December 16, 2016

Real Options Effect of Uncertainty and Labor Demand Shocks on the Housing Market

Abstract

This paper shows that uncertainty affects the housing market in two significant ways. First, uncertainty shocks adversely affect housing prices but not the quantities that are traded. Controlling for a broad set of variables in fixed-effects regressions, we find that uncertainty shocks reduce housing prices and median sales prices in the amount of 1.4% and 1.8%, respectively, but the effect is not statistically significant for the percentage changes of all homes sold. Second, when both uncertainty and local demand shocks are introduced, the effects of uncertainty on the housing market dominate that of local labor demand shocks on housing prices, median sell prices, the share of houses selling for loss, and transactions. The aforementioned effects are largest for the states that exhibit relatively high housing price volatilities, suggesting real options effects in the housing market during the times of high uncertainty.

- *JEL Classification: R1, R3, E3*
- *Keywords:* Bartik labor demand shocks; time-varying uncertainty shocks; real options effects; housing market.

Gabriel Lee (Corresponding author)
University of Regensburg
Universitaetsstr. 31, 93053 Regensburg, Germany
And
Institute for Advanced Studies
Josefstaedterstr. 39, 1080, Wien, Austria
gabriel.lee@ur.de, + 49 941 943 5060

Binh Nguyen Thanh
University of Regensburg
Universitaetsstr. 31, 93053 Regensburg, Germany
binh.nguyen-thanh@ur.de, + 49 941 943 2739

Johannes Strobel
University of Regensburg
Universitaetsstr. 31, 93053 Regensburg, Germany
johannes.strobel@ur.de,+ 49 941 943 5063

1 Introduction

Three well documented features of the recent Great Recession are the decline in housing prices, the increase in unemployment rate, and the increase in the presence of uncertainty in the U.S. Figure 1 shows the correlation between the U.S. housing price growth rate and some of the uncertainty measures in the recent literature over the period from 1990 to 2014 with the highlighted recession periods: a clear negative correlation between the housing price growth rate and the shown uncertainty measures.[1]

Figure 1 here

Figure 2 also shows a strong negative correlation between the monthly U.S. unemployment rate and the Bartik index that proxies the U.S. labor demand shocks from 1990 to 2014.

Figure 2 here

There are numerous recent papers that deal with the effects of uncertainty and labor demand shocks on aggregate economy as well as housing and labor markets separately. For example, Christiano, Motto and Rostagno (2014) show that uncertainty adversely impacts the economy, while Dorofeenko, Lee and Salyer (2014) show uncertainty shock can explain the U.S. housing price volatilities. For the labor demand shock on housing and labor markets, Edlund, Machado and Sviatschi (2016) examine the impact of labor demand shocks, using the Bartik index, on housing prices, and Shoag and Veuger (2014) empirically show that uncertainty may amplify labor demand shocks. This paper, however, examines the simultaneous effects of uncertainty and local labor demand shocks on the U.S. housing market.[2] More precisely, we seek to answer (i) does uncertainty directly affect the housing market, (ii) if a local labor demand shock occurs in

[1] We use four different uncertainty measures in our analysis: the macroeconomic uncertainty by Jurado, Ludvigson and Ng (2015), the VIX by Bloom (2009), the policy uncertainty by Baker, Bloom and Davis (2016), and our measure, which is analogous to Baker et al. (2016) but on a state level ("state" uncertainty). Correlations between these uncertainty measure over these periods range between 0.25 and 0.63.

[2] We specifically look at the average housing prices, the median selling prices, the share of houses selling for loss and transactions (houses sold).

a period of high uncertainty, is the impact different compared to a period of low uncertainty and (iii) how robust are the outcomes given the choice of the uncertainty proxy and the threshold level defining a period of high uncertainty?

First, controlling for a broad set of variables, we find that uncertainty shocks directly affect prices but not quantities. The median sell price as well as the housing price decrease on average by 1.80% and 1.42%, respectively. Second, a positive local labor demand shock significantly increases median sell prices, house prices and transactions and decreases the share of houses selling for loss. If a labor demand shock occurs during a period of high uncertainty, however, then it essentially affects neither prices nor quantities. This observation is consistent with the occurrence of a real options effect akin to the irreversibility of an investment described by Pindyck (1991, p.1117): "There will be a value to waiting (i.e., an opportunity cost to investing today rather than waiting for information to arrive) whenever the investment is irreversible and the net payoff from the investment evolves stochastically over time". For instance, Bloom, Bond and Van Reenen (2007) show that because of real options effects, firms' responsiveness to demand shocks is generally lower in periods of high uncertainty. Clapp, Eichholtz and Lindenthal (2013), Bulan, Mayer, and Somerville (2009), and Cunningham (2006, 2007) empirically show that real options play an important role for house prices dynamics, housing investment and land prices.

Analogous to the irreversible investment literature, we find the response of housing market variables to labor demand shocks to be much lower in times of high uncertainty, suggesting real options effects (option to "wait and see") in the housing market during times of high uncertainty. More specifically, we show that following an adverse shock in labor demand of one standard deviation, the real options value ("wait and see" effect) in the housing price amounts to 0.19%, and the effect increases to 0.32% for the states (locations) that exhibit relatively high housing price volatilities. Furthermore, we find that following an adverse labor demand shock, not only the share of houses selling for loss significantly decreases in times of high uncertainty when compared to normal times, but also the number of homes sold remains almost constant.[3] To show that the real options value increases with higher uncertainty, we sort the fifty one states into three equal-sized groups, according to the unconditional housing price volatility in each state. In doing so, we find that while the impact of local labor demand shocks is largest for the group with the highest housing price volatility, uncertainty completely offsets the labor demand shock - as opposed to the other two groups, where we find no significant impact of uncertainty.

Our results, thus, indicate uncertainty shocks affect housing price movements both directly and indirectly. On the one hand, uncertainty adversely affects housing prices. On the other hand, it alters the impact of shocks during uncertain times, with this latter effect consistent with the presence of real options effects arising in a period of high uncertainty in the housing market.[4] One important implication of our results, analogous to Bloom et al. (2007), is that in order for policy measures to work properly, highest priority should be given to the reduction of uncertainty.[5]

We address real options issues in housing markets using monthly U.S. state-level data from 1990 to 2014. We construct binary uncertainty dummies to indicate the periods of high uncertainty, as in Bloom (2009) and a variation of Bartik (1991) index as local labor demand shocks to quantify the impact of these two shocks on the housing market. Our approach thus corresponds to models using two-state Markov-switching processes, where regime changes can be documented by an uncertainty index crossing various threshold values, which are based on the percentiles of the distribution of the uncertainty proxy. Our approach in defining the threshold values differs from the one used in, for example, Bloom (2009), who defines periods of uncertainty as the proxy when 1.65 or more standard deviations above the mean. We use the macroeconomic uncertainty measure by Jurado et al. (2015) as our benchmark measure but we also include other uncertainty measures such as the policy uncertainty proxy by Baker et al. (2016), the VIX which is also used

[3] We show the robustness of the above results to different threshold values that are ranged from 80th, 85th, 90th and 95th percentile of an uncertainty proxy.

[4] See also Aastveit, Natvik and Sola (2013), in which structural Vector Autoregressions are used to document wait-and-see effects in monetary policy during periods of high uncertainty. See also Bloom (2014) for further discussion and sectors where real option effects arise.

[5] Especially in light of the results of Stroebel and Vavra (2015), who show that there is a causal relation between changes in housing prices and changes in retails prices and thus consumption.

by Bloom (2009), and the state-level policy uncertainty similar to Baker et al. (2016) to analyze the state level housing markets.

2 Data, Bartik Index and Uncertainty Measures

In the following section, we describe the data as well as the construction of the Bartik index and various uncertainty measures used in our empirical analysis.

2.1 Data

We use monthly state-level data from 1990:1 to 2014:12; the data and their sources are described in detail in the Appendix. Zillow Real Estate Research data and Freddie Mac provide information on various aspects of the housing market, such as the housing price, median sales price, the share of houses sold for loss and turnover. The housing price is the inflation adjusted housing price index from Freddie Mac; the median sales price is defined as the median of the selling price for all homes sold in a given state. The share of houses sold for loss is defined as the percentage of homes in an area that sold for a price lower than the previous sale price and turnover is defined as the percentage of all homes in a given area that are sold in the past 12 months. These housing variables constitute the vector of dependent variables.

