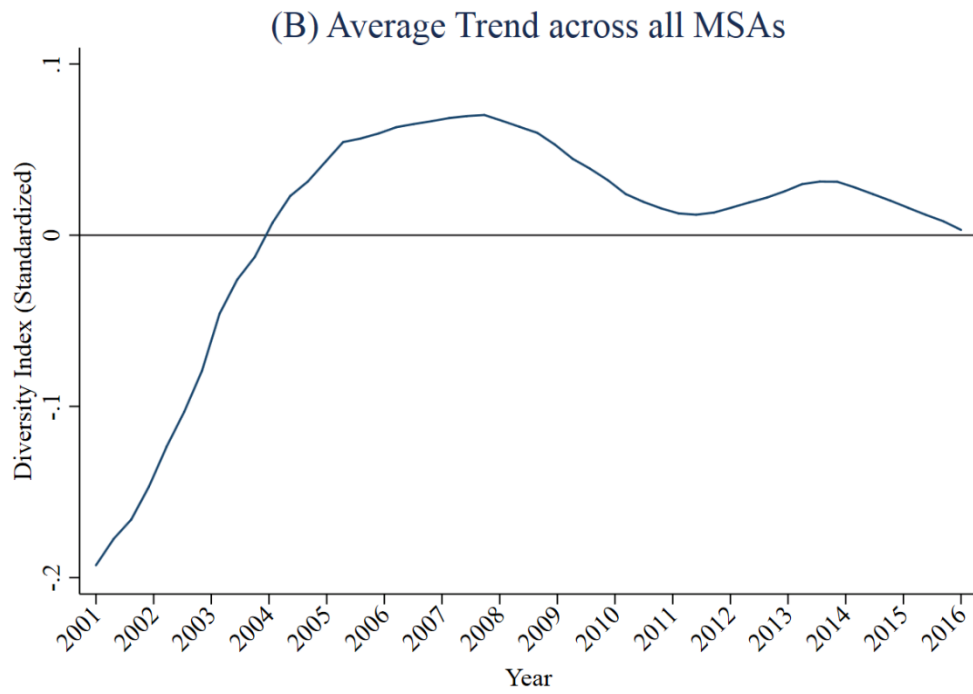
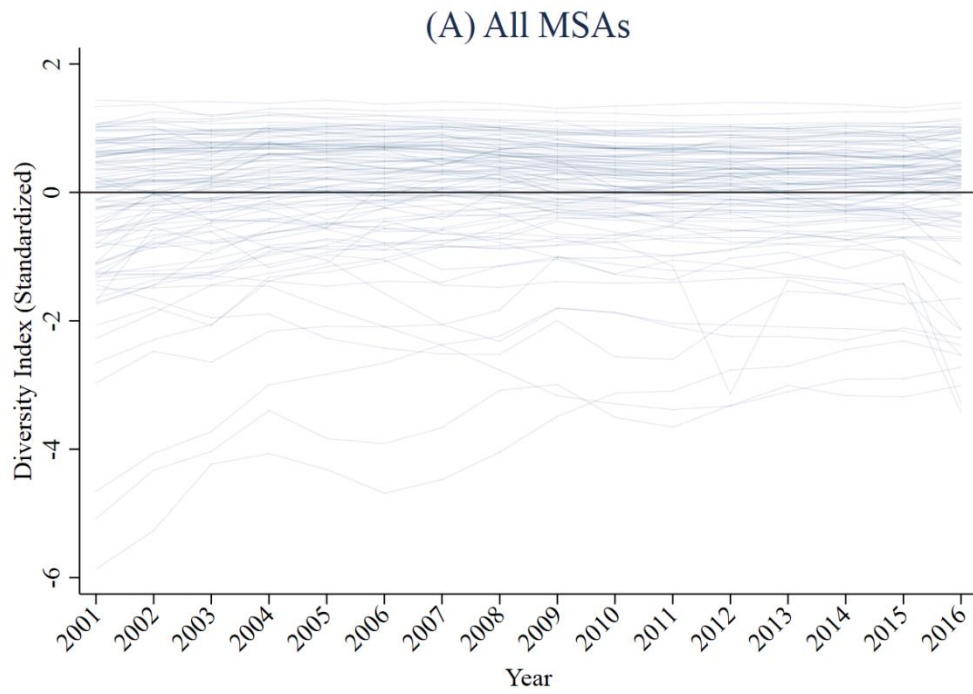
