State Political Uncertainty and Local Housing Markets - Evidence from U.S. Mid-term Gubernatorial Elections[*]

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Abstract

Using U.S. county-level data, this paper finds a significant negative impact of state political uncertainty on local house price growth. A unit increase in state political uncertainty is associated with about 3.4 percentage point decrease in county-level house price growth. The impact is asymmetric and varies widely across localities, with a weaker impact found in areas with a higher fraction of homeowners. The results are robust to endogeneity, sample selection, model specifications, and alternative measures of uncertainty. The main findings are further confirmed by a case study based on a difference-in-difference analysis.

Keywords: State political uncertainty; Gubernatorial elections; House price; U.S. county; Homeownership.

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1 Introduction

"*When an incumbent arises as a likely winner, cementing the continuation of familiar policies, the housing market may experience less jitters.*" - Forbes (Feb 16, 2020)

It has long been recognized that political events like elections have an important impact on the economy by creating uncertainty about future government policies and regulations. Indeed, extensive research finds that election-induced uncertainty has significant negative real and financial effects by depressing corporate investment or by raising risk premium in stock market (see Table 1 for a partial list of previous work on this topic). Julio and Yook (2012), for example, show that heightened political uncertainty around elections reduces firms' investment, and Pástor and Veronesi (2013), Brogaard et al. (2020) and Chan and Marsh (2021) document that stock prices tend to decline during periods of high political uncertainty.

Up to this point, though, studies on political uncertainty have centered on the effect on firms' activities and stock market responses at the national level. Little attention has been paid to the impact on housing markets, and far less at the sub-national level. Given that housing markets are susceptible to changes in the government's regulatory and fiscal policies such as building and tax codes, uncertainty from political sources is likely to exert a nontrivial influence on the housing markets, possibly through changes in the related policies and regulations. This is particularly the case for regional elections, such as gubernatorial elections, that have a direct influence on public policies related to local housing markets. Because housing markets are mainly driven by local factors, gubernatorial elections are believed to be more relevant for the political uncertainty surrounding housing markets than national elections.[1] Moreover, in light of the growing political polarization in the U.S., partisan divides on housing policy would make the impact of political uncertainty no less important.[2]

The objective of this study is to investigate whether and to what extent political uncertainty associated with gubernatorial elections (hereafter, state political uncertainty) influences

[1] Although the scope of gubernatorial power varies from state to state depending on state constitutions and legislations, governors in the U.S. generally have the power to regulate the state economy through various tools shaping housing markets that include, but not limited to, enforcing laws and regulations, imposing taxes, and providing rights and protection (e.g., Besley and Case 1995; Colak et al., 2017).

[2] The partisanship and ideology of elected local officials have a significant impact on shaping housing policy, such as policy on residential housing development. For instance, Democrats are more likely to favor development compared to Republicans, in particular as a response to housing supply shortages and the associated impact on economic inequality. Using city election data, de Benedictis-Kessner et al. (2022) find that electing a Democrat as mayor lowers housing prices in subsequent years by increasing the supply of multi-family housing units.

local housing markets. To this end, we look at the house prices in 1,358 counties in the 33 U.S. states where gubernatorial elections took place in the mid-term election cycles between 1994 and 2018.[3] Because state and local governments differ greatly in their regulations and tax rates, uncertainty regarding sub-national policy would vary non-trivially across locations. Thanks to the highly localized feature of housing markets and the large variation in election outcomes across counties, county-level analysis is well suited for the purpose of this study, especially in tracking the heterogeneous response of local housing markets to statewide political uncertainty. As an administrative unit, counties differ considerably in socio-demographic makeup, institutions, and industry mix, even though they share identical voting rules and methods in the same state (e.g., Cantoni and Pons, 2020). In addition, county-level analysis permits us to combine the election outcomes with detailed local demographic, social, and economic information.

Accordingly, we utilize a state-level measure of political uncertainty in lieu of popular national measures, such as the economic policy uncertainty (EPU) index of Baker et al. (2016), which are not able to capture large geographic variations in the uncertainty.[4] To be specific, we utilize the measure of political uncertainty proposed by Falk and Shelton (2018) based on vote margins between the winner and the second place finisher.[5] Intuitively, close elections are likely to elevate uncertainty regarding future policies much more than less competitive elections, especially when parties differ significantly in their policy on housing markets.

We conduct our empirical analysis within the framework of two-way fixed effect (TFE) model which has often been employed in the applied research to adjust for unobserved unit-specific and time-specific confounders simultaneously. To be specific, we estimate the impact of political uncertainty on local housing markets by regressing county-level house price growth onto the state-level political uncertainty after controlling for important covariates like local

[3] Gubernatorial elections in the U.S. are held in different years for different states. About two-thirds of them (33 out of 50 states) coincide with the midterm congressional election cycles on which the current study focuses. As shown in Table A.1 in the Appendix, the 1,358 counties considered here account for more than 70 percent of U.S. population during the sample period. Off-midterm year gubernatorial elections are not included in our analysis because they confound the interpretation of regression results as explained in Section 3.2.

[4] County-level political uncertainty can be measurable, but not considered here because it is of reduced merit for the purpose of our study. Jurisdictions of local elections, such as mayoral elections, do not match closely with the geographic boundaries of counties and the elected local officials do not have as significant influence as governors on housing markets. As further discussed in Section 3.5, the use of state-level uncertainty also facilitates our causal inference on the impact of state political uncertainty on local housing markets.

[5] Falk and Shelton (2018) use a two-party vote share of the gubernatorial candidates, assuming that elections which were close *ex post* were perceived to be uncertain *ex ante*. Refer to Section 3.1 for the measure.

economic and socio-demographic characteristics. Taking advantage of the fact that state-level events can influence county economy but less likely the other way around, this approach facilitates our causal inference on the impact of state political uncertainty on local housing markets.

Our TFE regression analysis delivers several interesting findings. First, we find a significant and negative impact of state political uncertainty on local house price growth, i.e., political uncertainty leads to a slow-down in the local housing market. On average a unit increase in state political uncertainty is associated with roughly a 3.4 percentage point decrease in house price growth relative to the rest of the country and to the past trend. This finding corroborates the previous literature that election-induced uncertainty exerts a negative impact on the economy (e.g., Çolak et. al., 2017; Jens, 2017; Gao et. al., 2019). Not surprisingly, the impact is stronger in the election years when political uncertainty is heightened compared to the off-election years. Furthermore, the impact is asymmetric such that the negative effect of uncertainty elevation is more sizable than the positive effect of uncertainty reduction. This asymmetry in the effect of uncertainty is conceptually aligned with the notion of loss aversion in which investors are more sensitive to increases in uncertainty than its decreases.

Interestingly, the impact of political uncertainty varies widely across locations. Political uncertainty affects local housing markets differently across counties depending on certain observable characteristics, such as the proportion of homeowners in the county. The impact turns out to be weaker in areas with a higher fraction of homeowners. This is perhaps because homeowners, who already own house, are likely less sensitive to the uncertainty about possible changes in policy and regulation regarding housing markets. Utilizing the information on the geographic heterogeneity observed in the data, we further attempt to identify the channels through which state political uncertainty affects local housing markets. The negative impact of political uncertainty, along with the crucial role of homeownership, points toward the housing demand channel as a key transmission mechanism of election-induced uncertainty to local housing markets.

We obtain these results using various model specifications, after controlling for local economic, socio-demographic, and labor market conditions. Our findings are also robust to election cycles because the main conclusions still hold when subsets of election results are dropped from our analysis. The main findings of the regression analysis are further confirmed by our case study based on difference-in-difference analysis in which we find that two treated states

(Kansas and South Carolina) had a slower growth in house price relative to their controls (Missouri and North Carolina) when the uncertainty related to gubernatorial elections rose in the treated states.

Our findings are also robust to endogeneity issue. While our TFE regression model is designed to minimize the risk of reverse causality by regressing state-level uncertainty onto county-level house prices, the causal relationships still could run in the opposite direction if, for example, a downturn in housing market generates political uncertainty. To deal with this endogeneity concern, we check the robustness of our findings by using lagged political uncertainty as instruments. Our lagged IV approach still shows that local house price growth is inversely affected by state political uncertainty after addressing the possible endogeneity issue.

To our knowledge, few studies have examined the effect of political uncertainty on housing markets. As a notable exception, Canes-Wrone and Park (2014) find that uncertainty over electoral outcomes is associated with a decline in private housing investment. Similarly, Nguyen and Vergara-Alert (2020) put forth evidence of negative effect of political uncertainty on the housing markets. These studies, however, measure political uncertainty in a binary manner using election-year dummy variables, without taking into account the closeness of election as is done in our study. As stressed in the literature (e.g., Julio and Yook, 2012; Redl, 2020), it is not the election *per se* but the closeness of election that matters for the political uncertainty and ultimately its impact on the economy. Additionally, our study distinguishes itself from earlier work by using counties as the units of analysis, in order to capture a great deal of geographic heterogeneity observed in both political uncertainty and housing markets.

This paper is structured as follows. The next section describes the sample data and provides a descriptive data analysis. Section 3 discusses the empirical analyses of our study. In this section, we also discuss the robustness of our empirical findings to alternative samples and model specifications. Section 4 conducts a difference-in-difference case study analysis based on two treated states, Kansas and South Carolina, against two control states, Missouri and North Carolina. Section 5 discusses potential transmission mechanisms of election-created uncertainty to local housing markets. Section 6 concludes the paper. The Appendix contains a detailed description of the data employed in the current study.

2 Data and summary statistics

Counties in the U.S. are the geographic unit of our analysis. As a primary administrative division for most states and political events, counties are appropriate for addressing the central question at hand, not just because electoral outcomes are typically available at the county level, but because ample variation exists in local housing market across county.[6] Among 3,142 counties in the U.S. (including independent cities and other statistically equivalent entities), we consider 1,358 counties in the 33 states where gubernatorial elections are held in the mid-term year over seven election cycles (1994, 1998, 2002, 2006, 2010, 2014 and 2018).[7] The resulting dataset is a balanced panel containing 9,506 county-election year observations in total. The data cover less than 50% of all counties, but they account for more than 70% of the total population as further detailed in Table A.1 in the Appendix. The data for gubernatorial elections are obtained from Congressional Quarterly (CQ) Press.

To get some sense of the key variable, we plot in Figure 1 the empirical densities of vote margins (in percent, on the horizontal axis), or vote share gap between the top two contenders in the past seven mid-term gubernatorial election cycles. The vote margin is less than five percent in more than a quarter of the elections and less than ten percent in almost a half of the elections, suggesting a tight race and hence large political uncertainty. Table A.2 in the Appendix presents the summary statistics (mean, median, min, and max) of the vote margins (VM) and the corresponding measure of election uncertainty (EU) over the past six election cycles, with the smaller value of VM indicating larger uncertainty related to election (see Section 3.1). The mean value of VM is in the wide range of 11.6−20.2% across election cycles, suggestive of a non-negligible election year effect. A large gap between maximum and minimum values of VM also indicates that the election-induced uncertainty differs widely across states in each election cycle. This large geographic dispersion in election uncertainty justifies our

[6] As an additional advantage, the boundaries of counties have been generally static compared to those of MSAs (Aguirregabiria et al., 2016).

