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Essays on Housing Market

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ESSAYS ON HOUSING MARKET

by

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ABSTRACT

ESSAYS ON HOUSING MARKET

by

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Under the Supervision of Professor Kundan Kishor

My dissertation studies different aspects and phenomena of the housing market in the United States. In the first chapter, I explore the long-run relationship between housing starts and building permits along with its short-run deviations. This paper fits a pre-specified cointegration model to verify the long-run co-movement property of building permits and housing starts in the U.S., and its census regions to improve the predictability of housing starts at different forecast horizons. The out-of-sample forecasting performance of housing starts is derived from the feature of the short-run vector error correction model that suggests that only housing starts adjusts to correct for any disequilibrium in the equilibrating relationship between housing starts and building permits. This result is robust to structural breaks, as well as the inclusion of additional controls in the short-run dynamics.

During the first decade of the 21^{st} century, the housing market in the U.S. was not only going through an episode of exuberance, but one of the major causes behind the Great Recession of 2008 was the crash of the housing market. Against this background, the second chapter of my dissertation proposes a method to decompose housing demand into Consumption and Investment motives. For this purpose, housing is allowed to enter both the utility function as well as the budget constraint. Since the two motives of the housing are not separately identifiable in the resulting Euler equations, an unobserved component model is proposed to estimate them. Using data from 1987 through 2019, it has been found that the share of consumption motive in total housing demand is 83%. The results also suggest that the investment motive is much more volatile than the consumption motive and witnessed a big increase before the 2008 financial crisis.

In the third chapter, I explore the time-varying response of the tradable and non-tradable employment if a shock appears in the house prices. I use monthly state-level data from 2001 through 2020 and compare the time-varying impulse responses of tradable and non-tradable employments over different horizons. The methodology I use is a time-varying parameter vector autoregressive model with stochastic volatility. The results show that for 16 out of 45 states, the response to non-tradable employment is higher than that to tradable employment.

To

my wife,

my parents,

and my teachers,

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Chapter 1

Introduction

Housing is one of the most important assets held by households across the globe. It affects the economy not only through the residential investment channel, but also through its effects on consumer wealth. A severe drop in residential investment can cause a recession throughout the economy because of residential investment's relationship to Gross Domestic Product (GDP) and the financial markets. Out of all the components of the GDP, residential investment offers, by far, the best early warning sign of an oncoming recession. The importance of the housing market is reflected in its importance in business as well as policy decision-making. A significant share of an economy's aggregate demand coming from housing assets supports this argument. The current average home ownership rate in the U.S. is 65.8%. Also, the National Income data of the U.S. documents that the average share of the residential asset in the total fixed asset to be 35.14%, thereby making it the most dominant component in the net wealth of U.S. households.

In my dissertation, I try to explore different aspects of the housing market in the United States. The first chapter of my dissertation exploits the long-run co-movement property of building permits and housing starts in the U.S., and its census regions to improve the predictability of housing starts at different forecast horizons. The out-of-sample forecasting performance of housing starts is derived from the feature of the short-run vector error correction model that suggests that only housing starts adjusts to correct for any disequilibrium in the equilibrating relationship between housing starts and building permits. This result is robust to structural breaks, as well as the inclusion of additional controls in the short-run dynamics.

The second chapter of my dissertation proposes a method to decompose housing demand into consumption and investment motives. For this purpose, housing is allowed to enter both the utility function as well as the budget constraint. Since the two motives of the housing are not separately identifiable in the resulting Euler equations, an unobserved component model is proposed to estimate them. Using data from 1987 through 2019, it has been found that the share of consumption motive in total housing demand is 83%. The results also suggest that the investment motive is much more volatile than the consumption motive and witnessed a big increase before the 2008 financial crisis.

In the third chapter of my dissertation, I explore the time-varying response of the tradable and non-

tradable employment to house price shocks. I use monthly data from 2001 through 2020 for 45 U.S. states and examine the time-varying impulse responses to employment for different states. The methodology I use is a *Time-varying Parameter Vector Autoregression model with Stochastic Volatility*. The results show that for 16 out of 45 states, the response of non-tradable employment is higher than that of tradable employment to house price shocks. The Granger-causality test results show that there are only 15 states where the house price Granger-causes both the types of employment. This result is in contrast to the widely cited work of Mian and Sufi (2014) where they find that non-tradable employment is much more responsive to house prices than tradable employment.