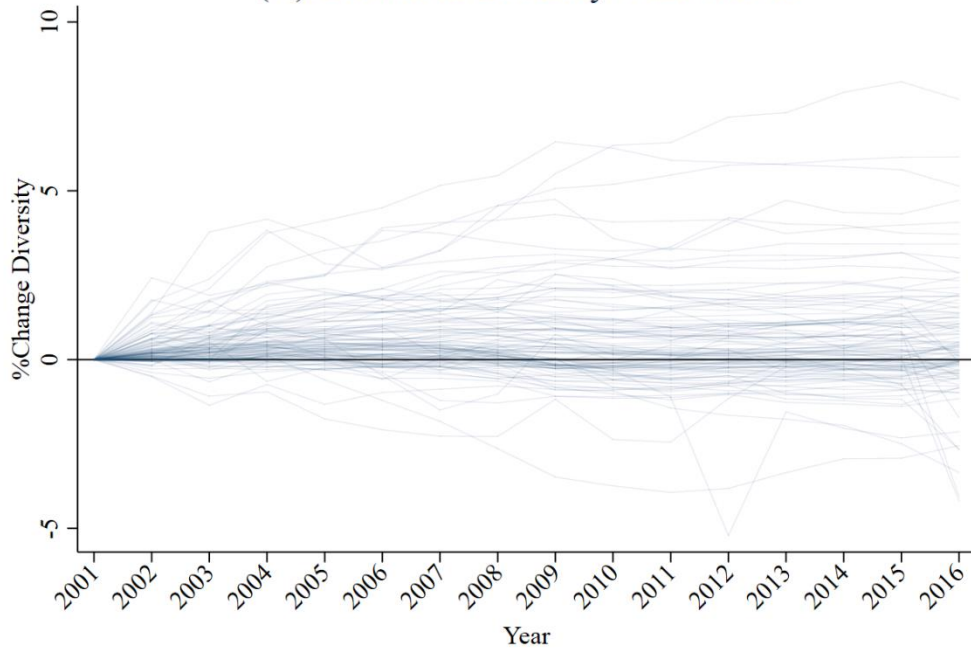