2.2 Bartik Index

The Bartik index is a measure of the predicted change in demand for employment in a state given by the interaction between a state's initial industry mix and national changes in industry employment. The index compares the preexisting differences in the sectoral composition of employment across states with the broad changes in national employment, especially changes subject to a trend, asymmetrically impact states. In this paper, we follow Saks (2005) to construct the Bartik index. We use the index of Saks (2005) due to its transparency and straightforward interpretation:

$$bartik_{it} = \sum_j \frac{e_{ijt-1}}{e_{it-1}} \left(\frac{\tilde{e}_{ijt} - \tilde{e}_{ijt-1}}{\tilde{e}_{ijt-1}} - \frac{e_t - e_{t-1}}{e_{t-1}}\right) \qquad (1)$$

where i=state, j=industry, t=month; $\tilde{e}_{ijt}$ = national industry employment outside of state i; e_{it}= state employment = $\sum\limits_j e_{ijt}$; e_t= national employment = $\sum\limits_i e_{it}$.

The first fraction reflects the share of industry j employment relative to the total employment in state i in $t-1$, the second fraction is the growth rate of industry j outside of state i and the third fraction reflects the change in national employment. Thus, the term in brackets reflects the change in industry j employment (outside state i) relative to changes in national employment. This term is weighted by the "importance" of industry j in state i in $t-1$. We use$j = 4$ sectors across $i = 51$ states in this analysis: manufacturing, private services, public services and construction and logging. We use the time series of the *bartik* index aggregated across states as displayed in Figure 2. The results remain unchanged if we exclude the construction sector from the Bartik index.

2.3 Uncertainty Measures

Various uncertainty proxies have been proposed in the recent literature. As shown in Figure 1, depending on the preferred proxy, the number of uncertainty shocks may differ considerably, although it is also possible that different proxies capture different aspects of uncertainty. The VIX is constructed as the square root of a weighted average of out-of-the-money put and call options forward prices for the next 30 days and measures the expected volatility of the S&P 500 index. The Policy uncertainty proxy of Baker et al. (2016) is a composite index, consisting of newspaper coverage of policy-related economic uncertainty, the number of expiring federal tax code provisions and the variation of economic forecasters estimates. Jurado et al. (2015) estimate uncertainty as the conditional standard deviation "of the purely unforecastable component of the future value", which translates to removing the forecastable component of a multitude of aggregated and weighted financial and real variables before calculating their conditional standard deviation. Finally, the U.S. state level uncertainty proxy consists of the newspaper coverage of policy-related economic uncertainty from 2000:1 to 2014:12. As can be seen in Figure 1, there are considerable differences in fluctuations, and thus in the periods classified as uncertain.[6]

A definition of the threshold value is needed in order to identify the number of uncertainty periods and to construct binary uncertainty series. Bloom (2009) suggests using "1.65 standard deviations above the mean, selected as the 5% one-tailed significance level treating each month as an independent observation". However, specifying the threshold in this manner does not leave any adjustment opportunity if the assumption of Normality and independently and identically distributed uncertainty shocks does not hold.[7] Table 1 shows the number of months defined as "uncertain" by various uncertain proxies. For example, using the Macro uncertainty measure of Jurado et. al (2015), when α equals 5% then the Normal Distributional assumption leads to seventy-six uncertain periods instead of fifty-eight periods when one uses the corresponding percentiles of the actual distribution. Consequently, we use the corresponding percentiles at various levels in our analysis to show the robustness of empirical results as well as to avoid the Normal i.i.d. assumption. Figure 3 shows the time periods defined as uncertain using different uncertainty proxies. The right-lower panel also displays the state uncertainty proxy after aggregating, although there is substantial variation across states. Note, however, the similarities between the Policy uncertainty indicator and our state uncertainty proxy.

Figure 3 and Table 1 here

[6] See Strobel (2015) for further elaboration on the reasons for this observation.

[7] We tested for the normality of the uncertainty proxies using the Jarque-Bera test, and the null of normality was rejected for each proxy.

3 Methodology and Results

3.1 Methodology

As we seek to investigate the role of uncertainty in the housing market, we interact uncertainty and labor demand shocks. To address various econometric issues in our emprical setup, we first use the standard errors developed in Driscoll and Kraay (1998) to account for spatial dependence, heterogeneity and autocorrelation. To guard against feedback effects, we lag the explanatory variables. Moreover, by construction, our uncertainty measure are exogenous. For example, our benchmark Macro uncertainty measure, by construction, avoids dependencies on any single (or small number) of observable economic indicators. The VIX, which captures the expected volatility of the S&P 500 index, is unlikely to be strongly influenced by housing prices. And, although, Policy uncertainty and the state-level uncertainty measure might be affected in the same period news, it seems rather unlikely that housing prices today affect yesterday's news coverage. Additionally, we include a rich set of controls to avoid an omitted variable bias.[8] As for the Bartik index, the local labor demand shocks $bartik_{it}$ are constructed to be exogenous given a constant labor supply. Binary uncertainty indicators are coded to be one if uncertainty is above a threshold value and zero otherwise.

Our empirical model is given by

$$y_{it} = x_{it-\tau}\vec{\gamma} + 1_{unc,it-\tau}\vec{\beta}_{1t-\tau} + bartik_{it-\tau}\vec{\beta}_{2t-\tau} + 1_{unc,it-\tau} \times bartik_{it-\tau}\vec{\beta}_{3t-\tau} + \alpha_i + u_{it} \quad (2)$$

where $x_{it-\tau}$ is a vector containing up to τ lags of the control variables, γ is the corresponding parameter vector, α_i is the state specific intercept, $1_{unc,it-\tau}$ and $bartik_{it-\tau}$ are $(1 \times \tau)$ vectors of lagged uncertainty indicators and labor demand shocks, respectively, and $\beta_{jt-\tau}$, $j = 1, 2, 3$ are the corresponding $(\tau \times 1)$ parameter vectors. An element of $\beta_{jt-\tau}$ reflects the impact of the respective

[8] Technical explanations for these uncertainty measures as well as the complete set of control variables used for our empirical analysis are given in the Appendix.

lag, while the sum of the elements gives the long-run impact.[9] The coefficients of main interest are $\beta_{1t-\tau}$, $\beta_{2t-\tau}$ and $\beta_{3t-\tau}$. $\beta_{1t-\tau}$ reflects the impact of a regime-change from low to high uncertainty, $\beta_{2t-\tau}$ reflects the impact of a local labor demand shock on the housing market and $\beta_{3t-\tau}$ states the (change in the) effect of a local labor demand shock in a period of high uncertainty. In other words, $\beta_{3t-\tau}$ is a measure for the change in the responsiveness of the housing market variables due to high uncertainty. If $\beta_{3t-\tau}$ is significantly different from zero and its sign is different (same) from $\beta_{2t-\tau}$, then uncertainty diminishes (amplifies) the impact of the local labor demand shock.

For example, in an uncertain period, even though the impact of an adverse labor demand shock on the housing price is negative, home sellers will most likely not sell at the lower prices as this would unnecessarily reduce the return of the most important asset of most households. The underlying assumption is that the investment opportunity (selling or buying the house) is irreversible once exercised but available until then. In that sense, $\beta_{3t-\tau}$ proxies the real options value by capturing the change in the equilibrium housing price or the median selling price that does not materialize following a labor demand shock because of uncertainty.

3.2 Baseline Results

Our empirical objectives are to show (i) the quantitative effect of uncertainty on the housing market, (ii) the change in the impact of local labor demand shocks on the housing market if they occur during periods of uncertainty and (iii) the sensitivity of the results with respect to varying threshold levels and different uncertainty proxies. Table 2 shows occurrence of the diminished responsiveness due to uncertainty in our benchmark regression results, based on the Macro uncertainty measure, $\mathbf{1}_{macro}$. The estimated $\vec{\beta}_j$ represent the long-run effect, i.e. the sum of the estimated elements of $\vec{\beta}_{jt-\tau}$.[10]

Table 2 here

[9] We experimented with different lag-lengths and use $\tau = 6$ lags as baseline specification, but the results are not sensitive to the number of lags as long as we use more than two and less than seven.