[7] The 33 states are Alabama (AL), Alaska (AK), Arizona (AZ), California (CA), Colorado (CO), Connecticut (CT), Florida (FL), Georgia (GA), Hawaii (HI), Idaho (ID), Illinois (IL), Iowa (IA), Kansas (KS), Maine (ME), Maryland (MD), Massachusetts (MA), Michigan (MI), Minnesota (MN), Nebraska (NE), Nevada (NV), New Mexico (NM), New York (NY), Ohio (OH), Oklahoma (OK), Oregon (OR), Pennsylvania (PA), South Carolina (SC), South Dakoda (SD), Tennessee (TN), Texas (TX), Vermont (VT), Wisconsin (WI), and Wyoming (WY). As such, our focus on the midterm gubernatorial elections was mainly guided by the availability of the largest data observations. Moreover, adding off-midterm year gubernatorial elections to our analysis complicates the interpretation of our TFE regression analysis because the year-fixed effects (θ_t) in it capture different nationwide macroeconomic shocks in different years.

use of the TFE regression model in which the heterogeneous county- and time-fixed effects are effectively controlled for.

For the house price data, we utilize the county-level annual house price indexes (HPI) downloaded from the Federal Housing Finance Agency (FHFA) website.[8] Originally constructed by Bogin et al. (2019), the HPI data are calibrated using appraisal values and sales prices for conformable mortgages purchased or guaranteed by Fannie Mae or Freddie Mac. Figure 2 illustrates the cross-county distribution (mean, median, min, and max) of the county-level house price growth rates over the past six election cycles. Except for the 2010 election, the mean value of the four-year cumulative house price growth is consistently positive and stable over time. Like the vote margin, the house price growth also exhibits a considerable cross-county dispersion in each election cycle. The largest dispersion is noticed in the 2006 election cycle when the national housing market was at the peak of the boom.

We further draw on a variety of sources for county-level economic and socio-demographic data used for our empirical analysis. As listed in Table A.3 in the Appendix, our control variables include county-level economic variables (per capita income, average wage/salary, population density, home ownership rate, unemployment rate) as well as diverse socio-demographic variables of county residents (average age, gender, race, marriage status, education attainment, and veteran status) that are related to local housing markets. Data for the socio-demographic variables are drawn from the 1990 and 2000 U.S. Census for the elections upto 2000, through Social Explorer. From 2008 onwards, the American Community Surveys (ACS) 5-year estimates are used, which are also obtained from Social Explorer.[9] We follow Weden et al. (2015) by using the mid-year of the five-year ACS estimates for attributing the data of the ACS to the corresponding election year. For the elections taken place between the ACS's 5-year intervals, we construct the corresponding demographic data based on linear interpolations using the Census and ACS data for the election year.[10]

As tabulated in Table A.1 in the Appendix, we face a clear trade-off between the number of

[8] $http://www.fhfa.gov/papers/wp1601.aspx$.

[9] Census data are available from both the Decennial Census and the American Community Survey (ACS) 5-year-estimates. While the Decennial Census data are gathered at a 'point of time' once per decade, the ACS estimates are gathered within a 'period of time' every year.

[10] Take the 2004 election for example, we compute the values of the demographic variables for 2004 by averaging the values from the 2000 Census and the 2008 ACS, and so on. According to Weden et al. (2015), this linear interpolation approach is reasonably accurate. Furthermore, because including these demographic variables do not significantly alter the main results, measurement error introduced through linear interpolation does not appear to be a critical issue for our results.

counties and the number of election cycles available for our empirical analysis, i.e., the number of counties can increase only at the expense of the sample span. The data availability for our key variables restricts us to focus on 1,358 counties for the past seven mid-term gubernatorial elections beginning in 1994. Figure 3 maps the 1,358 counties in 33 states considered in our analysis, with a darker color representing a faster growth of house prices.

Table 2 reports the summary statistics of some selected variables in our data. According to the table, the average vote margin (VM) is 15.4% and the corresponding electoral uncertainty (EU) measure is 2.11. Recall that by design a smaller VM corresponds to a higher EU (see further discussions in Section 3.1). The large values of standard deviation and the 10-90 percentile ratio of EU indicate a large cross-county dispersion in the election-induced uncertainty. House price has grown on average at an annual rate of 2.9%, but again with a considerable cross-county variation ranging from 8.5% annual appreciation in the 90^{th}-percentile to 3.3% annual depreciation in the 10^{th}-percentile.

3 Empirical analysis

We now estimate the impact of state political uncertainty on local house price growth within the framework of two-way fixed effect (TFE) model. Because teasing out the economic impact of political uncertainty can be particularly challenging in the context of time series analysis[11], empirical analyses based on cross-sectional data have been popularly adopted in the literature. Because the boom-bust house price cycle often coincides with the overall business cycle, however, it is also challenging to discern between the causal effect of political uncertainty on house price growth from that of the business cycle by using a single cross-section regression. This renders us to conduct a panel data analysis in which the confounding problem from using only within-time variation in local housing prices is mitigated. Before moving on to the regression analyses, it is useful to introduce our measure of state political uncertainty.

3.1 Measures of state political uncertainty

Studies on the economic impact of political uncertainty have often relied on nationwide political uncertainty measures, such as the economic policy uncertainty (EPU) index constructed by Baker et al. (2016) or the partisan conflict index (PCI) by Azzimonti (2018). Although

[11] Standard time series method can overstate the extent to which housing markets respond to political uncertainty if political uncertainty is affected by expected economic outcomes on housing markets, possibly through partisan biases in expectations.

intriguing, these national indexes are not suitable for our analysis because they do not vary across location. Given that state political uncertainty likely varies widely according to the local candidates' policies and ideologies, its impact on local housing markets would also be highly heterogeneous across location. An appropriate measure of political uncertainty therefore should capture this geographic variation.

Falk and Shelton (2018) propose such measures of political uncertainty based on the combination of vote margins and political polarization that vary geographically. The proposed uncertainty measures are constructed by combining measures of political uncertainty (based on the ex post electoral margin) and policy differences between the parties (based on the political polarization between the local Republican and Democratic parties).[12]

We adopt their measures of state-level uncertainty for our study. To be specific, we use the following measure of *political* uncertainty based on *realized* two-party vote share of the gubernatorial candidates,[13]

$$EU_{st} = \ln[101] - \ln[VM_{st} + 1], \tag{1}$$

where EU_{st} and VM_{st} respectively denote the electoral uncertainty (EU) and the vote margin (VM) in the gubernatorial election in state s in election year t. Beware that eq.(1) is to transform the vote margin (in which a small value represents a tighter race and thus large uncertainty) to electoral uncertainty (in which a large value represents large uncertainty).[14] The basic idea of this measure is that it is not the election *per se* but the closeness of election that matters for the political uncertainty surrounding elections (e.g, Julio and Yook, 2012; Redl, 2020). Elections in which the victor wins by a narrow margin therefore are likely to cause larger uncertainty than elections in which the outcome is not close.

[12] As noted by Falk and Shelton (2018), political uncertainty does not necessarily mean policy uncertainty. In states where there is little difference in policy between the parties, a given degree of political uncertainty might translate into little policy uncertainty. For this reason, the authors distinguish *political uncertainty* from *policy uncertainty* by taking into account the political polarization between the Democratic and Republican Parties. Using these measures of uncertainty, they show that electorally induced policy uncertainty reduces manufacturing investment in U.S. states.

[13] This measure is constructed under the assumption that elections which were close *ex post* were perceived to be uncertain *ex ante*. Falk and Shelton (2018) actually find a close positive association between the *ex post* measure and the average polling margin, with the regression coefficient of 0.9 and an adjusted R-squares of 0.83.

[14] After the log transformation, electoral uncertainty (EU) is bounded between zero (in an unopposed election) and 4.62 (=ln(101), a dead heat). According to Falk and Shelton (2018), the purpose of this nonlinear transformation is twofold. The first is to ensure a nonlinear effect of vote margin uncertainty, i.e., the effect on uncertainty is greater when the vote margin is smaller (or when race is tighter) than when it is larger. The second is to make coefficients interpretable as elasticities (or percentage change).

Another measure of uncertainty is *policy* uncertainty (PU_{st}) which is constructed by scaling the EU in eq.(1) by a state-and-year-specific measure of the political distance (polarization) between the two parties as,

$$PU_{st} = EU_{st} \times \frac{Polarization_{st}}{\frac{1}{ST}\sum_T \sum_S Polarization_{st}}, \tag{2}$$

where $Polarization_{st}$ represents the policy distance between the local Democrats and Republicans in state s in year t based on the data from Berry et al. (1998,2010). The resulting policy uncertainty measure therefore captures the difficulty in predicting the post-election economic policy stance of the governor's office.[15]

Apparently these state-level uncertainty measures allow for geographic variation in the uncertainty about elections and future policies regarding local housing markets. Throughout the paper, we focus on the electoral uncertainty (EU) in eq.(1) for our analyses and check the robustness of our results by using the policy uncertainty measure in eq.(2). Before proceeding, it is instructive to examine the empirical relevance of our measure of political uncertainty. We relate it to the state-level measure of economic policy uncertainty (EPU-S) recently constructed by Baker et al. (2022). According to Baker et al. (2022), closer elections for political leaders bring more policy uncertainty and it is effectively captured by the EPU-S.[16] Figure 4 top panel plots our measure of the EU on the vertical axis against the EPU-S by Baker et al. (2022) on the horizontal axis. Although the two measures of uncertainty capture somewhat different aspects of uncertainty (electoral uncertainty versus economic policy uncertainty), a moderate positive association is found between the two, implying that they contain some common information on the state-level uncertainty.

3.2 Baseline regression analysis

Because our dataset is a balanced panel with a large N (1,358 counties) and a small T (seven election cycles), regression with two-way fixed effect (TFE) estimation is suited for the empirical analysis.[17] Using variations in time across space in a linear panel data regression setup, TFE

[15] The raw data for state-level policy distance are obtained from the Fording's personal website at *https://rcfording.com/state-ideology-data/*. As explained in Berry et al. (1998,2010), this policy distance is a score, given to each party for each state and year, based on the voting record of the state's congressional delegation in Washington D.C. on a set of common bills.

[16] Claiming that the EPU-S includes more information than political uncertainty, Baker et al. (2022) show that election-related uncertainty leads to a high level of policy uncertainty at the state economic activity.

[17] TFE estimator is often viewed as equivalent to the multi-period diff-in-diff estimator (Favara and Imbs, 2015; Goodman-Bacon, 2019; Imai and Kim, 2021).

models permit us to gauge the marginal effect of the key explanatory variable while controlling for both county-level heterogeneity and common national macroeconomic shocks.