Figure (3): Trends in Economic Diversification

(A) Growth in Diversity: ALL MSAs



(B) Distribution of Growth in Diversity from 2001 to 2016

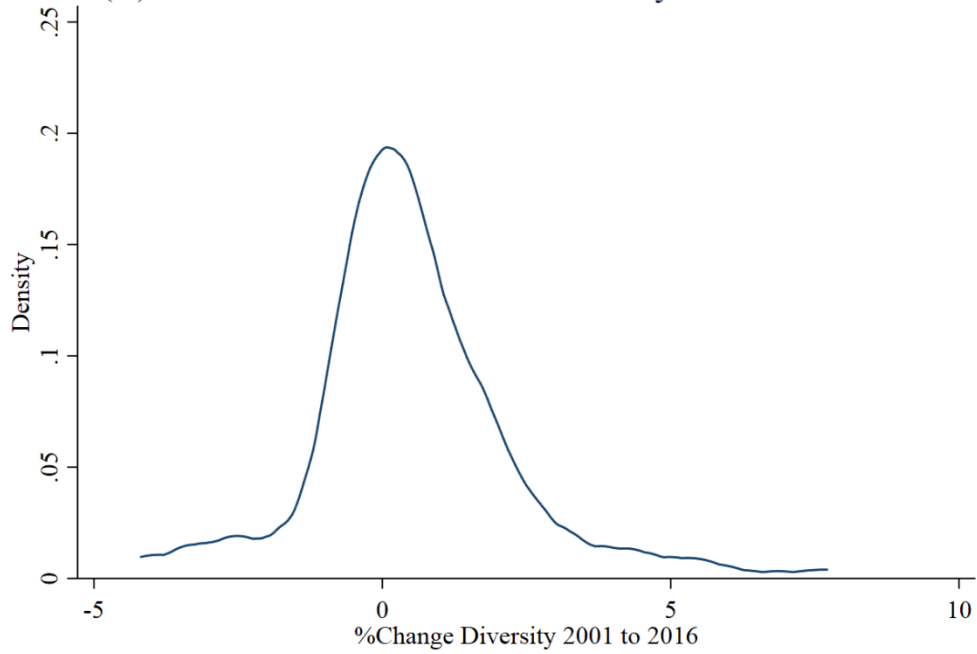
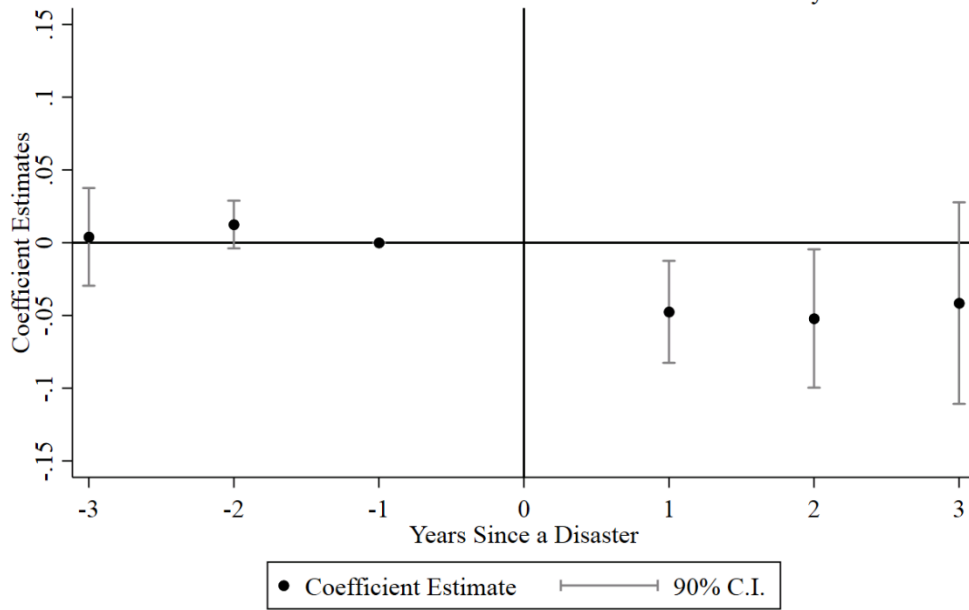