[10] We use 95th percentile as our cut off point for the Macro uncertainty measure.

The second column of Table 2 shows the long-run impact, $\overrightarrow{\beta}_1$, of uncertainty on housing prices, median sell prices, the percentage loss of houses selling and turnover; we control for the federal funds rate, housing starts proxying for residential investment, income, industrial production, inflation, population, and the S&P 500 and the unemployment rate.[11] As opposed to the predictions by Dorofeenko et al. (2014)[12], we find that uncertainty adversely affects the median sell prices and house prices on average by 1.80% and 1.42%, respectively. In other words, Dorofeenko et al. (2014) results are driven by the supply side, which our empirical results do not necessarily support. Moreover, we find uncertainty impacts neither turnover nor the share of houses selling for loss directly.

For the robustness check on the uncertainty measures, we also show the results for different threshold values (i.e. percentile cutoffs) as shown in Figure 4. Regardless of the threshold value, the sign and the significance of the estimated $\overrightarrow{\beta}_1$ for the log house price and log median sales price do not change.[13]

Figure 4 here

The column three of Table 2 shows the long-run impact of labor demand shocks, proxied by the *bartik* index. The impact is highly significant for all dependent variables, even after controlling for state-level unemployment. For example, one standard deviation increase in the local labor demand shock (i.e. the *bartik* index, which is defined as change in state-level employment relative to a change in national employment), increases house prices, median sell prices and transactions on average by .14%, .43% and 1.92%-points, respectively and decreases the share of houses selling for loss by 14.77%-points. Due to linearity, the signs reverse in the case of adverse labor demand

[11] We include these variables to capture the demand and supply factors that influence the local housing market and the information available to market participants (i.e. robustness checks for endogeneity and omitted variables). We also check for various Granger causality test. We conduct other variety of robustness checks described in the next subsection.

[12] Dorofeenko et al. (2014) show that an increase in their measure of uncertainty has an increasing effect on house prices due to the default premium on the housing developers: There is a markup on housing prices due to the bankruptcy possibility that is caused by uncertainty.

[13] All of the coefficients are significant at a 1% significance level, except for one which is significant at the 5% level.

shocks - as observed in most states during the Great Recession period.[14]

The above results indicate that the uncertainty and labor demand shocks affect the housing market variables in opposite direction. To determine the quantitative effects of these two shocks on the housing variables, we introduce an interaction term, $\vec{\beta}_3$: the results are shown in the fourth column of Table 2. When the labor demand shock occurs during a period of high uncertainty then, for almost every dependent variable and threshold level, the effect of uncertainty shock dominates the labor demand shock: a clear sign change from the estimated $\vec{\beta}_2$ being positive to the estimated $\vec{\beta}_3$ being negative.

As discussed above, $\vec{\beta}_3$ quantifies the homeowners' diminished response ("real options effect") following a labor demand shock: 0.19% (0.013% $\times$ 14.35) of the house price and 0.41% (0.013% $\times$ 31.68) of the median sell price. For the expositional purpose of the interaction term, Figure 5 shows the effects of a labor demand shock with - and without uncertainty shock (using our benchmark Macro uncertainty shock). The blue line (Bartik Normal Times) summarizes the long-run impact of labor demand shocks, $\vec{\beta}_2$, on the various dependent variables, while the red line (Bartik High Uncertainty) represents the impact of labor demand shocks in uncertainty times, i.e. $\vec{\beta}_2 + \vec{\beta}_3$. Figure 5 clearly shows that when uncertain periods occur then the effect of the labor demand shock is greatly muted. These dominating uncertainty shock effects suggest the presence of real options effects in housing market.[15] Figure 6 is analogous to Figure 5, but with the state-level uncertainty shock: the results are not overturned.

Figures 5 and 6 here

Table 3 here

Overall, we find that the results in Bloom et al. (2007) for the firm level carry over to the housing market: uncertainty greatly diminishes the responsiveness of housing market variables. We

[14] We report the impact of a standard deviation increase due to the scale of the bartik. Mean local labor demand decreases from 1990 until 2014 by 0.004%-points, while one standard deviation corresponds to 0.013%-points: For example, for the log house price, we report an increase of 0.14% as 0.013×10.93.

[15] This result is in line with the findings of Davis and Quintin (2014), who find that uncertainty about housing prices kept the default rate low relative to a situation without uncertainty.

note, however, our results are somewhat sensitive to the choice of the uncertainty proxy, which can be seen in Table 3. For example, the impact of uncertainty shocks on the growth rates of housing prices, median sell prices is robust although slightly differs quantitatively. One exception to the case is when the VIX is used to define periods of high uncertainty. This result is to be expected as the different uncertainty proxies indicate different periods of high uncertainty. Although we do not show the results with the Policy Uncertainty shock in Table 3, the real options effects ($\vec{\beta}_3$) from the Policy Uncertainy are not as strongly associated if high threshold values (90th or 95th percentile) are used. The reason might be that when the 95th percentile threshold, the Policy Uncertainty proxy represents only the periods that are associated with the post 2011 period (this includes the period during the European Debt crisis). And hence, there is not enough sample size to test for the interaction terms. If the 85th percentile, however, is taken as threshold value, the interaction effects become significant again, as more periods, especially the months before 2010, are classified as periods of high uncertainty.

3.3 Grouping States by Housing Price Volatility

To analyse whether the real options effect varies by regions, we sort the fifty one U.S. states into three groups according to the unconditional housing price volatility in each state over time, and we estimate our model (2) for each one of the groups. The three groups are equal size and we refer to them as *low*, *medium* and *high*: Our hypothesis is empirical to test whether the change in the responsiveness of housing market variables is larger in the states with higher housing price volatilities compared to the lower housing price volatilities states. Consequently, we focus on the dominant effect of uncertainty over the labor demand shocks for each one of the groups, using the 95th percentile of the state-level uncertainty proxy. The results for the three different groups are shown in Table 4.

Table 4 here

The most striking difference between the three groups is with respect to the significance and the magnitude of our responsiveness measure ($\overrightarrow{\beta}_3$) for the *high* group. As one moves away from the low to high volatility group, the interaction term ($\overrightarrow{\beta}_3$) not only increases in absolute magnitude from -6.85 to -25 but also becomes highly statistically significant. That is, the effect of a one standard deviation increase (i.e. 0.013%$-$points) in the interaction term changes from $-6.85 \times 0.013 = 0.09\%$ in the *low* group to $-25.0 \times 0.013 = 0.32\%$ of the housing price in the *high* group.

For the robustness check, we also sort groups by the impact of local labor demand shocks. We calculate the impact of the *bartik* index based on our model (2) with housing prices as dependent variable, but estimating time-series regressions for each state. We include states where the *bartik* has a significant impact (5% level) on the change in log housing prices, which results in 37 states. We sort these 37 states into three groups of almost equal size, depending on the magnitude of the *bartik*'s impact. Table 5 shows the long-run effects of the *bartik* and the interaction term. By construction, the impact of the *bartik* increases and is highly significant. The interaction term, however, is only statistically significant for the group *high,* with the sum of $\widehat{\overrightarrow{\beta}}_2$ and $\widehat{\overrightarrow{\beta}}_3$ ($e.g.$104.9 $-$ 102 = 2.9) very close to zero: the net effect on the change in log housing prices is almost zero. That is, in times of high uncertainty, home sellers and -buyers do not trade at the price and wait out until the uncertainty periods are over. Moreover, an explanation for the dominance of uncertainty over the shock for the *high* group, in contrast to the *medium* and *low* group, is that the larger the impact of the shock, the less responsive households are, ceteris paribus.