Chapter 2

Comovement in Housing Starts and Building Permits and its Forecasting Implications

2.1 Introduction

Housing wealth plays a pivotal role in business cycles across the global economies. Housing market affects economic activity directly through residential investment channel and indirectly through consumer wealth effect channel[1]. The importance of housing market is reflected in its importance in business as well as policy decision making. Although there are several indicators of the health of housing market, building permits and housing starts are the two most widely used measures (Joseph and Larrain, 2012).[2]

In a perfect foresight world, movements in building permits and housing starts should closely track each other and the difference between them should just be a random noise. However, as shown in Figure 1, there can be substantial deviation between these two series in the short-run even if they tend to move together in the long-run[3]. Not surprisingly, the literature has paid attention to this short-run anomaly[4]. Papers focusing on supply side factors have suggested residential construction cost, long-term production cost, large inventory carrying costs and illiquid outputs as reasons why housing starts may deviate from number of building permits[5]. Demand side factors like interest rate, final demand and inventory change, money supply and mortgage credit also play a role by affecting the decision to start new construction. Evidence in support of the demand side hypothesis have been provided by Guttentag (1961), Alberts (1962), Huang (1973) and

[1]There is also significant amount of work on balance sheet channel, see Adelino et al. (2015), Chaney et al. (2012), Favara and Imbs (2015), Gertler and Gilchrist (2018) and Mian et al. (2013) among others.

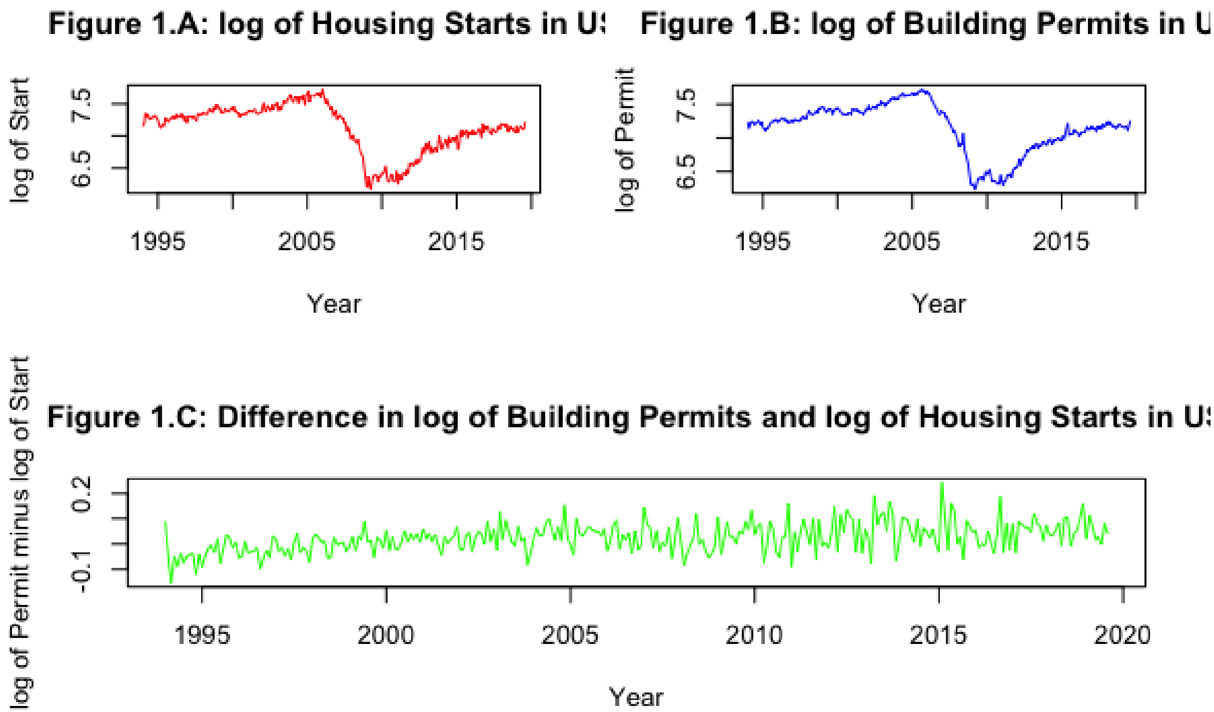
[2]Building permit refers to the total number of building permits issued by the building permit offices in a month. Housing start represents the total number of housing constructions started from those corresponding building permits in a particular month.