Figure (4): Growth in Diversification

### (A) Price Responses to Disasters among Non-Diversified MSAs

Estimates Evaluated at the 5th Percentile of Diversity



### (B) Price Responses to Disasters among Diversified MSAs

Estimates Evaluated at the 95th Percentile of Diversity

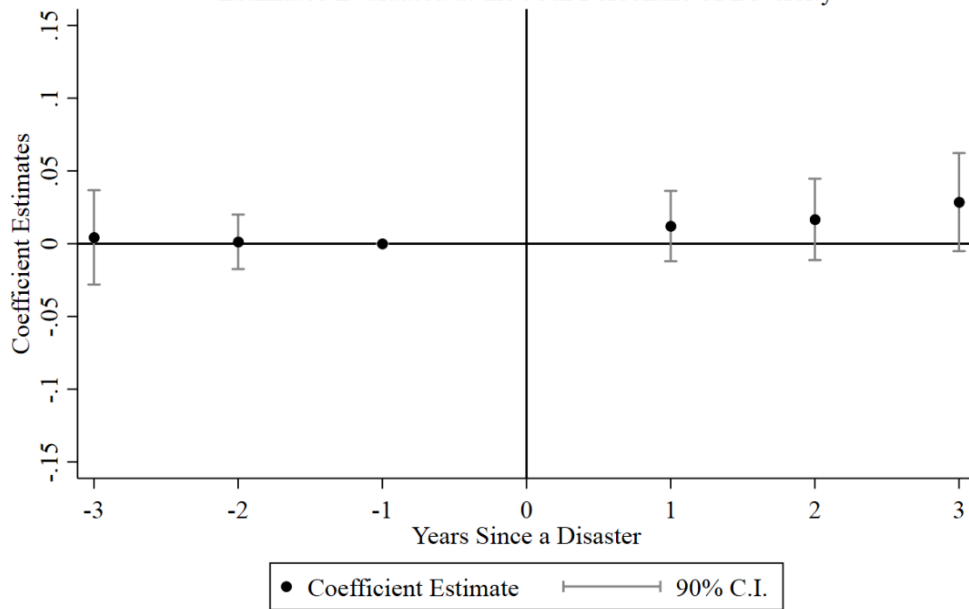


Figure (5): Estimated Home Price Responses to a Disaster among Non-Diversified and Diversified MSAs

Table (1): Parameter Estimates of  $\theta(\tau, DIV^j)$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Percentile of Diversity:	j=5th	j=10th	j=25th	j=Mean	j=75th	j=90th	j=95th
$\theta(-3, DIV^j)$	0.00401 (0.0204)	0.00412 (0.0136)	0.00420 (0.0122)	0.00424 (0.0131)	0.00431 (0.0168)	0.00434 (0.0188)	0.00436 (0.0197)
$\theta(-2, DIV^j)$	0.0125 (0.00996)	0.00890 (0.00650)	0.00624 (0.00639)	0.00503 (0.00719)	0.00267 (0.00968)	0.00174 (0.0109)	0.00132 (0.0114)
$\theta(+1, DIV^j)$	-0.0475 (0.0213)	-0.0284 (0.0128)	-0.0141 (0.00892)	-0.00769 (0.00883)	0.00490 (0.0118)	0.00991 (0.0138)	0.0121 (0.0147)
$\theta(+2, DIV^j)$	-0.0521 (0.0289)	-0.0300 (0.0179)	-0.0136 (0.0121)	-0.00615 (0.0112)	0.00836 (0.0138)	0.0141 (0.0159)	0.0167 (0.0170)
$\theta(+3, DIV^j)$	-0.0415 (0.0421)	-0.0190 (0.0270)	-0.00227 (0.0181)	0.00531 (0.0158)	0.0201 (0.0169)	0.0260 (0.0193)	0.0286 (0.0205)
Observations	5,100	5,100	5,100	5,100	5,100	5,100	5,100

*Notes.* This table reports parameter estimates  $\theta(\tau, DIV^j)$  obtained from estimating equation (2). Standard errors are reported in parentheses and are clustered by MSA.

Table (2): Hypothesis Tests of the Resiliency Parameters

(1) Parameter of Interest	(2) Parameter Estimate	(3) 90% Confidence Interval
$\tilde{\delta}_{(-3)}$	0.000114	[-0.01716, 0.01739]
$\tilde{\delta}_{(-2)}$	-0.00367	[-0.01313, 0.00579]
$\tilde{\delta}_{(+1)}$	0.0196	[0.00266, 0.03654]
$\tilde{\delta}_{(+2)}$	0.0226	[0.00138, 0.04382]
$\tilde{\delta}_{(+3)}$	0.0230	[-0.00562, 0.05162]