We consider the following baseline TFE regression model in which we further control for some county-level economic and socio-demographic attributes (X_{it}) in addition to the unobserved county-fixed (α_i) and year-fixed (θ_t) effects,

$$h_{it}^n = \beta EU_{st} + \delta(EU_{st} \times HO_{it}) + \eta(EU_{st} \times ID_{st}) + X_{it}'\Gamma + \alpha_i + \theta_t + \varepsilon_{it}, \tag{3}$$

where $s \in \{1, ..., M\}$ and $i \in \{1, ..., N\}$ respectively index states and counties, and $t \in \{1, ..., T\}$ index mid-term gubernatorial election years (with one time unit representing four calendar years). The dependent variable (h_{it}^n) represents the n-year cumulative growth rates of house prices in county i leading up to the election, where $n \in \{0, 1, 2\}$.[18] This is to probe whether political uncertainty affects housing markets differently in different years before elections.

EU_{st} in eq.(3) is the key explanatory variable representing the political uncertainty in state s in election year t. Hence, β is the main coefficient of interest which measures the marginal effect of state political uncertainty (EU_{st}) on local house price growth (h_{it}^n).[19] A negative sign is expected for β if uncertainty hampers local house price growth. Note that county fixed effects (α_i) absorb all time-invariant county-level characteristics, such as natural amenities, relative income, and average housing prices. Year-fixed effects (θ_t) account for the time-varying macroeconomic shocks or the nationwide political uncertainty that are common to all counties. In consequence, β in eq.(3) captures the *relative* impact of political uncertainty on house price growth compared to the past trend and to the rest of the nation.

The baseline TFE model also includes a couple of interactive terms with EU_{st}. δ is the coefficient for the interaction between state political uncertainty and homeownership rate ($EU_{st} \times HO_{it}$) which gauges the extent to which the impact of political uncertainty varies with the fraction of homeowners in the county. The expectation is that the impact of political uncertainty will be weaker in the counties with a higher concentration of homeowners (or with a lower fraction of renters). This is because homeowners, who already own houses, are likely less sensitive to future changes in policies or regulations regarding housing markets,

[18] h_{it}^0 therefore represents the growth rate of house price in the election year and h_{it}^1 denotes the cumulative house price growth rates for the election year and one year before the election, and so on.

[19] It is worth noting that the level, instead of the change, of political uncertainty is used as the main explanatory variable. This is because the *closeness* of the election, which is the underlying justification of the measure of political uncertainty, is conceptually better aligned with the level of political uncertainty rather than the change in political uncertainty. In a partisan state that is dominated by a specific political party, for instance, a change in voting share from say 85% to 80% does not affect much the political uncertainty.

while renters, as potential home buyers, are more sensitive to them. EU_{st} is also interacted with the incumbency dummy variable (ID_{st}) that takes on the value of one if the political party of the state's governor is the same as the party of the U.S. President and zero otherwise. This product term ($EU_{st} \times ID_{st}$) is to tease out the so-called *mid-term effects* when voters penalize the party controlling the White House in the gubernatorial elections (Alesina and Rosenthal,1996).[20]

Still, some time-varying unobserved characteristics that correlate with the key variable (EU_{st}) may directly affect the local house price growth. To address this concern, we include two sets of county-level attributes (X_{it} in eq.(3)) as controls to isolate the effect of political uncertainty from other features of the local economy. The first set of control variables is related to the local economic conditions, such as per capita income, unemployment rate, and population density, that typically influence housing markets. The second set of control variables embraces county-level socio-demographic attributes, such as average age, gender, race, marriage status, educational attainment, and veteran status. The baseline regression model in eq.(3) is then estimated using standard errors clustered at the county level.[21]

Table 3 presents our baseline regression results using house price growth rates for three different periods ($n \in \{0, 1, 2\}$) as dependent variable (h_{it}^{n}). Several observations can be made from Table 3. First of all, the impact of state political uncertainty on local house price growth is negative and significant in all cases considered. To interpret, an elevated political uncertainty (EU) slows down local house price growth relative to their own past trend and to other counties. The key coefficient of interest estimated is around -3.4 (in the election year), suggesting that on average a unit increase in our measure of electoral uncertainty (EU) is associated with about 3.4 percentage point decrease in county-level house price growth, after controlling for both county-level socio-economic and demographic attributes and other covariates.[22] Alternatively,

[20] Since midterm elections give voters an opportunity to settle up with the president (rather than gubernatorial candidates) for the past two years (Peltzman, 1987), gubernatorial candidates of the same party as the current President often have poor electoral performances. We also investigate whether uncertainty stemming from leaving incumbents (either voluntarily or involuntarily due to term limits) affects local house price growth, but find little evidence on it. Moreover, the results of our analysis are unaltered when the states with independent governors (ME and MN) are dropped. These results, not reported here to conserve space, will be available upon request.

[21] Clustering errors by county allows correlation between different observations within a county (over different years). Our results are robust to the choice of different clustering approaches based on state level or alternative county traits. Clustering at the state level, however, is of reduced appeal in capturing the large cross-county heterogeneity found in almost all states.

[22] Because our EU measure is constructed from a nonlinear log transformation of vote margin (VM) as stipulated in eq.(1), it is not straightforward to interpret the unit increase in the EU measure. From eq.(1), however,

the average value of the dependent variable, from Table 2, is 2.86% and the explanatory variable of interest, EU, has a standard deviation of 0.18. Therefore, the effect of a one standard deviation (s.d.) increase in electoral uncertainty (EU) is around -0.61 ($= 0.18 \times -3.4$). That's a reduction of about one-fifth in the average value of the dependent variable. Taken together, the key variable of interest is not just statistically significant, but also non-trivial in magnitude. Interestingly, the marginal effect is strongest in election year and monotonically declines over time from it. This indicates that election-induced uncertainty matters most for local house price growth in the period near the election.

The interactive term of political uncertainty with homeownership rate ($EU_{st} \times HO_{it}$) has significant and positive coefficients in all specifications under study, indicating that the impact of political uncertainty is weaker in counties with a higher concentration of homeowners. This may reflect that homeowners, who already possess houses, are less responsive to the uncertainty regarding possible changes in policies and regulations related to housing markets after election. Contrastingly, the product term of the incumbent dummy variable ($EU_{st} \times D_{st}$) enters with mixed signs and it is statistically insignificant in all cases. Put alternatively, there is little evidence of the mid-term effects in the impact of state political uncertainty on local housing markets.

The control variables for economic fundamentals largely take the expected signs and are statistically significant: positive signs for the growth of income and population density and a negative sign for unemployment rate, consistent with our economic intuition. To interpret, a faster growth of per capita income or population density is associated with a faster growth of house prices, while a higher unemployment rate is associated with a slower growth of house prices. The control variables for socio-demographic characteristics, however, have mixed signs. Local house price growth is faster in the counties with a larger fraction of residents with college education and Hispanic population, and with a smaller fraction of residents aged between 18-65 years. Their quantitative impacts are not substantive in general though.

EU = 1 when VM = 36% and EU is around 2 when VM = 12%. Thus, the coefficient estimate suggests that local house price growth declines by about 3.4 percentage point if vote margin decreases (and hence uncertainty surrounding election increases) from 36% to 12%. Put differently, house price growth declines by approximately 0.14 percentage point ($= 3.4 \div 24$) per percentage point decrease in vote margin. With the average house price growth of 2.86 in our sample, this indicates that one percentage point decrease in vote margin leads to about 5 percent ($= 0.14 \div 2.86$) decrease in house price growth relative to the sample average. This magnitude of the marginal effect can be viewed as nontrivial.

3.3 Asymmetry in the impact of political uncertainty

Recent studies in the literature often document that economic factors respond asymmetrically to the uncertainty. Foerster (2014), for example, shows that increases in uncertainty have a much more significant effect on the economy than decreases in uncertainty do. A similar pattern of asymmetry is also reported in Alessandri and Mumtaz (2019). In this sense, it is worth examining whether state political uncertainty affects local house price growth in an asymmetric manner, i.e., whether increases in political uncertainty have differential effects on house price growth than uncertainty decreases, not just in terms of the sign, but in terms of the magnitude.

To bear this out, we refine our model specification and estimation as

$$h_{it}^{n} = \beta_1 \Delta EU_{st}^{+} + \beta_2 \Delta EU_{st}^{-} + X_{it}'\Gamma + \alpha_i + \theta_t + \varepsilon_{it} \quad (4)$$

$$= \beta_1 (\Delta EU_{st}^{+} - \Delta EU_{st}^{-}) + \delta \Delta EU_{st}^{-} + X_{it}'\Gamma + \alpha_i + \theta_t + \varepsilon_{it} \quad (5)$$

where $\delta = \beta_1 + \beta_2$, ΔEU_{st}^{+} and ΔEU_{st}^{-} respectively denote the increase and decrease in political uncertainty since the previous election. We expect a priori negative effect of political uncertainty increase and a positive effect of political uncertainty decrease, i.e., $\beta_1 < 0$ and $\beta_2 > 0$. Symmetry in the effect between uncertainty increases and decreases therefore implies that $|\beta_1|$ equals $|\beta_2|$, or $\beta_1 = -\beta_2$. Then, testing the null hypothesis of symmetry ($H_0 : \beta_1 = -\beta_2$ in eq.(4)) is equivalent to testing $H_0 : \delta = 0$ in eq.(5).

Table 4 reports the results of this exercise. The regression results accord closely with our expectations. The coefficient estimate of ΔEU_{st}^{+} takes a negative sign and the coefficient estimate of ΔEU_{st}^{-} takes a positive sign. Interestingly, the negative impact of uncertainty increase appears to be bigger than the positive impact of uncertainty decrease, $|\beta_1| > |\beta_2|$, i.e., the decline in house price growth due to an increase in uncertainty is more sizable than the rise in house price growth due to a reduction in uncertainty. This is further confirmed by the coefficient estimate of δ in eq.(5) which is negative (-0.147) and significant, implying that the null hypothesis of symmetric effect ($H_0 : \delta = 0$ or $H_0 : \beta_1 = -\beta_2$) can be rejected at the usual significance level. This outcome suggests an asymmetric effect of state political uncertainty on local house price growth.

The asymmetric effect of uncertainty is conceptually aligned with the loss aversion behavior of investors who are more sensitive to increases in uncertainty (which reduces house price growth) than to decreases (which enhances house price growth). In fact, it is growingly recognized that loss aversion induces various types of asymmetry in the transmission of shocks to the economy (e.g., Barberis et al., 2001).

3.4 Robustness check

Because our regression analysis so far is based on a specific sample and a specific measure of political uncertainty, the conclusions drawn here could be sensitive to the choice of samples and uncertainty measures. This leads us to conduct some robustness checks on our main findings along several dimensions.

First, we investigate whether or not our results are unduly driven by a specific election year. Because the dependent variable of our TFE regression analysis, local house price growth, is vulnerable to the housing boom-bust cycle in the 2000s, a legitimate concern arises as to the sensitivity of our main conclusion to the subset of data. To address this concern, we drop from our analysis two election cycles in 2006 and 2010 when the U.S. housing market made a drastic transition from boom to bust, and check whether our main conclusions still hold up. Table 5 provides the regression results using the same set of explanatory variables as before, but with different subsamples. The results presented in Table 5 are qualitatively and quantitatively very similar to those from the baseline analysis in Table 3. The marginal effect of state political uncertainty remains consistently negative and significant in all cases under study, reasserting the robustness of our key conclusions to the housing market boom-bust cycles.