Table 5 here

3.4 Robustness Checks

Our empirical results are robust to a variety of alternative specifications, such as including a recession dummy, monthly dummies, using different lag lengths, constructing the Bartik index following Charles, Hurst and Notowidigdo (2013) or omitting some of the variables from the vector of controls variables.[16] However, the results are not robust to omitting the Great Recession period, i.e. using the sample from 1990:1 until 2007:12. This may not be too surprising in light of Figure 3, which shows a lot of the variation in the uncertainty dummy comes from the differences between the time before and after 2008.

4 Conclusion

Our empirical results lend support for the real options effects in the U.S. housing market and are in line with some of the predictions of Bloom et al.'s (2007) theoretical model. Using the state-level panel data from 1990:1 to 2014:12, we show (i) uncertainty has a small but highly significant impact on the level of housing prices but not on quantities, (ii) uncertainty dominates the effects of (adverse) labor demand shocks and (iii) the results are robust to changes in the threshold defining times of high uncertainty but are somewhat sensitive to the choice of uncertainty proxy. We interpret this result as the different proxies capturing different aspects of uncertainty, with the proxy of Jurado et al. (2015) being well suited, due to its construction, to capture the spells of uncertainty that induce macro-level real options effects. These findings might be helpful for housing policy makers to mitigate adverse effects of real shocks on housing markets during periods of high uncertainty before they materialize.

[16] The robustness checks are available from the authors on request.

5 Acknowledgements

We thank the seminar and conference participants at the 2016 Asian Econometric Society Meeting, 2016 European Real Estate Society Meeting, 2016 Asian Real Estate Society Meeting, the Econometric Seminar at the University of Regensburg and the Bavarian Graduate Program in Economics for constructive comments. Gabriel Lee and Johannes Strobel gratefully acknowledge financial support from the German Research Foundation ((DFG) LE 1545/1-1).

6 Bibliography

1. Aastveit, K. A., Natvik, G. J., & Sola, S. (2013). Economic uncertainty and the effectiveness of monetary policy. Norges Bank mimeo.

2. Baker, S. R., Bloom, N., & Davis, S. J. (2016). Measuring economic policy uncertainty. *Quarterly Journal of Economics*, forthcoming.

3. Bartik, T. (1991). Who benefits from state and local economic development policies? Kalamazoo: W.E. Upjohn Institute for Employment Research.

4. Bloom, N. (2009). The impact of uncertainty shocks. *Econometrica*, 77 (3), 623-685.

5. Bloom, N., Bond, S. and Van Reenen, J. (2007). *Review of Economic Studies*, (74), 391-415.

6. Bloom, N. (2014). Fluctuations in uncertainty. *Journal of Economic Perspectives*, 28 (2), 153-76.

7. Bulan, L., Mayer, C. & Somerville, C. T. (2009). Irreversible investment, real options, and competition: evidence from real estate development. *Journal of Urban Economics.* 65, 237-251.

8. Charles, K., Hurst, E., & Notowidigdo, M. (2013). Manufacturing decline, housing booms, and non-employment. *Chicago Booth mimeo.*

9. Christiano, L. J., Motto, R., & Rostagno, M. (2014). Risk shocks. *American Economic Review*, 104 (1), 27-65.

10. Clapp, J. M., Eichholtz, P. & Lindenthal, T. (2013). Real option value over a housing market cycle. *Regional Science and Urban Economics*, 43 (6), 841-1040

11. Cunningham, C. R. (2006). House price uncertainty, timing of development, and vacant land prices: evidence for real options in Seattle. *Journal of Urban Economics,* 59 (1), 1-31.

12. Cunningham, C. R. (2007). Growth controls, real options, and land development. *The Review of Economics and Statistics,* 89 (2), 343-358.

13. Davis, M. A., & Quintin, E. (2014). Default when current house prices are uncertain. University of Wisconsin-Madison mimeo.

14. Dorofeenko, V., Lee, G. S., & Salyer, K. D. (2014). Risk shocks and housing supply: A quantitative analysis. *Journal of Economic Dynamics and Control* , 45, 194-219.

15. Driscoll, J. C., & Kraay, A. C. (1998). Consistent covariance matrix estimation with spatially dependent panel data. *Review of Economics and Statistics*, 80 , 549-560.

16. Edlund, L., Machado, C., & Sviatschi, M.M. (2016). Bright minds, big rent: gentrification and the rising returns to skill. *NBER Working Paper No. 21729.*

17. Jurado, K., Ludvigson, S., & Ng, S. (2015). Measuring uncertainty. *American Economic Review*, 105 (3), 1177-1216.

18. Saks, R. E. (2005). Job creation and housing construction: constraints on metropolitan area employment growth. *Finance and Economics Discussion Series No. 2005-49 Board of Governors of the Federal Reserve System.*

19. Shoag, D., & Veuger, S. (2014). Uncertainty and the geography of the great recession. *American Enterprise Institute mimeo.*

20. Strobel, J. (2015). On the different approaches of measuring uncertainty shocks. *Economics Letters*, 134 , 69-72.

21. Stroebel, J., & Vavra, J. (2015). House prices, local demand, and retail prices. *Kilts Center for Marketing at Chicago Booth – Nielsen Dataset Paper Series 1-030.*

7 Data Appendix

7.1 Description of the Uncertainty Proxies

7.1.1 Macro Uncertainty

The Macro uncertainty $U_t^y(h)$ builds on the unforecastable components of a broad set of economic variables. Jurado et al. (2015) estimate Macro uncertainty as the conditional standard deviation of the purely unforecastable component of the future value, which translates to removing the forecastable component of a multitude of aggregated and weighted financial and real variables before calculating their conditional standard deviation. More specifically, they calculate for 132 macroeconomic time series $y_{jt} \in Y = \{y_{1t}, ..., y_{132t}\}$ the conditional standard deviation of the unpredictable component of the h-step-ahead realization:

$$U_{jt}^y(h) = \sqrt{E[(y_{jt+h} - E(y_{jt+h}|I_t))^2|I_t]}$$

with $E(.|I_t)$ the expectations taken conditional on information I_t. Then, they aggregate these unpredictable componentsto obtain

$$U_t^y(h) = p \lim_{N_y \to \infty} \sum_{j=1}^{N_y} w_j U_{jt}^y(h)$$

with w_j the aggregation weight. To compute $U_{jt}^y(h)$, Jurado et al. (2015) first form factors from a large set of economic and financial indicators, which represent I_t. These factors are used to approximate the forecastable component $E(y_{jt+h}|I_t)$ and to calculate the forecast error $E[(y_{jt+h} - E(y_{jt+h}|I_t))^2|I_t]$. Then, Jurado et al. (2015) estimate a parametric stochastic volatility model for the $one-step$ ahead prediction error to obtain the conditional volatility the conditional variance of this error, $E[(y_{jt+h} - E(y_{jt+h}|I_t))^2|I_t]$. Given these estimates, $h-step$ ahead prediction errors can be calculated recursively. Finally, Jurado et al. (2015) aggregate over the individual forecast errors using equal weights w_j for each time series $U^y_{jt}(h)$.

7.1.2 VIX

The VIX measures the expected volatility of the S&P 500 index and is the square root of the sum of squared standard deviations of the S&P 500 rate of expected returns for the next 30 days. More technically, the VIX is the square root of a weighted average of the forward prices of out-of-the-money put and call options and approximates the price of a portfolio of options that replicates the payoff on a variance swap.

7.1.3 Policy Uncertainty

The Policy uncertainty proxy of Baker et al. (2016) is a composite index, consisting of newspaper coverage of policy-related economic uncertainty, the number of expiring federal tax code provisions and the variation of economic forecasters estimates.

7.1.4 State-level uncertainty

The state-level uncertainty indicator was constructed as the monthly number of news-paper articles in a state containing either one of the keywords "economic uncertainty", "economy uncertain" or "economy uncertainty" from 2000:1 until 2014:12 from the homepage www.newslibrary.com. In creating this proxy, we follow Baker et. al (2016).

7.2 Data Description

Tables 6 - 12 here

Figure 1: House Price Growth Rates and Uncertainty Proxies.