Table (3): Parameter estimates of  $\exp[\theta(\tau, DIV^j)] - 1$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Percentile of Diversity:	j=5th	j=10th	j=25th	j=Mean	j=75th	j=90th	j=95th
$\exp[\theta(-3, DIV^j)]-1$	0.00402 (0.0204)	0.00413 (0.0136)	0.00421 (0.0123)	0.00425 (0.0131)	0.00432 (0.0169)	0.00435 (0.0189)	0.00437 (0.0198)
$\exp[\theta(-2, DIV^j)]-1$	0.0126 (0.0101)	0.00894 (0.00656)	0.00626 (0.00643)	0.00504 (0.00723)	0.00268 (0.00971)	0.00174 (0.0109)	0.00132 (0.0114)
$\exp[\theta(+1, DIV^j)]-1$	-0.0464 (0.0203)	-0.0280 (0.0125)	-0.0140 (0.00880)	-0.00766 (0.00876)	0.00491 (0.0119)	0.00996 (0.0139)	0.0122 (0.0149)
$\exp[\theta(+2, DIV^j)]-1$	-0.0507 (0.0274)	-0.0295 (0.0173)	-0.0135 (0.0119)	-0.00613 (0.0111)	0.00840 (0.0139)	0.0142 (0.0161)	0.0168 (0.0173)
$\exp[\theta(+3, DIV^j)]-1$	-0.0407 (0.0404)	-0.0188 (0.0265)	-0.00227 (0.0180)	0.00532 (0.0159)	0.0203 (0.0173)	0.0263 (0.0198)	0.0290 (0.0211)
Observations	5,100	5,100	5,100	5,100	5,100	5,100	5,100

*Notes.* This table reports parameter estimates  $\exp[\theta(\tau, DIV^j)]-1$  obtained from estimating equation (2). Standard errors are reported in parentheses and are clustered by MSA.

Table (4): Testing for Non-Linear Effects – Parameter Estimates of  $\theta'(\tau, DIV_{it})$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Percentile of Diversity:	j=5th	j=10th	j=25th	j=Mean	j=75th	j=90th	j=95th
$\theta'(-3, DIV^j)$	0.00338 (0.0201)	0.00381 (0.0134)	0.00412 (0.0122)	0.00426 (0.0131)	0.00453 (0.0167)	0.00464 (0.0186)	0.00468 (0.0195)
$\theta'(-2, DIV^j)$	0.0120 (0.00977)	0.00863 (0.00642)	0.00614 (0.00644)	0.00506 (0.00721)	0.00287 (0.00963)	0.00202 (0.0107)	0.00165 (0.0113)
$\theta'( +1, DIV^j)$	-0.0471 (0.0213)	-0.0278 (0.0127)	-0.0138 (0.00889)	-0.00771 (0.00883)	0.00465 (0.0118)	0.00944 (0.0137)	0.0116 (0.0146)
$\theta'( +2, DIV^j)$	-0.0516 (0.0289)	-0.0294 (0.0177)	-0.0132 (0.0120)	-0.00615 (0.0112)	0.00813 (0.0137)	0.0136 (0.0158)	0.0161 (0.0168)
$\theta'( +3, DIV^j)$	-0.0416 (0.0426)	-0.0187 (0.0270)	-0.00198 (0.0180)	0.00524 (0.0158)	0.0200 (0.0169)	0.0256 (0.0192)	0.0282 (0.0204)
Observations	5,100	5,100	5,100	5,100	5,100	5,100	5,100

*Notes.* This table reports parameter estimates  $\theta'(\tau, DIV^j)$  obtained from estimating equation (3). Standard errors are reported in parentheses and are clustered by MSA.

Table (5): OLS and 2SLS Results of the Impact of Diversification on Housing Prices

Variable	(1) OLS	(2) OLS	(3) 2SLS	(4) 2SLS
DIV <sub>it</sub>	-0.0134 (0.0109)	- -	-0.00246 (0.00659)	- -
ln(DIV <sub>it</sub> )	-	-0.602 (0.469)	-	-0.108 (0.288)
Observations	5,000	5,000	5,000	5,000
Kleibergen-Paap First-Stage F	n/a	n/a	42.74	39.05
Kleibergen-Paap Under Id. (p-value)	n/a	n/a	0.027	0.030

*Notes:* Exclusion restriction constructed via the shift-share methodology used by Ottaviano and Perri (2006), Card (2001), and Bartik (1991). See text for more details.