[3]The AR coefficient on regression of this deviation on its own past lag is 0.67.

[4]In the U.S., a builder has to obtain a legitimate building permit from the corresponding building permit office before starting a housing construction. At the same time, an application for permit shows the builder's intent for starting new construction. That's why, building permits and housing starts are expected to co-move with each other in the long run.

[5]See for example, Somerville (1999, 2001); Coulson (1999); Falk and Lee (2004); Croce and Haurin (2009)

Figure 1: Start and Permit in the US



Maisel (1963). There is also some evidence that the usury law[6] and weather play a role in the short-run deviation between building permit and housing start as well [See for example, Yandle and Proctor (1978) and Cammarota (1989)].

Although the literature has attempted to study the causes of the divergence in the housing starts and building permits over time, there is no comprehensive study on exploiting the long-run relationship between these two important indicators of housing market. The objective of this paper is two fold: first, we formally examine the existence of long-run equilibrium relationship between building permits and housing starts. Secondly and more importantly, we investigate if the long-run comovement property can be used to improve the forecastability of one of these two variables. Using monthly data from January 1994 through July 2019 for the U.S. and its four census regions, we do find overwhelming evidence in support of the cointegrating relationship between building permits and housing starts[7]. For the short run dynamic adjustment, the Vector Error Correction Model (VECM hereafter) suggests that housing starts does most of the error correction if there is a disequilibrium in the short-run. That is, if the long-run ratio of building permits and housing starts deviates from its steady state value, it is corrected by the subsequent movements in housing starts.

[6]It is a state specific law in the US housing market enacted in 1966 which prohibits the mortgage rate to increase beyond a certain threshold level.

[7]Building permits and housing starts by themselves are non-stationary as supported by the unit root tests.

Only in case of Northeast and West, we do find weak evidence of error correction by building permit. This result is robust to the break in the VECM model parameters, as well as the inclusion of additional controls like unemployment rate, yield spread, consumer sentiment and a measure of credit spread.

Since housing starts plays a dominant role in correcting for the disequilibrium in the short-run, it is imperative to examine if this property can be exploited to obtain a superior forecast of housing start in out-of-sample. For this purpose, we examine if the inclusion of the last period disequilibrium error from the cointegrating relationship between building permits and housing starts leads to a significant improvement in the forecasting performance of changes in housing starts compared to the popular benchmark models. The results do clearly suggest that the information from the long-run relationship between housing starts and building permits lead to significant improvement in forecasting performance of changes in housing starts at short and medium horizons. The improvement in forecasting performance is highest at short-horizons where the model with disequilibrium error from the last period reduces root mean squared error (RMSE) of a univariate model by more than 30 percent. On the other hand, the improvement in forecasting performance for changes in building permits is tenuous at best. This is consistent with the full-sample VECM results, where we find that building permit does not participate in error correction in most of the cases. These results are also robust to a break in the sample period around the financial crisis and the inclusion of additional controls like unemployment rate, sentiment index and different measures of spread in the VECM specification.

The remainder of this paper is structured as follows: Section II provides a brief discussion on existing literature. Section III discusses the conceptual framework adopted in this paper. Section IV details the data used in this paper. Empirical results are presented in Section V. Section VI shows the robustness results. Section VII reports the forecasting results and Section VIII concludes.