We further check the robustness of our results to the use of an alternative measure of political uncertainty. This time we use the policy uncertainty (PU) stipulated in eq.(2) as the measure of state political uncertainty. Recall that the major difference between EU in eq.(1) and PU in eq.(2) is that the latter takes into account the political polarization, or the political distance between the local Democrats and Republicans parties, in addition to the vote margins. The results of such exercise are presented in Table 6 for the same model specifications as in the baseline regression. Again, all of the key conclusions drawn from the baseline regression hold with the alternative measure of uncertainty.

Next, we have so far maintained that the causality runs from political uncertainty to local housing markets. This assumption on causal inference seems to be innocuous because state government policies such as homeownership tax benefits and mortgage credit subsidies affect local housing markets, as often documented in the literature. The causal relationship, however, can be endogenous if an economic downturn, which also affect local housing markets, generates political uncertainty by making the incumbent governor less popular.[23] In this case, local house prices could influence political uncertainty as well as being influenced by political uncertainty, giving rise to a simultaneity or reverse causality problem. The endogeneity problem can also arise from potential omitted variable bias if latent confounders are both correlated with political uncertainty and local house price growth. We mitigate this omitted variable problem by augmenting the extensive set of controls described earlier in our regression model. If control variables like local economic conditions and socio-demographic characteristics indirectly affect political uncertainty, however, they still could cause the effect of political uncertainty on local house price growth to be biased.

We attempt to address this endogeneity concern on a couple of dimensions. First, in the TFE regression analyses we regress county-level house price growth onto state-level political uncertainty. By so doing, we intend to alleviate the simultaneity problem as state-level political uncertainty is likely to influence county-level house prices, but not the other way around. This is because no single county is large enough to create statewide political uncertainty. Figure 4 bottom panel makes this point clear by plotting the empirical densities of the fraction of county-level vote margin in the entire state. In the vast majority of counties, the share is relatively small, less than five percent, implying that no single county is substantially large to generate statewide political uncertainty.[24]

Additionally, we conduct "a lagged IV regression" by using lagged key explanatory variable as instrumental variables (e.g., Bøler et al., 2015; Doraszelski et al., 2018).[25] The intuition behind this lagged IV approach is that the causality is likely to run from previous political uncertainty to current political uncertainty due to the high persistence of political uncertainty (exclusion restriction), while previous political uncertainty is unlikely affected by the current house price growth and other latent factors (independent assumption). That is, the lagged values of the key explanatory variable (political uncertainty) are closely associated with the current value of political uncertainty[26], but not much related to the current house price growth

[23] According to the theory of economic voting, for example, voters are likely to vote the incumbent governor out of office when the economic performance of incumbent government is poor, raising the uncertainty surrounding election outcomes.

[24] Although not reported here, we reestimate the TFE model in eq.(3) by dropping the three largest counties in each state. The results are largely unaltered as well.

[25] As is well established in the literature, finding a valid instrumental variable (IV), which satisfies both the independence assumption and the exclusion restriction, is challenging. In our case, a valid IV should predict political uncertainty, but is not directly related to local housing market performance. Unfortunately, such an ideal instrument is elusive. This leads us to consider the lagged values of the key variable as an instrument.

[26] Over years, gubernatorial elections have become increasingly polarized, and uncertainty in these races bear

(dependent variable) because the former precedes the latter in time.

We run the following lagged IV regression using lagged values of state political uncertainty as an instrument,

$$h_{it}^{n} = \beta \widetilde{EU}_{st} + X_{it}'\Gamma + \alpha_i + \theta_t + \varepsilon_{it}, \quad (6)$$

where $\widetilde{EU}_{st} = \hat{\delta}_i + \hat{\kappa} z_{st} + X_{it}'\hat{\Gamma}$ is the predicted values of EU_{st} estimated from $EU_{st} = \delta_i + \kappa z_{st} + X_{it}'\Gamma + \epsilon_{it}$ and $z_{st} = EU_{s,t-1}$ is the lagged values of EU_{st} in the previous election used as instrument. All other variables remain the same as in the baseline specification in eq.(3). Eq.(6) is estimated using 2SLS.

Table 7 presents the lagged IV regression results for two cases: one for the election year (column 1) and the other for two cumulative years before election (column 2). The first thing to note from Table 7 is that the IV estimates for EU_{st} are statistically significant and have the expected negative signs in both cases. Although the coefficients are now a bit smaller than the baseline case, the IV estimates consistently confirm that state political uncertainty exerts a significant negative effect on local house price growth. The qualitative effects of other explanatory variables are largely similar to those outlined in the baseline regression analysis, except for some demographic control variables.

To sum, our additional regression analyses show that the key conclusions drawn from the baseline regression analysis are robust to endogeneity, sample selection, model specifications, and alternative measures of uncertainty.

4 A case study in a difference-in-difference setting

Although intriguing, regression analysis is of reduced merit in providing a detailed explanation for the issue at hand. In the literature, case studies are often used to evaluate the impact of policy changes through detailed examinations of economic conditions before and after the policy implementations. Following this convention, we here conduct a case study based on difference-in-difference (diff-in-diff) analysis in an effort to draw further inference on the impact of state political uncertainty.

The basic idea of our diff-in-diff analysis is to assess the impact of state political uncertainty by comparing the paths of local house price growth in two states sharing similar paths of outcome variable but different in the treatment (the timing of gubernatorial elections). This data-driven approach allows us to evaluate the causal impact of state political uncertainty

a striking resemblance to those in previous races, i.e., high persistence of political uncertainty over time.

by building a counterfactual based on comparative characteristics between the treatment and control groups. A critical assumption in this regard is that the path of the key outcome variable of the state under comparison follows very closely with its control before the treatment, but diverge after the treatment. Identifying rigorous control groups is therefore crucial for the analysis (e.g., Peri and Yasenov, 2015).[27] We view neighboring states as reasonable controls because geographic proximity is an arguably decent metric for similarity when regions share substantial similarities in political, economic or cultural environments.

We consider two treated states for the case study, Kansas and South Carolina, due mainly to the availability of reasonable control groups, Missouri (for Kansas) and North Carolina (for South Carolina), in which gubernatorial elections are held in off-midterm years. Located in the Midwest region where states share similar climate and cultural and societal attributes, Kansas is a decent choice for the case study because the house price growth has been relatively stable over time, making our analysis less vulnerable to the recent housing boom-bust cycle. Moreover, Kansas had frequent shifts of the party affiliations of incumbent governors over time, providing an ideal setting for studying the impact of state political uncertainty. In a similar context, South Carolina is a natural choice for the case study due to the existence of its sibling state, North Carolina. In fact, North and South Carolinas are known to be one of the closest pair in the U.S. Other than population and size, the two Carolinas share a lot in common, including climates and topography, median household income, median property value, and cost of living. More importantly, the two states had similar patterns of house price movements over time, a desirable feature for the diff-in-diff analysis.

Figure 5 plots the level and growth rates of house prices in the two treated (KS and SC) along with their controls (MO and NC) during 1983.Q1 - 2021.Q4. As shown in Panel (a) of Figure 5, Missouri exhibits a very similar profile in the house price movements with Kansas, in support of our empirical design.[28] The pattern of house price growth rate in Kansas, as displayed in Panel (c) of Figure 5, also closely matches that of Missouri, with the correlation coefficient exceeding 0.95 after 1990. A similar picture is painted between the two Carolina

[27] The synthetic control method (SCM) suggested by Abadie et al. (2010) is another promising tool to track the treatment effect. However, it is not considered here because the SCM typically assumes non-repeated treatments while the treatment in our case (gubernatorial election) is repeated every four years. Furthermore, because the pool of potential donor states is relatively small in our data (states in which gubernatorial elections are held in off-mid-term years), the synthetic state may poorly approximate the treated state.

[28] Kansas and Missouri arguably share similarities in many aspects. They have similar climate as they are at the same latitude, and both are landlocked, sparsely populated, and have most of their land devoted to agriculture, with a high percentage of White people and the political preference toward the Republican Party.

states as displayed in Panels (b) and (d) of Figure 5. The level and growth rate of house prices move in lockstep between the two states and the correlation in house price growth rates is close to 1.

Our diff-in-diff strategy here is to check whether the house price growth gap between the treated and control states is meaningfully associated with the political uncertainty in the treated states. Intuitively, the gap should be inversely related to the political uncertainty in the treated state because house price in the treated state grows slower relative to the control state when the election-induced uncertainty rises in the former. We set the treatment period as four quarters prior to each election. Figure 6 exhibits the results of this exercise based on statewide house prices: Panel (a) for KS-MO; and Panel (b) for SC-NC. In both Panels of Figure 6, we notice a strong inverse relationship between the political uncertainty of the treated states (on the horizontal axis) and the house price growth gap (on the vertical axis) across nine election cycles. To interpret, house price in the treated states (KS and SC) has grown slower relative to those in the control states (MO and NC) when the uncertainty surrounding their gubernatorial elections was elevated, and vice versa.[29]

Overall, our diff-in-diff case study verifies that state political uncertainty plays an important role in the local house price growth, with a slower growth relative to their neighboring states when their election uncertainty rises.

5 Transmission mechanism of political uncertainty to housing markets

While our empirical analysis convincingly suggests that state political uncertainty has a significant and negative impact on local house price growth, it still remains an open question through which channel political uncertainty influences local housing markets. This section explores the transmission mechanisms underlying our empirical findings. Given that house price changes reflect an equilibrium of changes in both the housing supply and housing demand, in theory any forces behind supply and demand of housing markets should be related to the transmission mechanism.

There are several potential channels through which political uncertainty might affect hous-

[29] In unreported results, we also find similar results based on the urban areas of the states in which housing markets are generally more active and thus are more sensitive to election uncertainty than their rural counterparts.

ing markets. On the demand side, political uncertainty affects housing markets mainly through buyers' decision making. Because the incentives of owning houses hinge on the tax policies like property tax rate and capital gains taxes, (potential) home buyers may put off their decisions until related tax policies are determined by the new policymakers. Political uncertainty may also affect housing demand through the confidence of home buyers. Given that the election-induced uncertainty could create more pessimism than optimism, and that buyers are less likely to purchase home when they feel less confident, election-induced uncertainty would hamper house price growth by slowing down the housing demand.[30]

On the supply side, research also has shown that the uncertainty surrounding an election would negatively affect housing supply by making it more difficult for sellers to sell a home. In consequence, sellers are holding off on listing their homes until they can score the best possible prices after the uncertainty is gone. This explains why home sales tend to spike following elections as political uncertainty disappears. In a similar context, home builders may delay construction projects until the policy uncertainty is resolved.

As such, political uncertainty would affect both housing demand and housing supply. The overall impact on house price is therefore a priori ambiguous and it is ultimately determined by the equilibrium between demand and supply. Our empirical evidence on the negative impact of state political uncertainty, however, is better aligned with the housing demand channel. This is because house price would drop when demand decreases, while it increases as housing supply decreases. Our interpretation here is also consistent with what is documented in the previous literature (Glaeser and Gyourko, 2006; Head et al., 2014) that house price growth in the U.S has largely been demand-driven as the supply side is strongly persistent and responds less to external factors. Taken together, it is fair to view that state political uncertainty affects local housing markets primarily through housing demand channel.