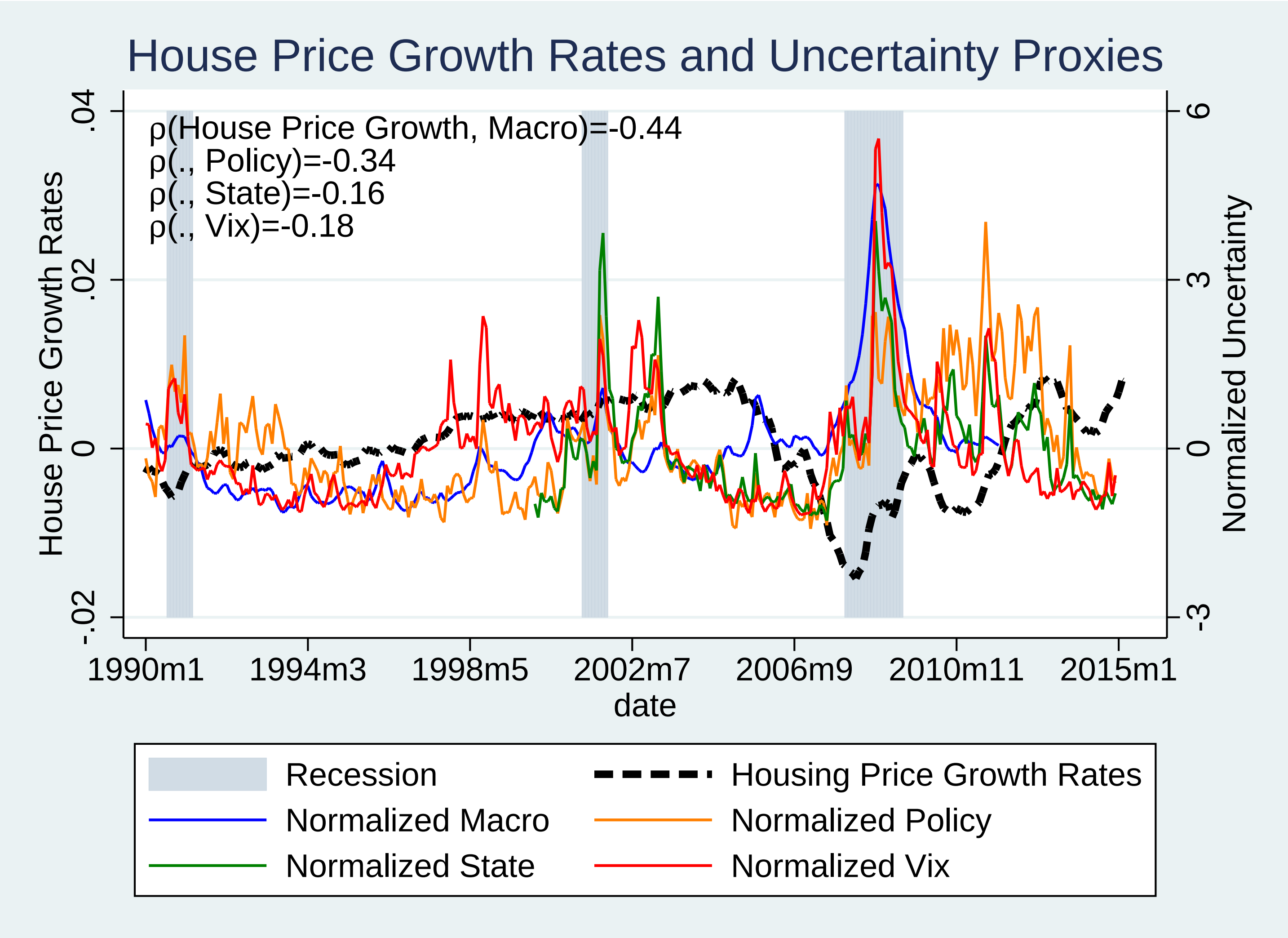


Figure 2: U.S. Unemployment Rate and Bartik Index.

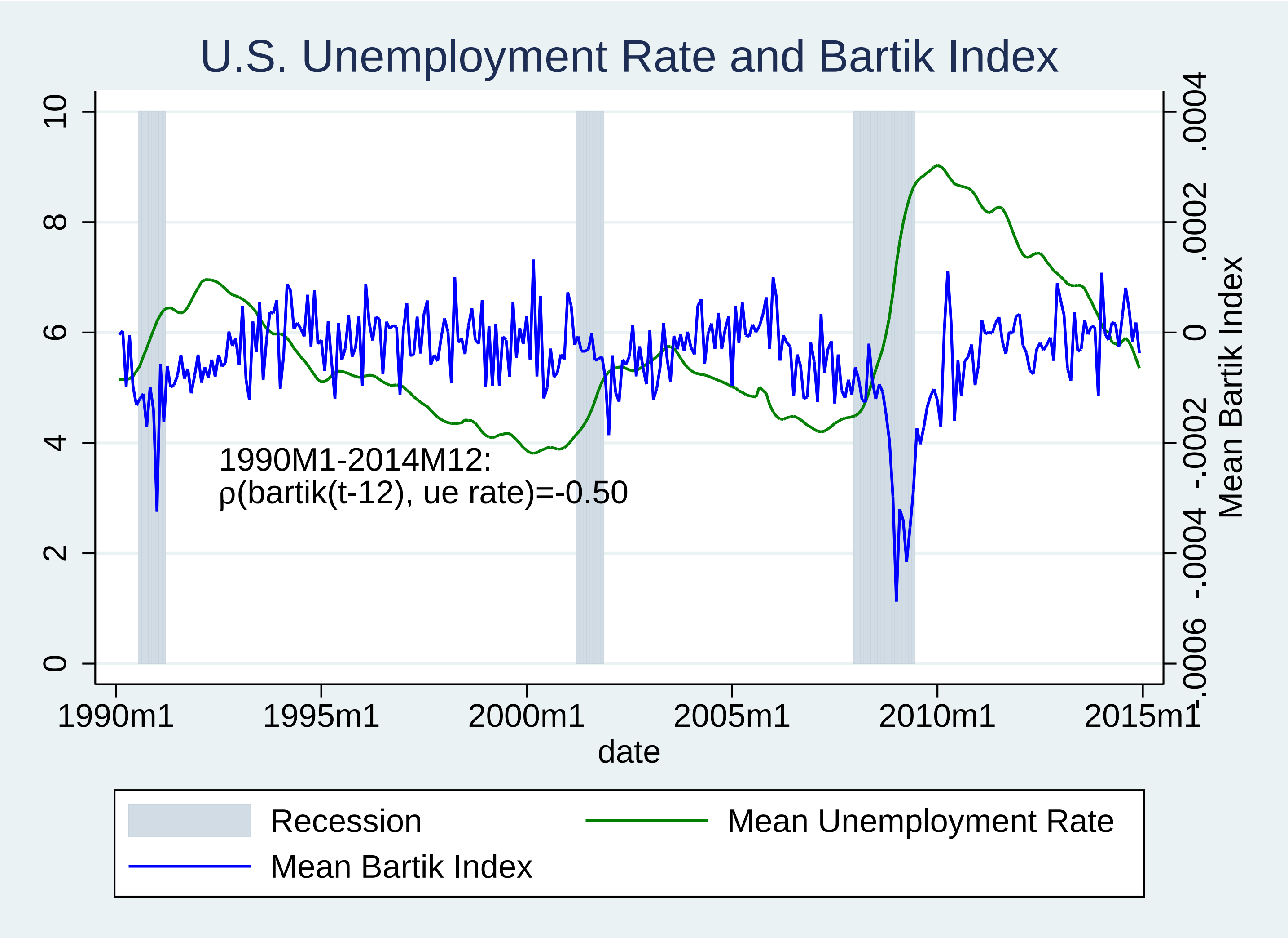


Figure 3: Periods of high uncertainty for different uncertainty proxies.