2.2 Related Literature

Although literature on housing market is vast, research on the two important indicators of housing activity- building permits and housing starts- is relatively scarce. The importance of these indicators can be gauged by the fact that in a widely cited paper, Leamer (2007) argued that housing is the business cycle and he suggested replacing output gap measure in Taylor's rule with housing starts and the changes in housing starts. This is similar in flavor to Joseph and Larrain (2012) findings, where they suggest the importance of building permits and housing starts in overall economic activity. They also show comovement in these two variables. Taking a structural view on the relationship between the housing start and completion, Somerville

(2001) has used the building permit as a proxy for start. Somerville (2001) justification for using building permit as a proxy for the housing start data is that housing start is derived from a sub-sample of the total count; whereas building permit is a full-count data. Therefore, building permits can be used as a proxy for housing starts. In another paper, Goodman Jr (1986) has showed that estimated building permit issuance is subject to far less sampling error than housing starts. At the same time, there is a strong contemporaneous correlation between the two. Hence, according to Goodman Jr (1986) in order to reduce the error in the monthly housing start estimates, the building permit data should be used.

The other strand of literature has analyzed the short run dynamic adjustments of the two variables. In this line of research, the literature has suggested a number of institutional factors that only affect housing starts, and not the building permit. The inception of this branch of articles dates back to the early 1960s, when Guttentag (1961), Alberts (1962) and Maisel (1963) used inventory theoretic approaches to show the effects of fixed interest rate, final demand and inventory change and mortgage credit on housing start. In a related work, Huang (1973), combined residual fund theory with inventory theoretic approach to show the effects of a short term interest rate and the monetary base on housing starts. Coulson (1999) and Falk and Lee (2004) have also showed that the housing starts and completions are related through a process of inventory management; and this factor doesn't affect building permits. Croce and Haurin (2009) have highlighted the role of long horizon production, large inventory-carrying costs and illiquid outputs in making the transition from building permits to housing start. In another line of research, Yandle and Proctor (1978) studied the effect of interest rate on housing start in the presence of the state Usury law and they found that in the presence of the Usury law a tight monetary policy can create an incentive for the investors to move their funds out of the housing market. Later on, Cammarota (1989) showed that unseasonable weather is one of the important factors affecting the housing start. Residential construction cost has also been found to be an important factor that can explain the deviation between housing start and building permit (Somerville, 1999, 2001).

2.3 Long-run Relationship between Housing Starts and Building Permits

The modeling framework used in this paper utilizes the long-run relationship between building permit and housing start. The decision to file for a building permit and start housing construction are intertwined. If there is a short-run deviation, these two series should move together in the long-run. The natural way to model this behavior is the cointegration methodology proposed by Engle and Granger (1987)

since both the series by themselves are non-stationary (shown later). This method has a rich history in macroeconomics and finance, and has been applied widely[8]. Let p_t and s_t denote the total number of building permits issued and the total number of housing starts in a particular period respectively.

$$lnp_t = \beta_0 + \beta_1 lns_t + \epsilon_t \tag{1}$$

Equation 1 represents the linear relationship between two non-stationary variables: housing starts and building permits. lnp_t and lns_t are the natural logarithms of building permit and housing start respectively. 'ϵ_t' denotes any short run shocks in this equilibrium relationship. If there exists a cointegration between the two variables, then ϵ_t will be the cointegrating residual and, it will be stationary and mean reverting in the long-run.

According to the Granger Representation Theorem (Engle and Granger, 1987), cointegration between a set of variables implies the existence of a Vector Error Correction Mechanism. The VECM representation implies that in the presence of cointegration one of the error-correction coefficients has to be significant.

$$\left.\begin{aligned} \Delta lnp_t &= \mu_1 + \phi_{11}^1 \Delta lnp_{t-1} + \phi_{12}^1 \Delta lns_{t-1} + \cdots + \alpha_1 \epsilon_{t-1} + u_{1t} \\ \Delta lns_t &= \mu_2 + \phi_{21}^1 \Delta lnp_{t-1} + \phi_{22}^1 \Delta lns_{t-1} + \cdots + \alpha_2 \epsilon_{t-1} + u_{2t} \end{aligned}\right\} \tag{2}$$

Equation 2 represents the VECM system adopted for the purpose. Δlnp_t and Δlns_t represent the growth rates of building permit and housing start respectively; and ϵ_{t-1} represents any short run shocks in this equilibrium relationship that took place in the last period. In order for the housing starts and building permits to have the error correcting property, the corresponding α's need to be significant with their expected sign.