6 Concluding remarks

Due to the high costs of transaction and an '*irreversible*' nature of investment, housing markets are intrinsically sensitive to any uncertainty. It is particularly the case to the uncertainty stemming from political events like elections which can lead to possible changes in government policies and regulations highly related to housing markets. Inspired by this, the current study

[30] Because households in general do not have access to complete financial markets, it less realistic to explain the transmission mechanism of uncertainty within the standard option-pricing framework as in Nguyen and Vergara-Alert (2020).

investigated the link between election-induced political uncertainty and housing markets at the subnational level. Specifically we focused on how and to what extent uncertainty related to the mid-term gubernatorial elections affects county-level house price growth, by exploiting large geographic variations in both local house prices and election outcomes.

Via a series of panel data regression analyses, we found that state political uncertainty has a significant negative impact on local housing markets, i.e., a slow-down in local house price growth in the states with a tighter gubernatorial election race. On average a unit increase in the measure of state political uncertainty leads to about a 3.4 percentage point decrease in local house price growth relative to the national average and the past trend. Interestingly, the impact is asymmetric in that local house price growth is more responsive to uncertainty increase than to uncertainty decrease.

More importantly, the impact varies widely across location depending on certain county-level characteristics such as homeownership. Counties with a higher concentration of homeowners tend to have a weaker impact of state political uncertainty, probably because homeowners, who already own houses, are less sensitive to possible changes in policies and regulations related to housing markets, compared to renters. Our results are robust to sample selection, to the use of an alternative measure of political uncertainty, and after controlling for a range of relevant covariates. We also confirm the robustness of our findings to the endogeneity concern. Our main findings are further strengthened by a diff-in-diff case study based on two treated states, KS and SC.

Our results also yield insights on the underlying channel through which political uncertainty influences housing markets. Studies in the literature often focus on the supply side impact of political uncertainty through changes in the related regulations. But, our empirical findings indicate that political uncertainty is transmitted to the local housing markets mainly through housing demand channel.

With that said, we reckon that there still exists room for improving our understanding of the relationship between political uncertainty and housing market. Our data used here are in annual frequency and hence do not permit us to capture more frequent responses of housing markets to the uncertainty especially near elections. Availability of such higher frequency data, in combination with various pre-election polling results, may provide additional insights into the issue at hand. Future studies may benefit from analysis in this direction.

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Table 1: Summary of selected previous studies on economic impact of political uncertainty

Study	Measure of political uncertainty	Economic factor	Impact
Brogaard et al. (2020)	U.S. Presidential and mid-term elections	Risk premium in equity markets outside U.S.	Decline in equity returns in foreign markets before U.S. elections
Canes-Wrone & Park (2014)	Staggering U.S. gubernatorial elections	Housing prices of 300 U.S. MSAs	Decline in house price in the pre-election period
Chan & Marsh (2021)	Baker et al's (2016) EPU and Azzimonti's (2018) PCI	Equity premium	Higher equity premiums after mid-term elections
Çolak et al. (2017)	Gubernatorial elections & neighboring state effect	IPO activity	Fewer IPOs in states with gubernatorial elections
Falk & Shelton (2018)	Election margin combined with political polarization	Manufacturing investment in U.S. states	Policy uncertainty reduces manufacturing investment
Hoke (2018)	Azzimonti's (2018) Partisan Conflict Index (PCI)	National macroeconomic variables	Negative impact of political risk on macroeconomic variables
Jens (2017)	Staggering U.S. gubernatorial elections	Firm investment	Firm investment declines before gubernatorial elections
Julio & Yook (2012)	National elections	Corporate investment	Firms reduce investment during election years
Kelly et al. (2016)	National elections & global summit	Equity options	Option price reflects political uncertainty
Nguyen and Vergara-Alert (2020)	Staggering U.S. gubernatorial elections	Housing markets in U.S. states	Higher political uncertainty lowers house prices
Pástor & Veronesi (2013)	Baker et al's (2016) EPU index	Risk premium of stocks	Higher political uncertainty is associated with larger risk premium

Table 2: Summary statistics

Variables	Mean	median	SD	N
Vote margin (VM_{st}, %)	15.48	13.45	12.17	9,506
Electoral uncertainty (EU_{st})	2.11	1.95	0.18	9,506
House price growth (%)	2.86	3.13	5.16	9,506
Unemployment rate (%)	6.12	5.53	2.77	9,506
Population density growth (%)	0.66	0.41	1.24	9,506
Average wage/salary growth (%)	2.96	2.96	1.31	9,506
Per capita income growth (%)	3.45	3.51	1.84	9,506
Homeownership rate (%)	71.9	73.0	8.2	9,506
Male population share (%)	49.7	49.4	1.5	9,506
Female population share (%)	50.3	50.6	1.5	9,506
Share of population age below 18 (%)	24.0	24.1	3.3	9,506
Share of population age 18-64 (%)	60.6	60.4	3.4	9,506
Share of population age over 64 (%)	15.4	15.1	4.2	9,506
Share of White population (%)	85.2	89.8	13.6	9,506
Share of Black population (%)	7.1	2.2	11.1	9,506
Share of Hispanic population (%)	9.4	4.0	13.5	9,506
Share of married households (%)	54.4	55.0	6.3	9,506
Share of adults with at least bachelor degree (%)	21.1	18.8	9.0	9,506
Share of homes owned with no mortgage (%)	28.7	29.0	8.4	9,506
Share of veteran (%)	11.6	11.4	3.4	9,506

Notes: 'N' denotes the total number of observations for the entire sample period.

Table 3: Results of baseline TFE regression analysis

Explanatory variables	election year	One year before	2 years before
Political uncertainty (EU_{st})	-3.468‡[0.817]	-2.535‡[0.897]	-1.740* [0.894]
EU_{st} × Homeownership rate	0.029‡[0.008]	0.041‡[0.008]	0.016* [0.008]
EU_{st} × Incumbent dummy (ID)	0.011 [0.041]	0.101†[0.048]	0.023 [0.048]
Unemployment rate	-0.465‡[0.054]	-0.789‡[0.073]	-0.919‡[0.067]
Per capita income growth	0.542‡[0.040]	0.519‡[0.041]	0.357‡[0.040]
Population density growth	0.770‡[0.084]	1.123‡[0.107]	1.409‡[0.104]
Share of age between 18-65 years	-0.197‡[0.062]	-0.167‡[0.063]	-0.116* [0.066]
Share of White population	-0.020 [0.030]	-0.051 [0.036]	-0.105‡[0.039]
Share of Black population	0.120†[0.059]	0.088 [0.060]	-0.012 [0.062]
Share of Hispanic population	0.107‡[0.032]	0.145‡[0.034]	0.060* [0.036]
Share of married households	-0.001 [0.034]	-0.050 [0.036]	-0.053 [0.034]
Share of bachelor and above	0.061* [0.036]	0.097‡[0.037]	0.027 [0.037]
Share of veteran population	0.194‡[0.074]	0.102 [0.078]	0.205‡[0.078]
County fixed effect (α_i)	Yes	Yes	Yes
Year fixed effect (θ_t)	Yes	Yes	Yes
Adjusted R-squared	0.376	0.351	0.240
Observations	9,506	9,506	9,506

Notes: The regression equation is

$$h_{it}^{n} = \beta EU_{st} + \delta(EU_{st} \times HO_{it}) + \eta(EU_{st} \times ID_{st}) + X_{it}'\Gamma + \alpha_i + \theta_t + \varepsilon_{it},$$

where $h_{i,t-j}$ denotes the change in *cumulative* growth rates of house price in county i in j-year before election where $j \in \{0, 1, 2\}$. EU_{st} denotes the elctoral uncertainty in state s in year t, measured by $EU_{st} = \ln[101] - \ln[VM_{st} + 1]$ where VM_{st} denotes the vote margin in the gubernatorial election in state s at time t. As noted in Falk and Shelton (2018), the resulting measure of political uncertainty varies from 0 in an unopposed election to $\ln(101) = 4.62$ in a dead heat. HO_{it} represents the average homeownership rate in county i in the election cycle t. ID_{it} is a dummy variable for incumbent party which takes on the value of one if governor is in the *different* party with the incumbent president and zero otherwise. X_{it} is a vector of control variables, which we arrange into two sets: (i) fundamental local economic factors, such as per capita income, population density, and unemployment rate; and (ii) socio-demographic characteristics that are important for any model of voting behavior. ‡, † and asterisk (*) respectively indicate the statistical significance at the 1%, 5%, and 10% significance levels with the corresponding clustered s.e. inside square brackets.

Table 4: Asymmetry in the effect of political uncertainty

Explanatory variables	Model 1	Model 2
Increase in uncertainty (β_1)	-0.461‡[0.087]	-0.461‡[0.087]
Decrease in uncertainty (β_2)	0.306‡[0.079]	
$\delta(=\beta_1+\beta_2)$		-0.156* [0.082]
Unemployment rate change	-0.463‡[0.059]	-0.463‡[0.059]
Per capita income growth	0.667‡[0.049]	0.667‡[0.049]
Population density growth	0.718‡[0.094]	0.718‡[0.094]
Share of age under 18 years	-0.246‡[0.082]	-0.246‡[0.082]
Share of White population	-0.050 [0.041]	-0.050 [0.041]
Share of Black population	0.074 [0.086]	0.074 [0.086]
Share of Hispanic population	0.128‡[0.045]	0.128‡[0.045]
Share of married households	-0.056 [0.042]	-0.056 [0.042]
Share of bachelor and above	0.045 [0.046]	0.045 [0.046]
Share of homeowners	-0.057* [0.034]	-0.057* [0.034]
Shareof veteran population	0.268‡[0.095]	0.268‡[0.095]
County fixed effect (α_i)	Yes	Yes
Year fixed effect (θ_t)	Yes	Yes
Adjusted R-squared	0.369	0.371
Observations	8,148	8,148

Notes: The regression equation is

$$\begin{aligned} h^n_{it} &= \beta_1 \Delta EU^+_{st} + \beta_2 \Delta EU^-_{st} + X'_{it}\Gamma + \alpha_i + \theta_t + \varepsilon_{it} \quad \text{Model 1} \\ &= \beta_1(\Delta EU^+_{st} - \Delta EU^-_{st}) + \delta \Delta EU^-_{st} + X'_{it}\Gamma + \alpha_i + \theta_t + \varepsilon_{it} \quad \text{Model 2} \end{aligned}$$

where $\delta = \beta_1 + \beta_2$, EU^+_{st} and EU^-_{st} respectively denote the increase and decrease in the election uncertainty since the last election. If the estimation implies that β_1 equals β_2, then there is no asymmetry in the effect between uncertainty increases and decreases. The dependent variable is the local house price growth in the election year. Note that testing the null hypothesis of symmetry ($H_0 : \beta_1 = -\beta_2$) is equivalent to testing $H_0 : \delta = 0$. EU^+_{st} and EU^-_{st} respectively denote the increase and decrease in election uncertainty in state s in year t compared to the previous election. Refer to the notes in Table 3 for the rest.