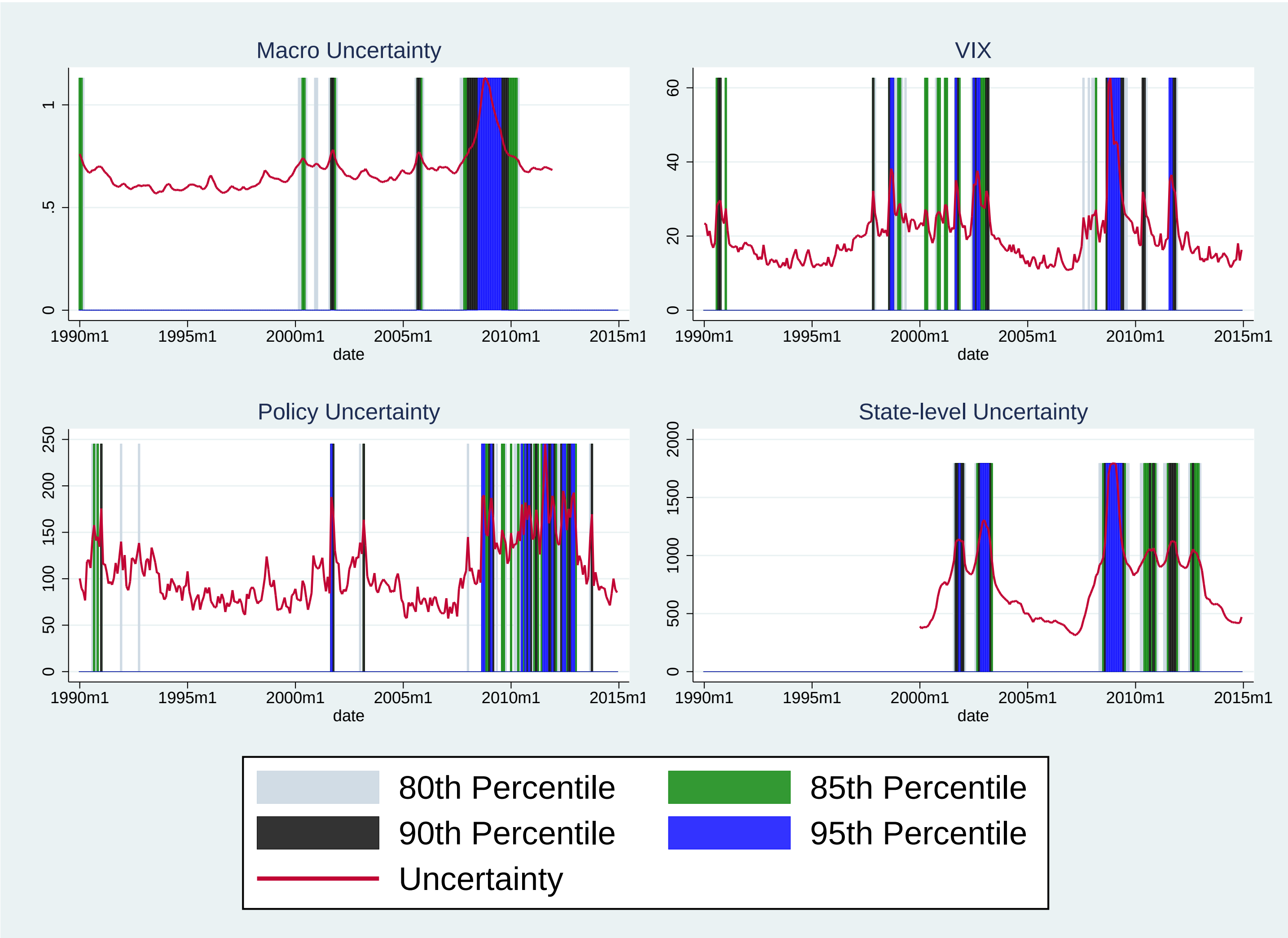


Figure 4: Impact of Macro Uncertainty.

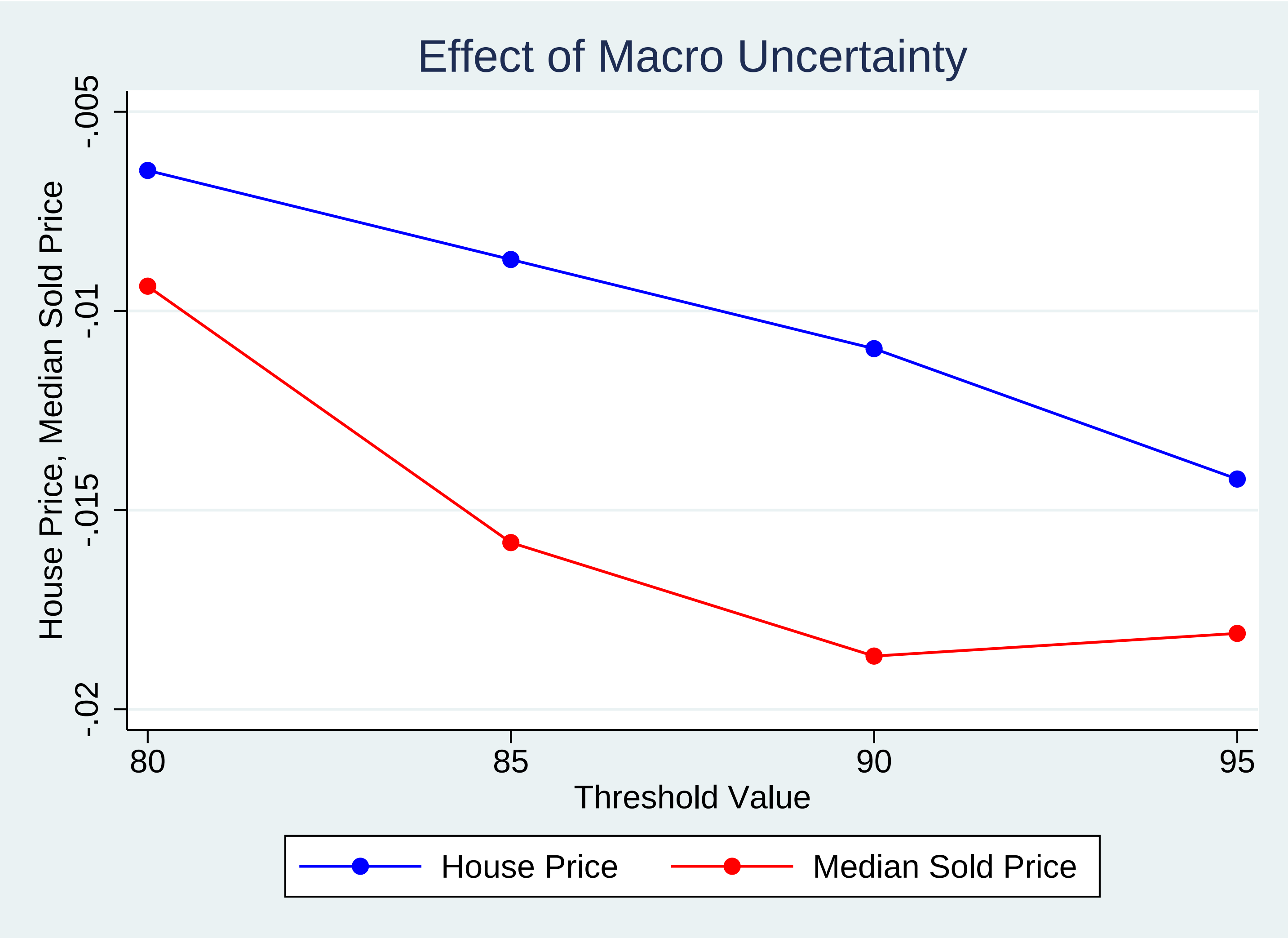


Figure 5: Impact of Bartik and Macro Uncertainty.