Table (A1): Home prices and diversity levels by MSA 2001q1 vs. 2016q1

MSA	HPI (2001q1)	HPI (2016q1)	%Change	Diveristy Index* (2001q1)	Diveristy Index* (2016q1)	%Change
Akron, OH	152.84	171.20	10.72%	-1.00	-0.43	3.30%
Albany-Schenectady-Troy, NY	101.36	183.93	44.89%	0.57	0.45	0.10%
Albuquerque, NM	145.26	214.69	32.34%	0.42	-0.28	-0.98%
Allentown-Bethlehem-Easton, PA-NJ	114.71	168.39	31.88%	-1.11	-0.06	4.48%
Anaheim-Santa Ana-Irvine, CA (MSAD)	129.79	282.12	53.99%	0.51	0.66	0.75%
Atlanta-Sandy Springs-Roswell, GA	157.90	213.30	25.97%	0.90	1.09	0.45%
Austin-Round Rock, TX	202.44	396.18	48.90%	-0.57	0.16	3.15%
Bakersfield, CA	98.89	179.90	45.03%	1.14	0.92	-0.65%
Baltimore-Columbia-Towson, MD	128.40	237.68	45.98%	0.59	0.45	0.04%
Baton Rouge, LA	157.95	252.67	37.49%	0.14	-0.39	-0.36%
Birmingham-Hoover, AL	153.97	221.36	30.44%	0.88	0.73	-0.27%
Boise City, ID	162.74	283.71	42.64%	-0.21	0.21	2.07%
Boston, MA (MSAD)	172.17	278.57	38.20%	-1.37	-2.01	0.98%
Bridgeport-Stamford-Norwalk, CT	144.90	196.60	26.30%	-1.78	-3.23	-0.44%
Buffalo-Cheektowaga-Niagara Falls, NY	111.19	181.29	38.67%	-0.57	0.36	3.57%
Cambridge-Newton-Framingham, MA (MSAD)	175.23	272.97	35.81%	-0.41	-1.02	0.02%
Camden, NJ (MSAD)	114.49	173.87	34.15%	0.23	0.17	0.59%
Cape Coral-Fort Myers, FL	132.39	230.65	42.60%	0.50	0.57	0.60%
Charleston-North Charleston, SC	165.59	305.77	45.84%	0.34	0.27	0.43%
Charlotte-Concord-Gastonia, NC-SC	146.08	219.96	33.59%	0.48	0.42	0.34%
Chicago-Naperville-Arlington Heights, IL (MSAD)	153.13	198.46	22.84%	0.61	0.48	0.05%
Cincinnati, OH-KY-IN	147.69	182.82	19.22%	0.25	0.17	0.51%
Cleveland-Elyria, OH	151.08	163.78	7.75%	-0.31	-0.01	1.93%
Colorado Springs, CO	194.88	282.50	31.02%	0.29	0.14	0.31%
Columbia, SC	140.19	190.56	26.43%	0.31	0.55	1.12%

Table continues on next page.