Table 5: Robustness check for election cycle

Explanatory variables	Election year dropped	
	2006 election	2010 election
Political uncertainty (EU_{st})	-1.942‡[0.819]	-3.571‡[0.868]
EU_{st} × Homeownership rate	0.026‡[0.008]	0.022‡[0.008]
EU_{st} × Incumbent dummy (ID)	0.060 [0.042]	-0.059 [0.038]
Unemployment rate	-0.203‡[0.055]	-0.441‡[0.059]
Per capita income growth	0.545‡[0.042]	0.326‡[0.039]
Population density growth	0.745‡[0.086]	0.380‡[0.079]
Share of age between 18-65 years	-0.218‡[0.064]	-0.031 [0.066]
Share of White population	0.029 [0.030]	-0.019 [0.030]
Share of Black population	0.122†[0.058]	0.128‡[0.051]
Share of Hispanic population	0.124‡[0.031]	0.186‡[0.033]
Share of married households	-0.027 [0.035]	0.002 [0.035]
Share of bachelor and above	0.037 [0.035]	0.099‡[0.036]
Share of veteran population	0.186‡[0.074]	0.005 [0.075]
County fixed effect (α_i)	Yes	Yes
Year fixed effect (θ_t)	Yes	Yes
Adjusted R-squared	0.376	0.279
Observations	8,148	8,148

Notes: For the dependent variable, we consider the house price growth in the election year only. For the subsample analysis of '2006 election', we consider only six election cycles after dropping 2006 election (1994, 1998, 2002, 2010, 2014, and 2018) in which data are available for 8,148 observations ($= 1,358 \times 6$). So is the subsample analysis of '2010 election'. ‡, † and asterisk (*) respectively indicate the statistical significance at the 1%, 5%, and 10% significance levels with the corresponding clustered s.e. inside square brackets. Refer to the notes in Table 3 for the regression model specification.

Table 6: Robustness check using Policy uncertainty (PU) as explanatory variable

Explanatory variables	election year	One year before	2 years before
Policy uncertainty (PU_{st})	-3.630* [1.916]	-2.130* [1.205]	-1.105 [1.949]
PU_{st} × Homeownership rate	0.094‡[0.020]	0.037†[0.018]	0.031 [0.021]
PU_{st} × Incumbent dummy (ID)	0.303‡[0.133]	0.035 [0.114]	0.097 [0.139]
Unemployment rate change	-0.816‡[0.073]	-0.489‡[0.055]	-0.930‡[0.068]
Per capita income growth	0.501‡[0.041]	0.528‡[0.040]	0.351‡[0.040]
Population density growth	1.109‡[0.107]	0.761‡[0.083]	1.402‡[0.105]
Share of age between 18-65 years	-0.172‡[0.067]	-0.112* [0.067]	-0.136* [0.070]
Share of White population	-0.050 [0.036]	-0.020 [0.030]	-0.107‡[0.039]
Share of Black population	0.064 [0.059]	0.114* [0.059]	-0.024 [0.063]
Share of Hispanic population	0.153‡[0.034]	0.106‡[0.032]	0.062* [0.035]
Share of married households	-0.071†[0.035]	-0.025 [0.034]	-0.061* [0.034]
Share of bachelor and above	0.079†[0.037]	0.035 [0.036]	0.021 [0.037]
Share of veteran population	0.109 [0.079]	0.185‡[0.075]	0.211‡[0.078]
County fixed effect (α_i)	Yes	Yes	Yes
Year fixed effect (θ_t)	Yes	Yes	Yes
Adjusted R-squared	0.377	0.352	0.239
Observations	9,506	9,506	9,506

Notes: Refer to the notes in Table 3 for the regression model specification. For the key explanatory variable, policy uncertainty (PU) stipulated in eq.(3) is used. All the other variables remain the same as the baseline regression model reported in Table 3.

Table 7: Lagged IV analysis results

Explanatory variables	election year	One year before
Political uncertainty (EU_{st})	-2.482‡[0.789]	-2.206‡[0.699]
Unemployment rate change	-0.888‡[0.090]	-1.192‡[0.084]
Per capita income growth	0.451‡[0.047]	0.309‡[0.045]
Population density growth	1.200‡[0.137]	1.636‡[0.130]
Share of age between 18-65 years	-0.131 [0.082]	-0.028 [0.086]
Share of White population	0.006 [0.043]	-0.045 [0.047]
Share of Black population	0.198‡[0.077]	0.034 [0.082]
Share of Hispanic population	-0.102‡[0.049]	-0.102* [0.053]
Share of married households	-0.029 [0.042]	-0.097‡[0.040]
Share of bachelor and above	-0.015 [0.046]	-0.190‡[0.047]
Share of veteran population	0.322‡[0.092]	0.454‡[0.089]
County fixed effect (α_i)	Yes	Yes
Year fixed effect (θ_t)	Yes	Yes
Adjusted R-squared	0.349	0.254
Observations	9,506	9,506

Notes: The regression equation is

$$h_{it}^{n} = \beta \widetilde{EU}_{st} + X_{it}'\Gamma + \alpha_i + \theta_t + \varepsilon_{it},$$

where $\widetilde{EU}_{st} = \hat{\delta}_i + \hat{\kappa} z_{st} + X_{it}'\hat{\Gamma}$ is the predicted values of EU_{st} estimated from $EU_{st} = \delta_i + \kappa z_{st} + X_{it}'\Gamma + \epsilon_{it}$ and $z_{st} = EU_{s,t-1}$ is the lagged values of EU_{st} used as an instrument variable.

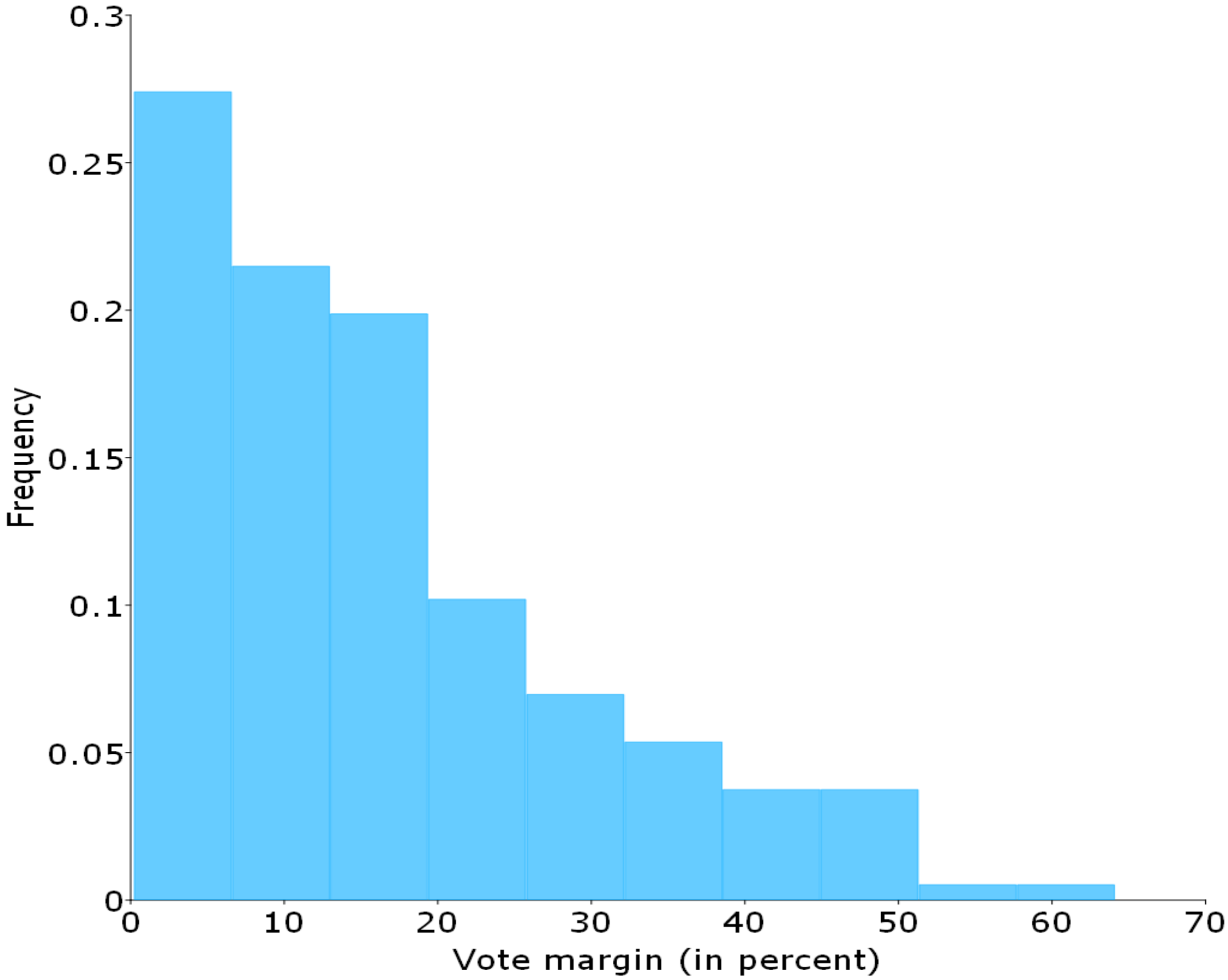


Figure 1: Empirical densities of the vote margins of the past seven election cycles

Note: This figure shows the empirical densities of vote margins (in percent, on the horizontal axis), or vote share difference between the top two contenders, against the corresponding frequency (on the vertical axis) in the past seven mid-term gubernatorial election cycles.

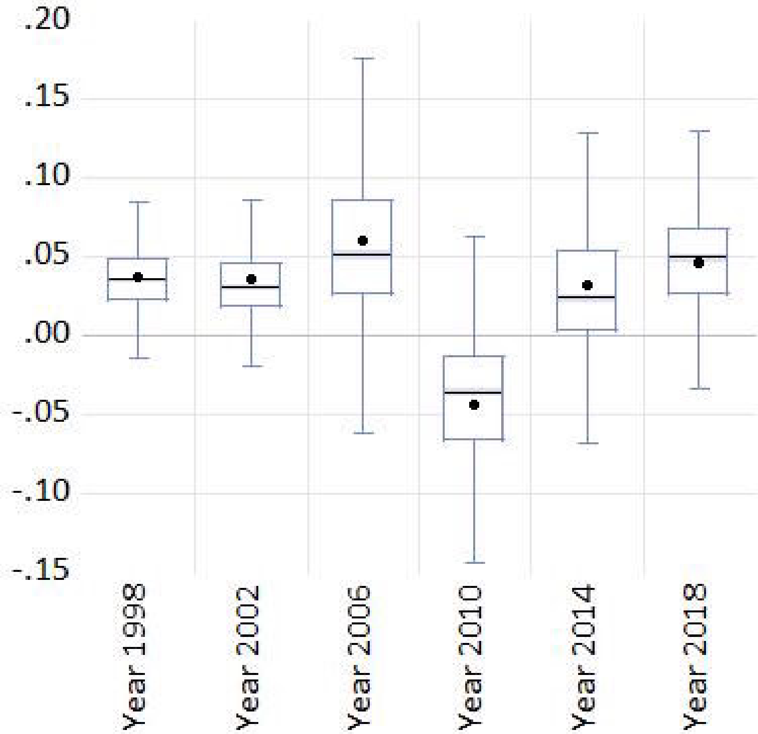


Figure 2: Boxplots of county-level house price growth rates for each gubernatorial election

Note: This figure plots the cross-county distribution (mean, median, min, and max) of the county-level house price growth rates over the last six election cycles.