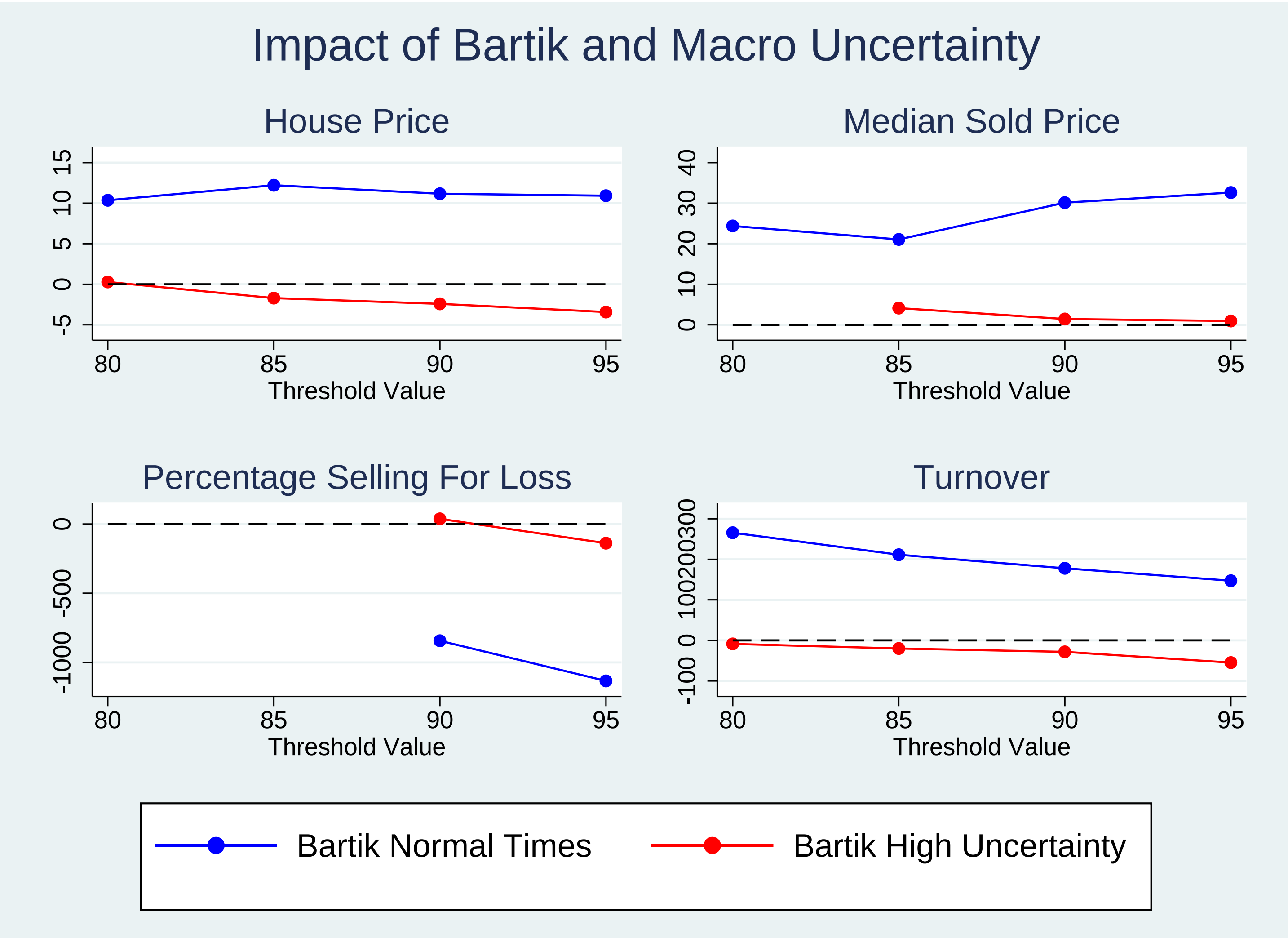
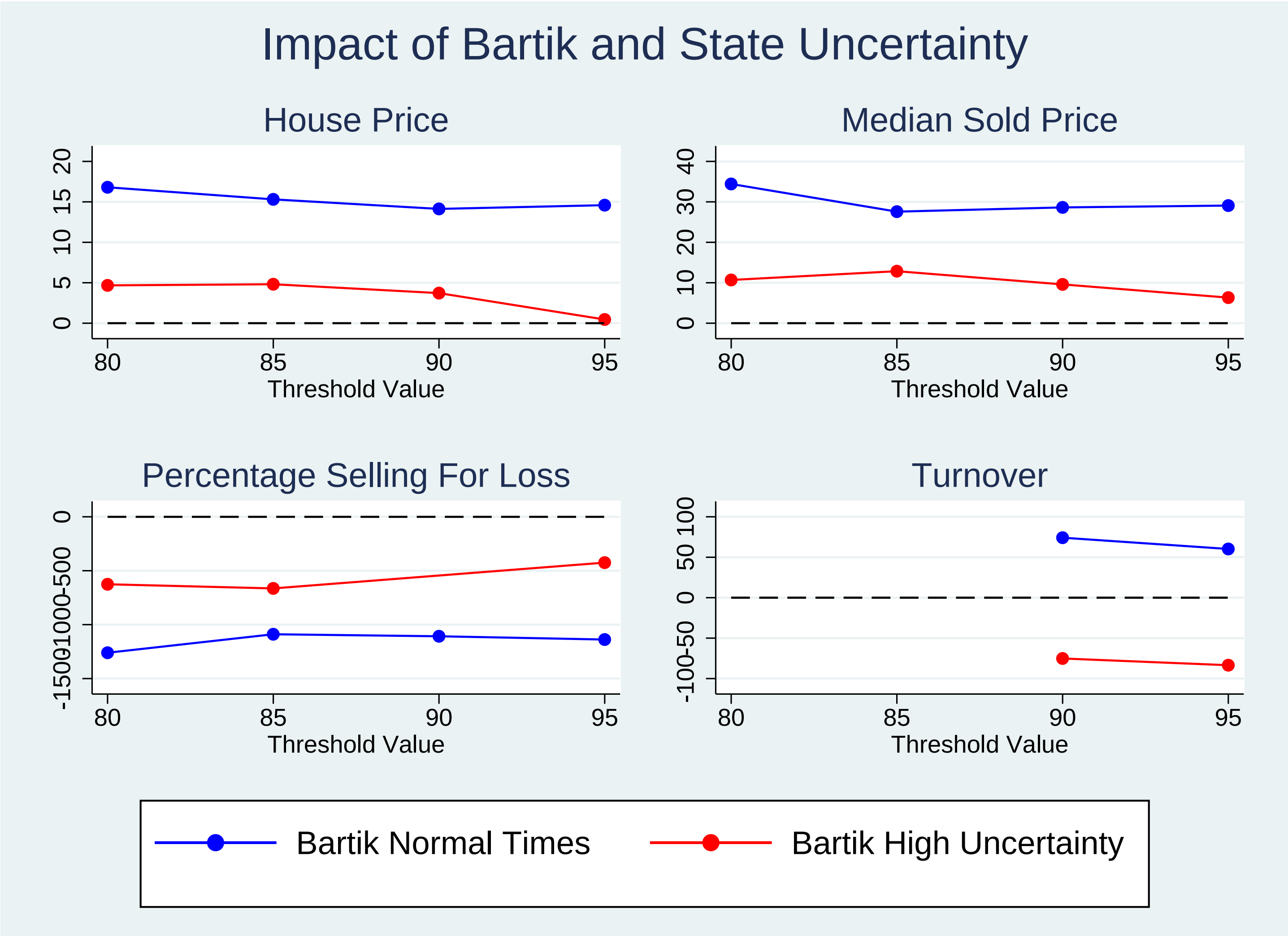


Figure 6: Impact of Bartik and State Uncertainty.



1 Tables

Table 1: Number of months defined as uncertain.

	20 %		15%		10%		5%	
	$1-\alpha$ Percentile (P)	α Normal (N)	$1-\alpha$ P	α N	$1-\alpha$ P	α N	$1-\alpha$ P	α N
Macro	124	104	103	96	80	86	58	76
Policy	192	188	174	175	156	162	138	148
State-level	36	27	27	21	18	18	9	13
VIX	240	222	225	217	210	206	195	197

Note: Number of months defined as uncertain from 1960:1 - 2011:12 for Macro Uncertainty, 1985:1 - 2015:2 for Policy Uncertainty, 2000:1 -2014:12 for State-level uncertainty and 1990:1 - 2015:2 for the VIX; the α one-tailed significance level is from the Normal Distribution and the series assume to follow i.i.d. as in Bloom (2009).