2.4 Data

This study uses 26 years of monthly data from January 1994 through July 2019. Our sample includes both the recessionary and the non recessionary period so that the sample is not only constrained by one phase of the business cycle. For housing starts, New privately owned housing starts data has been

[8]For example, see Cochrane (2008), Campbell and Shiller (1988), Lettau and Ludvigson (2001), Kishor (2007) among others.

Table 1: Summary Statistics

Variable	Min	1st Quartile	Mean	Median	3rd Quartile	Max.
U.S.						
Start	478	1018	1320	1369	1620	2273
Permit	513	1062	1349	1361	1652	2263
Midwest						
Start	59.0	150.5	240.1	239.0	329.5	446.0
Permit	83.0	163.0	243.5	250.0	331.5	408.0
Northeast						
Start	36.0	97.0	127.9	132.0	154.0	236.0
Permit	58.0	110.5	136.9	137.0	166.0	306.0
West						
Start	79.0	234.0	322.2	339.0	396.0	583.0
Permit	97.0	250.5	332.7	340.0	405.5	619.0
South						
Start	230.0	512.0	629.3	645.0	741.5	1146.0
Permit	257.0	528.5	635.4	627.0	746.5	1104.0

The data are on thousands of Units. The sample period is 1994:m01-2019:m07.

collected from the Survey of Constructions done by the U.S. Census Bureau. Building permit is, New private housing units authorized by building permits and it is collected from the Building Permit Survey done by the U.S. Census Bureau along with the U.S. Department of Housing and Urban Development. The data has been collected for the U.S. as well as for all the four census regional levels, i.e. Midwest, Northeast, West and South. Note that this data is also available at the Federal Reserve Bank of St. Louis' FRED website. For robustness check, we use data on Consumer sentiment (obtained from the Surveys of Consumers); Spread between 10-year and 2-year government bond yields (from the Federal Reserve Bank of St. Louis); Unemployment(from the U.S. Bureau of Labor Statistics) and Excess bond premium, (obtained from the Federal Reserve Board).

A summary of the data can be found in Table 20. As shown earlier, a cursory look at the data shows that there is high degree of comovement between building permits and housing starts in the long-run. As reported in the table, the mean and the median of the housing starts and building permits are very close to each other for all the regions as well as the U.S. If we look at the distribution, similar conclusion can be drawn for all the regions.

2.5 Empirical Results

2.5.1 Common Trend in Housing Starts and Building Permits

As shown earlier, building permits and housing starts tend to move together in the long-run. To examine this pattern in data econometrically, we apply cointegration methodology. Since conventional

cointegration involves a linear equilbrating relationship between non-stationary variables, we first examine for the presence of a unit root in both of these series. The results from Phillips-Perron test are shown in Table 2. The results clearly support the existence of unit root in housing start and building permit for the U.S. as well as for all the census regions. On the other hand, the null of unit root is rejected for the growth rate of housing start and building permit at all conventional levels of significance. These results are robust to the use of the most widely used unit root tests. The equation representing the long term relationship between housing start and building permit can be hypothesized as:

$$lnp_t = \beta_0 + \beta_1 lns_t + \epsilon_t \tag{3}$$

The existence of cointegration implies that a linear combination of building permits and housing starts as represented in Equation 3 above is stationary. In other words, lnp_t and lns_t can be said to share a common trend in the long run if the estimated cointegrated residual $\hat{\epsilon}_t = lnp_t - \hat{\beta}_0 - \hat{\beta}_1 lns_t$ is stationary[9]. In the present study, we assume a pre-specified cointegrating vector $(1, -1)'$. This assumption is based on the theoretical underpinnings of the model that suggests one-to-one relationship between housing starts and building permits in the long-run. This assumption has also been verified by the estimation of cointegration vector which turns out to be $(1, -0.97)'$. Our assumption is also motivated by econometric theory that associates higher power for models with pre-specified cointegration vector.

Table 2: Unit Root Test (Phillips-Perron)

Variable:	Test Statistic				
	US	Midwest	Northeast	West	South
lnp_t	-1.15	-1.16	-3.65	-1.41	-1.24
lns_t	-1.28	-2.37	-5.50	-1.82	-1.72
Δlnp_t	-20.14	-28.08	-29.99	-24.42	-25.19
Δlns_t	-26.27	-35.42	-36.18	-34.06	-29.51

Critical values of the test statistic are -3.453, -2.871 and -2.571 for 1%, 5% and 10% respectively.