Table (A1) Continued

MSA	HPI (2001q1)	HPI (2016q1)	%Change	Diveristy Index* (2001q1)	Diveristy Index* (2016q1)	%Change
Columbus, OH	150.84	203.87	26.01%	0.69	0.79	0.48%
Dallas-Plano-Irving, TX (MSAD)	141.46	242.68	41.71%	0.56	0.90	1.10%
Dayton, OH	131.98	147.70	10.64%	-1.00	-0.47	3.21%
Denver-Aurora-Lakewood, CO	235.73	413.24	42.96%	0.88	1.00	0.31%
Detroit-Dearborn-Livonia, MI (MSAD)	186.24	179.61	-3.69%	-0.71	-0.41	2.37%
El Paso, TX	119.28	179.33	33.49%	0.21	0.42	1.19%
Elgin, IL (MSAD)	141.33	159.57	11.43%	-1.03	-0.48	3.26%
Fort Lauderdale-Pompano Beach-Deerfield Beach, FL (MSAD)	144.36	287.34	49.76%	1.00	1.13	0.21%
Fort Worth-Arlington, TX (MSAD)	138.37	218.69	36.73%	0.29	0.63	1.36%
Fresno, CA	110.67	200.21	44.72%	0.82	0.24	-1.12%
Gary, IN (MSAD)	143.92	189.63	24.10%	-1.86	-2.12	2.36%
Grand Rapids-Wyoming, MI	160.98	202.93	20.67%	-3.22	-2.23	7.04%
Greensboro-High Point, NC	141.13	172.15	18.02%	-0.61	-0.30	2.28%
Greenville-Anderson-Mauldin, SC	149.98	223.45	32.88%	-1.33	-0.33	4.63%
Hartford-West Hartford-East Hartford, CT	110.21	153.69	28.29%	-1.22	-2.00	0.51%
Honolulu ('Urban Honolulu'), HI	89.78	239.54	62.52%	1.21	0.95	-0.81%
Houston-The Woodlands-Sugar Land, TX	145.85	285.03	48.83%	0.98	1.05	0.11%
Indianapolis-Carmel-Anderson, IN	139.35	180.51	22.80%	-0.05	0.21	1.56%
Jacksonville, FL	154.73	254.26	39.14%	0.83	0.43	-0.72%
Kansas City, MO-KS	159.55	214.76	25.71%	0.96	0.49	-1.01%
Knoxville, TN	140.06	212.53	34.10%	-0.29	0.27	2.46%
Lake County-Kenosha County, IL-WI (MSAD)	145.17	173.18	16.17%	-0.71	-2.38	-2.01%
Las Vegas-Henderson-Paradise, NV	126.81	180.34	29.68%	-0.65	-0.31	2.40%
Little Rock-North Little Rock-Conway, AR	143.22	201.57	28.95%	0.75	0.58	-0.17%
Los Angeles-Long Beach-Glendale, CA (MSAD)	108.78	255.60	57.44%	0.76	0.99	0.67%

*Table continues on next page.*

Table (A1) Continued

MSA	HPI (2001q1)	HPI (2016q1)	%Change	Diveristy Index* (2001q1)	Diveristy Index* (2016q1)	%Change
Louisville/Jefferson County, KY-IN	159.90	225.54	29.10%	-0.19	0.01	1.58%
Memphis, TN-MS-AR	145.03	175.59	17.40%	0.40	0.13	-0.04%
Miami-Miami Beach-Kendall, FL (MSAD)	158.79	336.83	52.86%	0.75	0.92	0.55%
Milwaukee-Waukesha-West Allis, WI	165.92	227.46	27.06%	-0.47	-0.26	1.90%
Minneapolis-St. Paul-Bloomington, MN-WI	181.32	254.64	28.79%	0.48	0.26	-0.02%
Montgomery County-Bucks County-Chester County, PA (MSAD)	122.64	205.75	40.39%	-0.02	-0.13	0.75%
Nashville-Davidson--Murfreesboro--Franklin, TN	158.58	280.75	43.52%	0.39	0.83	1.50%
Nassau County-Suffolk County, NY (MSAD)	156.92	269.46	41.77%	0.65	0.34	-0.39%
New Haven-Milford, CT	116.29	161.98	28.21%	0.08	0.26	1.25%
New Orleans-Metairie, LA	164.89	289.16	42.98%	1.30	1.36	-0.21%
New York-Jersey City-White Plains, NY-NJ (MSAD)	142.90	247.60	42.29%	-2.67	-3.09	2.94%
Newark, NJ-PA (MSAD)	148.91	238.96	37.68%	0.55	0.28	-0.20%
North Port-Sarasota-Bradenton, FL	151.60	272.07	44.28%	0.14	0.38	1.32%
Oakland-Hayward-Berkeley, CA (MSAD)	168.47	297.90	43.45%	0.50	0.42	0.27%
Oklahoma City, OK	145.97	237.29	38.48%	0.85	1.03	0.47%
Omaha-Council Bluffs, NE-IA	163.24	219.03	25.47%	0.78	0.66	-0.11%
Orlando-Kissimmee-Sanford, FL	136.71	224.80	39.19%	1.23	1.28	-0.18%
Oxnard-Thousand Oaks-Ventura, CA	130.21	248.16	47.53%	-0.92	-1.05	1.64%
Philadelphia, PA (MSAD)	119.25	243.61	51.05%	0.47	-0.02	-0.57%
Phoenix-Mesa-Scottsdale, AZ	165.53	290.16	42.95%	0.73	0.93	0.63%
Pittsburgh, PA	135.87	226.01	39.88%	0.72	0.65	0.09%
Portland-Vancouver-Hillsboro, OR-WA	187.75	386.92	51.48%	0.08	0.41	1.57%
Providence-Warwick, RI-MA	130.62	207.67	37.10%	-0.27	0.24	2.35%
Raleigh, NC	150.95	229.84	34.32%	0.87	0.62	-0.45%
Richmond, VA	137.36	230.38	40.38%	0.45	0.50	0.60%