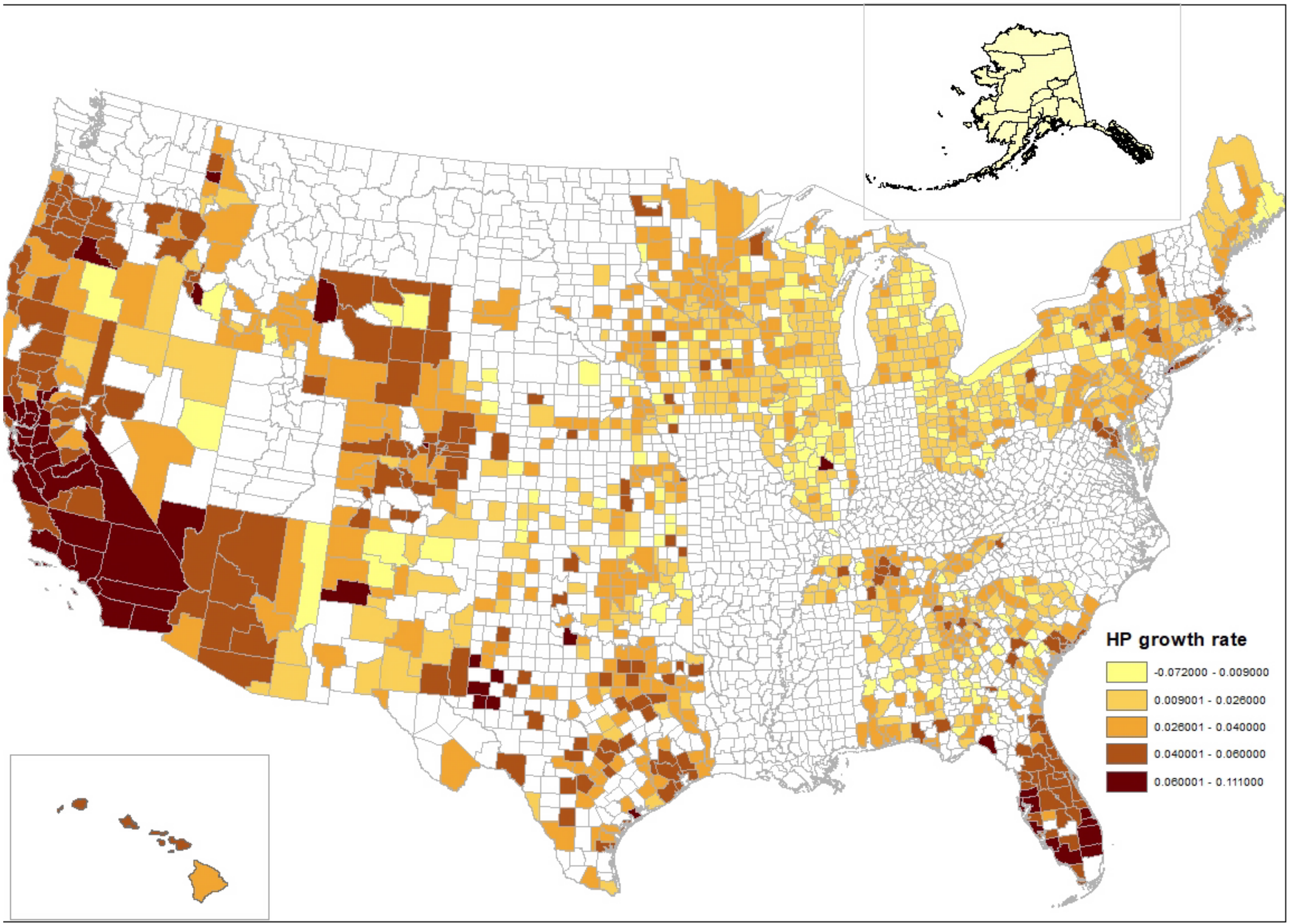
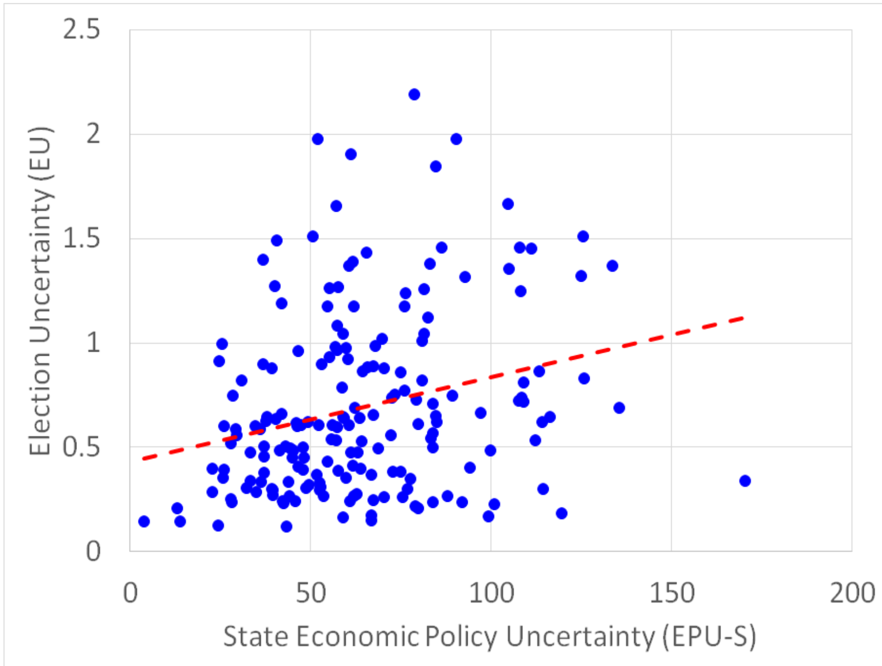
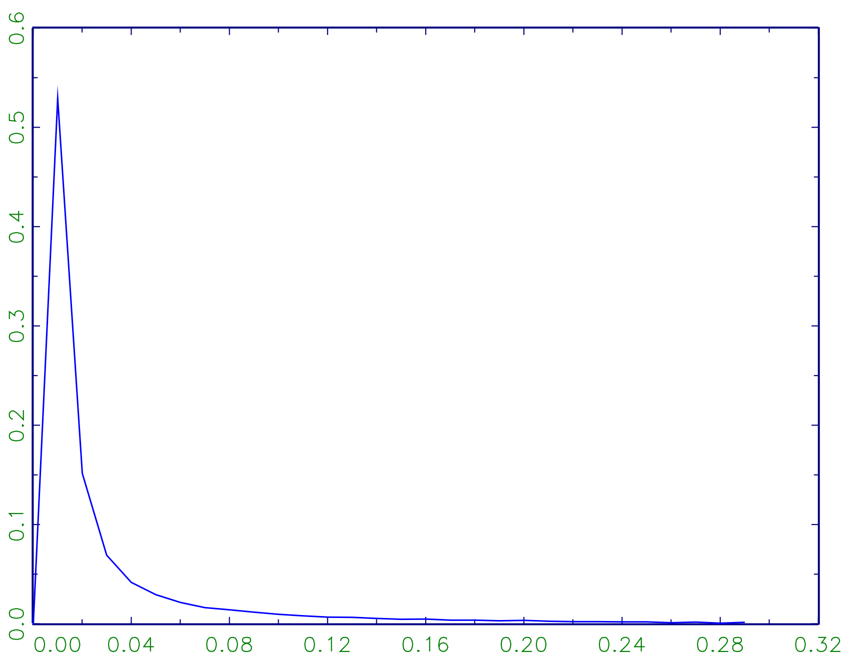


Figure 3: 1,358 U.S. counties by average house price growth rates

Note: This map shows the 1,358 counties in 33 states used in our analysis, with a darker color representing a faster growth of house prices.



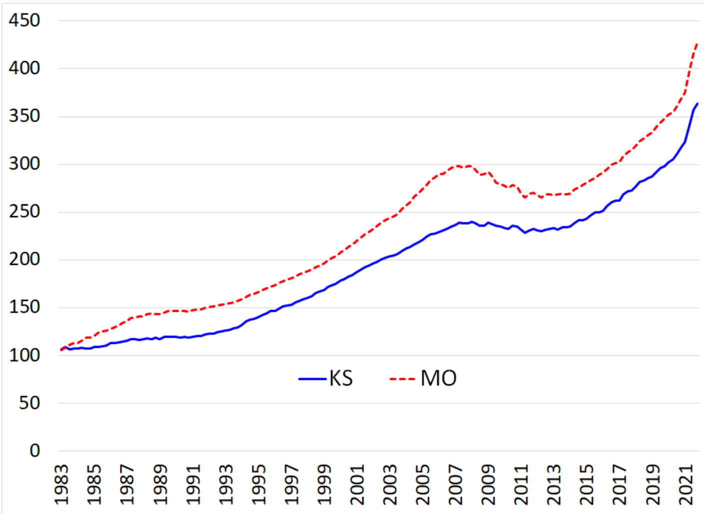
(a) Relationship between EPU-S (on the horizontal axis) and EU (on the vertical axis)



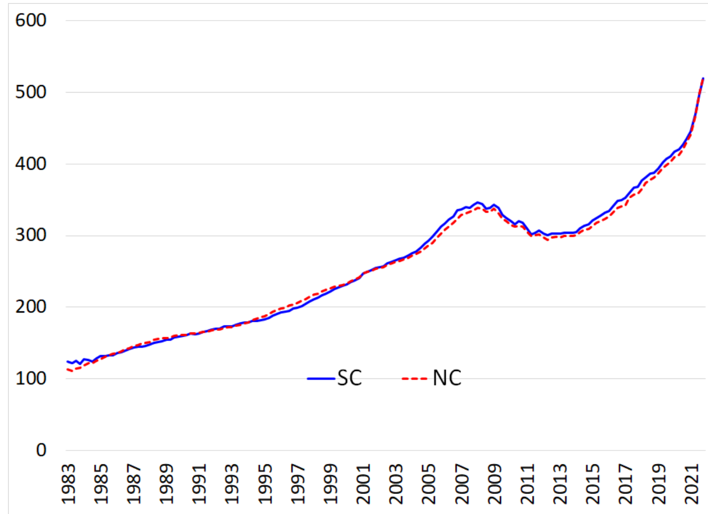
(b) Empirical densities of the share of county-level vote margin out of state-level vote margin

Figure 4: The relationship between EPU-S and political uncertainty measure (top panel) and empirical densities of the share of county-level vote margin (bottom)

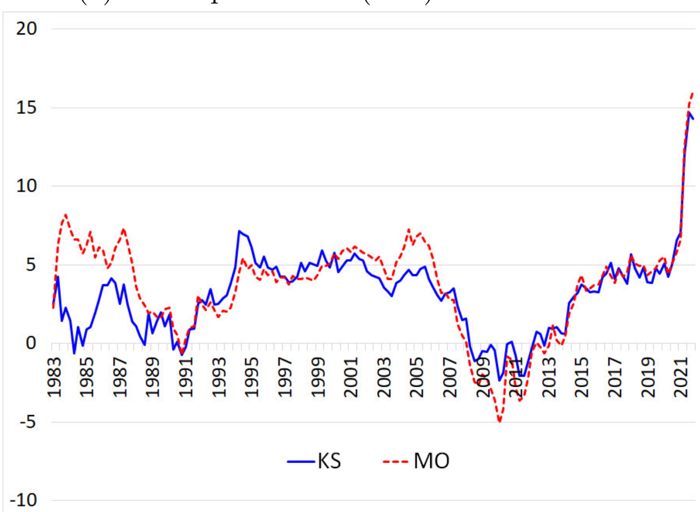
Note: The top panel plots our measure of the state political uncertainty (SPU) on the vertical axis against the EPU-S by Baker et al. (2022) on the horizontal axis. The bottom panel plots the empirical densities of the fraction of county-level vote margin in the entire state.