Table 2: Long-run Effects of Uncertainty, Bartik and Interaction term

Dependent Variable	$\mathbf{1}_{macro}$	Bartik	Bartik*$\mathbf{1}_{macro}$
Δlog(median sales price)	-.0180**	32.63***	-31.68***
	(.00752)	(10.679)	(11.765)
Δlog(house price)	-.0142***	10.93***	-14.35***
	(.00344)	(3.8337)	(4.3892)
Δ% selling for loss	.52575	-1133.00**	994.94**
	(.37032)	(492.26)	(485.88)
Δturnover	-.0036	147.26**	-202.00**
	(.05451)	(66.317)	(79.781)

Note: Sample period from 1990 onwards. The long-run effects of uncertainty (95th percentile threshold), bartik and interaction term are presented with corresponding standard errors in brackets. * indicates significance at 10% level, ** indicates significance at 5% level, *** indicates significance at 1% level

Table 3: Long-run Effects of Uncertainty, Bartik and Interaction term: Other Uncertainty measures

Dep. Variable	1_{macro}	Bartik (B)	B*1_{macro}	1_{State}	B	B*1_{State}	1_{vix}	B	B*1_{vix}
$\Delta_{\text{log(med sell price)}}$	-.0180**	32.627***	-31.68***	-.0033	30.296***	-24.84**	-.0058	42.316***	-44.64***
	(.00752)	(10.679)	(11.765)	(.00405)	(11.723)	(12.330)	(.00930)	(12.339)	(16.513)
$\Delta_{\text{log(house price)}}$	-.0142***	10.925***	-14.35***	-.0048***	15.315***	-17.63***	.00191	12.625***	-11.40
	(.00344)	(3.8337)	(4.3892)	(.00144)	(4.2199)	(4.4932)	(.00482)	(4.2128)	(7.1745)
$\Delta\%_{\text{ selling for loss}}$	.52575	-1133.**	994.94**	.48216**	-1229.**	1038.6*	.48033	-1584.0***	1517.5**
	(.37032)	(492.26)	(485.88)	(.23001)	(479.62)	(558.01)	(.54268)	(524.17)	(699.86)
Δ_{turnover}	-.0036	147.26**	-202.0**	-.0577***	81.225*	-152.3***	.05951*	95.007*	-102.4
	(.05451)	(66.317)	(79.781)	(.02065)	(43.376)	(57.010)	(.03517)	(54.964)	(98.765)

Note: As the months defined as high uncertainty differ across the proxies, the variation used to identify $\vec{\beta}_{1t-\tau}$and $\vec{\beta}_{3t-\tau}$, the coefficients of uncertainty and the interaction term, differs as well. The long-run effects of uncertainty (95th percentile threshold), bartik and interaction term are presented with corresponding standard errors in brackets. * indicates significance at 10% level, ** indicates significance at 5% level, *** indicates significance at 1% level. We do not include policy uncertainty by Baker et al (2016) as the results similar to other measures and due to the space limitation.

Table 4: Long-run Effects of Bartik and Interaction term grouped by the magnitude of the housing price volatility over time.

Housing Price Volatility	low		medium		high	
	Bartik (B)	B*1^{low}_{state}	B	B*1^{medium}_{state}	B	B*1^{high}_{state}
Δlog(house price)	18.47**	-6.85	7.055***	-9.26	21.26***	-25.0***
	(7.802)	(7.131)	(2.596)	(6.253)	(6.899)	(8.905)

Note: The long-run effects of bartik and interaction term based on State-level uncertainty (95th percentile threshold) are presented with corresponding standard errors in brackets grouped by housing price volatility across States. * indicates significance at 10% level, ** indicates significance at 5% level, *** indicates significance at 1% level.

Table 5: Long-run Effects of Bartik and Interaction term grouped by the impact of the bartik in each State.

Bartik Index	low		medium		high	
	Bartik (B)	B*1^{low}_{State}	B	B*1^{medium}_{State}	B	B*1^{high}_{State}
Δlog(house price)	9.835***	-5.16	52.98***	-16.1	104.9***	-102**
	(2.328)	(5.947)	(9.703)	(14.43)	(21.13)	(45.07)

Note: The long-run effects of bartik and interaction term based on State-level uncertainty (95th percentile threshold) are presented with corresponding standard errors in brackets grouped by housing price volatility across States. * indicates significance at 10% level, ** indicates significance at 5% level, *** indicates significance at 1% level.

Table 6: Uncertainty Proxies

Variable	Availability	Source	Regional level
Macro Uncertainty	1960M1-2011M12	Jurado et al. (2015)	National
Policy Uncertainty	1985M1-2015M2	Baker et al. (2012)	National
State Uncertainty	2000M1-2014M12	Self constructed	State
Vix Uncertainty	1990M1-2015M2	FRED	National

Table 7: Dependent Variables

Variable	Availability	Source	Regional level
House Price	1975M1-2014M12	Freddie&Mac	State
Median Sales Price	1996M4-2014M12	Zillow Database	State
% Selling For Loss	1998M1-2014M12	Zillow Database	State
Total Turnover	1998M1-2014M12	Zillow Database	State

Table 8: Control Variables

Variable	Availability	Source	Regional level
Federal Funds Rate	1954M7-2015M1	FRED	State
Housing Starts	1988M1-2015M1	FRED	State
Income	1950Q1-2014Q3	BEA	State
Industrial Production	1919M1-2015M1	FRED	National
Inflation Rate	1947M1-2015M1	FRED	National
Population	1972-2013	FRED	State
S&P 500	1970M1-2015M3	Datastream	National
Unemployment Rate	1976M1-2014M12	FRED	State

Table 9: Descriptive statistics of the housing market variables.

	Obs.	Mean	Std. Dev.	Min	Max
house price	2448	125.5488	25.6362	61.0220	275.6024
Δhouse price	24429	0002795	0.0073951	-0.1098976	0.0773649
Median Sales Price	7790	191184.8	74180.34	47519.08	518470.1
ΔMedian Sales Price	7751	0.001178	0.025107	-0.256864	0.308221
% Selling For Loss	7234	12.8908	13.5806	0.0612	70.5068
Δ% Selling For Loss	7158	0.107329	1.18954	-15.6326	16.4346
Turnover	7308	4.81494	2.253468	0.008869	17.16583
ΔTurnover	7271	0.0032471	0.106966	-12.71301	2.019346

Table 10: Descriptive statistics of the uncertainty measures as well as the *bartik* index.

	Obs.	Mean	Std. Dev.	Min	Max
Macro Uncertainty	264*51	0.67773	0.0961123	0.568981	1.130619
Policy Uncertainty	300*51	106.3401	34.38186	57.20262	245.1267
State-level Uncertainty	9180	18.23878	7.730284	0	233
VIX	300*51	19.9604	7.730284	10.82	62.64
Bartik	15249	-0.000041	0.0001304	-0.002793	0.0009686

Table 11: Sorted states, according to their unconditional housing price volatility over time.

low	*medium*	*high*
Alabama	Alaska	Arizona
Arkansas	Colorado	California
Georgia	Delaware	Connecticut
Iowa	Idaho	District of Columbia
Indiana	Illinois	Florida
Kansas	Louisiana	Hawaii
Kentucky	Maine	Massachusetts
Missouri	Michigan	Maryland
Mississippi	Minnesota	New Hampshire
North Carolina	Montana	New Jersey
Nebraska	North Dakota	Nevada
New Mexico	Oklahoma	New York
Ohio	Pennsylvania	Oregon
South Carolina	Texas	Rhode Island
South Dakota	Utah	Virginia
Tennessee	Vermont	Washington
Wisconsin	West Virginia	Wyoming

Table 12: Sorted states, according to the impact of the *bartik* index in each state.

low	*medium*	*high*
Colorado	Arkansas	Alaska
Georgia	Kansas	Arizona
Iowa	Massachusetts	District of Columbia
Illinois	Maryland	Delaware
Kentucky	Minnesota	Hawaii
Louisiana	Missouri	Maine
Michigan	North Dakota	New Hampshire
Mississippi	Nebraska	New Mexico
North Dakota	New Jersey	Oregon
New York	South Carolina	South Dakota
Oklahoma	Virginia	West Virginia
Tennessee	Washington	Wyoming
Texas		