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Table (A1) Continued

MSA	HPI (2001q1)	HPI (2016q1)	% Change	Diversity Index* (2001q1)	Diversity Index* (2016q1)	% Change
Riverside-San Bernardino-Ontario, CA	109.70	209.55	47.65%	0.46	0.39	0.33%
Rochester, NY	112.33	151.06	25.64%	-1.70	0.15	7.05%
Sacramento--Roseville--Arden-Arcade, CA	122.02	206.28	40.85%	0.81	0.22	-1.12%
Salt Lake City, UT	206.79	370.39	44.17%	1.03	0.97	-0.20%
San Antonio-New Braunfels, TX	143.87	265.27	45.76%	0.75	0.77	0.25%
San Diego-Carlsbad, CA	144.11	284.08	49.27%	0.61	0.10	-0.74%
San Francisco-Redwood City-South San Francisco, CA (MSAD)	182.80	377.28	51.55%	-0.82	-1.54	0.21%
San Jose-Sunnyvale-Santa Clara, CA	202.02	342.17	40.96%	-3.55	-2.83	6.83%
Seattle-Bellevue-Everett, WA (MSAD)	166.94	329.71	49.37%	0.07	0.09	0.91%
Silver Spring-Frederick-Rockville, MD (MSAD)	128.47	249.68	48.55%	-0.01	-0.63	-0.40%
St. Louis, MO-IL	149.85	212.29	29.41%	0.43	0.64	0.95%
Stockton-Lodi, CA	135.12	190.00	28.88%	0.63	0.37	-0.25%
Syracuse, NY	105.30	156.26	32.61%	-0.38	0.63	3.54%
Tacoma-Lakewood, WA (MSAD)	151.73	265.53	42.86%	0.35	-0.15	-0.48%
Tampa-St. Petersburg-Clearwater, FL	148.26	263.76	43.79%	0.77	0.60	-0.18%
Tucson, AZ	159.36	236.79	32.70%	0.13	-0.57	-0.70%
Tulsa, OK	149.40	206.70	27.72%	0.83	0.84	0.16%
Virginia Beach-Norfolk-Newport News, VA-NC	131.86	230.37	42.76%	0.37	0.49	0.84%
Warren-Troy-Farmington Hills, MI (MSAD)	180.87	194.83	7.17%	-0.82	-0.66	2.19%
Washington-Arlington-Alexandria, DC-VA-MD-WV (MSAD)	131.41	281.92	53.39%	-0.55	-2.56	-2.91%
West Palm Beach-Boca Raton-Delray Beach, FL (MSAD)	134.10	274.97	51.23%	1.07	0.97	-0.34%
Wichita, KS	142.55	192.29	25.87%	-3.74	-2.38	8.66%
Wilmington, DE-MD-NJ (MSAD)	121.34	187.18	35.17%	0.35	-1.32	-3.00%
Winston-Salem, NC	142.40	172.48	17.44%	-1.27	-0.28	4.53%
Worcester, MA-CT	148.30	202.57	26.79%	-0.74	-0.70	1.82%

Notes. \*Diversity indexes are standardized mean zero standard deviation one.