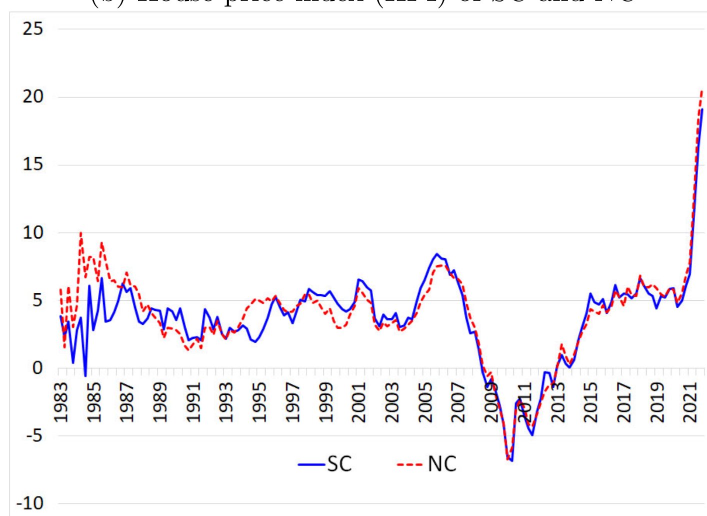
(a) House price index (HPI) of KS and MO



(b) House price index (HPI) of SC and NC



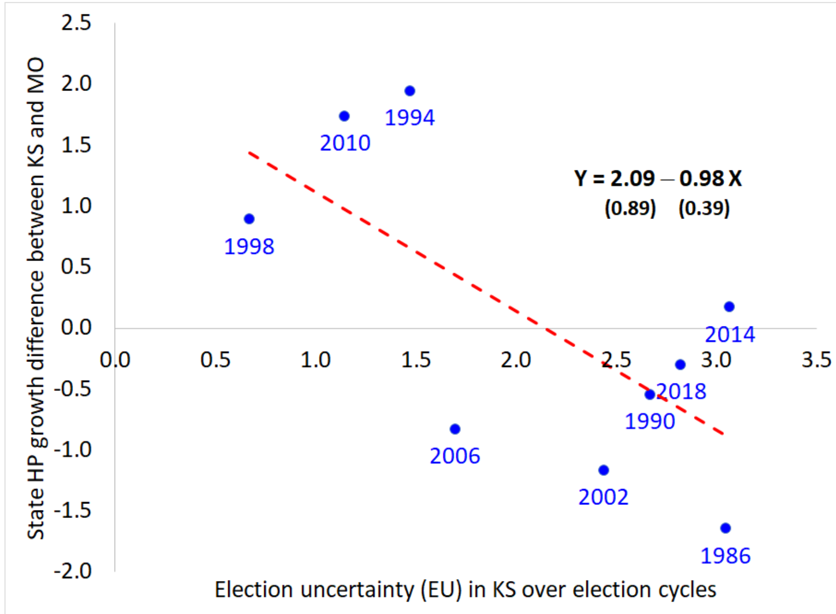
(c) House price growth of KS and MO



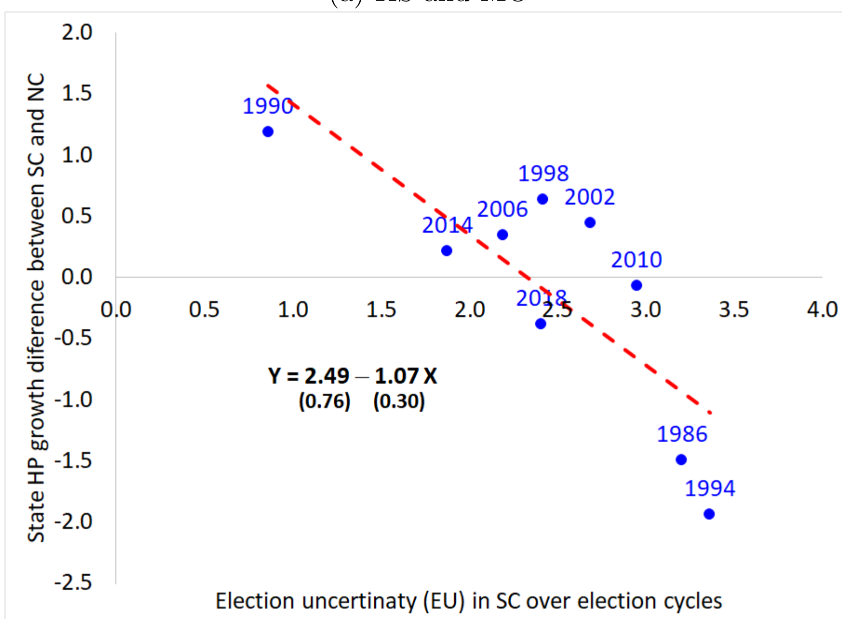
(d) House price growth of SC and NC

Figure 5: House price movements of treated states (KS and SC) and control states (MO and NC) during 1983.Q1-2021.Q4

Note: Panel (a) plots the House price index (HPI) of KS (solid line) and MO (dotted line) over the period 1983.Q1 - 2021.Q4. Panel (b) plots the House price index (HPI) of SC (solid line) and NC (dotted line) over the same period. Panel (c) plots the growth rates of HPI (in percent) of KS (solid line) and MO (dotted line) over the same period. Panel (d) plots the growth rates of HPI (in percent) of SC (solid line) and NC (dotted line) over the same period.



(a) KS and MO



(b) SC and NC

Figure 6: Relationship between state political uncertainty (on the horizontal axis) and relative house price growth of treated states to control states over the nine gubernatorial election cycles (1986-2018)

Note: Panel (a) plots the association between the political uncertainty of KS (on the horizontal axis) and the *state-level* house price growth gap between KS and MO (on the vertical axis) over eight election cycles. Panel (b) plots the association between the political uncertainty of SC (on the horizontal axis) and the *state-level* house price growth gap between SC and NC (on the vertical axis) over eight election cycles.

Appendix: Data Description

County-level per capita personal income, wage/salary, and population data are obtained from the websites of BEA ($https://www.bea.gov/data$) and the Census Bureau ($https://www.census.gov/$). County-level unemployment rates are seasonally adjusted observations and are downloaded from the BLS website ($https://www.bls.gov/web/$). Data for the demographic variables are obtained from Social Explorer website ($https://www.socialexplorer.com/$). County housing units per population are constructed by the number of housing units in county divided by county population, which are also obtained from the Census Bureau.

Natural amenities scale data are downloaded from the website of the Economic Research Service at USDA ($http://www.ers.usda.gov/$). As a measure of the physical characteristics of a county area that enhance the location as a place to live, the scale was constructed by combining six measures of climate, topography, and water area that reflect environmental qualities most people prefer. These measures are warm winter, winter sun, temperate summer, low summer humidity, topographic variation, and water area. The data are available at the USDA website for counties in the continental 48 States.

Table A.1: Population and share of 1,358 counties for each election cycle

Election cycle	U.S.	1,358 counties	Share
1994 election	263,454,667	188,162,156	71.4%
1998 election	276,154,250	197,577,802	71.5%
2002 election	287,954,583	206,640,638	71.8%
2006 election	298,817,667	214,861,296	71.9%
2010 election	309,774,500	222,731,253	71.9%
2014 election	318,631,083	229,878,800	72.1%
2018 election	326,949,250	235,436,247	72.4%

Note: 'share' denotes the fraction of 3,141 counties in the U.S.

Table A.2: Distribution of vote margins and political uncertainty

Election cycle	Vote margin (VM, %)				political uncertainty (PU)			
	mean	median	min	max	mean	median	min	max
1998 election	18.3	15.8	0.6	52.8	1.98	1.79	0.63	4.15
2002 election	11.6	7.9	0.2	51.1	2.43	2.43	0.66	4.43
2006 election	20.2	17.8	1.0	50.0	1.77	1.68	0.68	3.92
2010 election	17.5	13.0	0.5	64.1	2.11	1.98	0.44	4.21
2014 election	16.2	14.3	2.0	51.0	2.08	1.89	0.66	3.52
2018 election	13.9	12.5	1.1	41.8	2.14	2.01	0.86	3.87

Note: 'political uncertainty' is computed by $PU_{st} = \ln[101] - \ln[VM_{st} + 1]$ where VM_{st} denotes the vote margin in state s in election year t as in Falk and Shelton (2018).

Table A.3: Description of county-level variables

Variable	Description	Source
Election outcome	Presidential and Gubernatorial election results for 1992-2018	Congressional Quarterly Press Voting and Elections Collection
House price	Annual FHFA county-level house price index (HPI) with the base year of 2000 over 1988-2017	FHFA website (*www.fhfa.gov*)
Unemployment rate	Annual county-level unemployment rate (s.a.)	BLS website (*www.bls.gov*)
Income	Annual per capita personal income of the U.S. county	BEA website
Wage & salary	Annual average wage and salary of the U.S. county	BEA website
Digitization rate	Share of population with internet subscription (average of 2013-19 period)	BLS website
Population density	County population divided by the county land area in square miles during 1990-2018	U.S. Census Bureau (*www.census.gov*)
Share of population by gender	Share of male (or female) population out of the entire population	U.S. Census Bureau
Share of population by age	Share of population based on age groups (below 18 years old, 18-64 years old, over 64 years old)	U.S. Census Bureau
Share of population by race	Share of population based on race (white, Black, or Hispanic population)	U.S. Census Bureau
Share of married households	Share of households who are not married	U.S. Census Bureau
Share of college graduate	Share of adults over 25 years old with a bachelor's or higher degree	U.S. Census Bureau
Share of Homeownership	Fraction of houses occupied by owners	U.S. Census Bureau
Share of veteran	Fraction of population who are veterans	U.S. Census Bureau