Table 3 shows the result of a Phillips-Perron test applied on the cointegrating residuals for the U.S. as well as all the regions. It is clearly evident that there is cointegration between housing start and building permit for all the regions as the test rejects the null of unit root in the cointegrating residuals at all

[9] The hat denotes the estimated value.

Table 3: Cointegration Test Results

Variable: $\hat{\epsilon}_t$

	US	Midwest	Northeast	West	South
Test Statistic	-15.26	-17.01	-19.42	-16.94	-15.29

Critical values of the test statistic are -3.453, -2.871 and -2.571 for 1%, 5% and 10% respectively.

conventional levels of significance.

2.5.2 Short Run Dynamic Relationship

Having the cointegration between housing starts and building permits established, we can use Engle-Granger theorem to write down the VECM representation of the model presented in the previous section. According to this theorem, if cointegration exists, then at least one of the variables moves to correct for any short-run disequilibrium from the long-run equilibrating relationship. The VECM representation for the cointegration model outlined in the previous section can be written as:

$$\left.\begin{aligned} \Delta lnp_t &= \mu_1 + \phi_{11}^1 \Delta lnp_{t-1} + \phi_{12}^1 \Delta lns_{t-1} + \cdots + \alpha_1 \epsilon_{t-1} + u_{1t} \\ \Delta lns_t &= \mu_2 + \phi_{21}^1 \Delta lnp_{t-1} + \phi_{22}^1 \Delta lns_{t-1} + \cdots + \alpha_2 \epsilon_{t-1} + u_{2t} \end{aligned}\right\} \tag{4}$$

where the terms Δlnp_t and Δlns_t denote the growth rate of building permit and housing start respectively; $\epsilon_{t-1} = lnp_{t-1} - lns_{t-1}$ is the short run disequilibrium error (or shock) that appeared in the last period. And, the α_1 and α_2 are the error correcting coefficients of building permit and housing start respectively. If building permit does the error correction, then α_1 should be negative and significant. In case housing start moves to correct for the disequilibrium, then α_2 should be positive and significant. To provide the intuition behind the sign of the error correction coefficients, consider a positive shock that pushes the ratio of permit and start above its long-run value. To bring the ratio back to its steady state level, either permits has to go down (-ve coefficient) or starts has to go up (+ve coefficient).

Table 4 shows the result of the VECM for the permit variable. The lag length criteria implies zero lags for the U.S. and one for the four census regions[10]. From the results in this table, it can be observed that the error correction coefficients of permit is significant with its expected sign (i.e. negative) only for the Northeast and West region; whereas for the US, Midwest and South region the error correction coefficient is insignificant.

[10]The lag lengths are chosen based on Schwarz information criterion.

Table 4: VECM Results for Building Permits

Dep Var :	Δlnp_t				
	US	Midwest	Northeast	West	South
Intercept	0.001	-0.000	0.017	0.007	0.000
Δs_{t-1}		-0.054	-0.116*	-0.158**	-0.003
Δp_{t-1}		-0.359***	-0.190**	-0.129·	-0.378***
α_1	-0.063	-0.077	-0.242**	-0.237***	–0.001

The symbols '***', '**', '*' and represents level of significance at 1%, 5% and 10% level respectively. The lag length for US is 0, and 1 for the Midwest, Northeast, West and the South.

Table 5 shows the same set of results for the start variable. From this table, it is clear that if there is any disequilibrium in the short run, then housing starts moves in the subsequent period to correct it, implying the significance of error correction coefficient of housing starts at all conventional levels of significance. This result holds for all the census regions as well as for the national level, as the error correction coefficients are positive and significant for all of them at all conventional levels of significance. There are several

Table 5: VECM Results for Housing Starts

Dep Var :	Δlns_t				
	US	Midwest	Northeast	West	South
Intercept	-0.017***	-0.027**	-0.066***	-0.025***	-0.007
Δs_{t-1}		-0.030	-0.029	-0.132*	-0.179**
Δp_{t-1}		-0.219*	-0.266***	-0.193*	0.000
α_2	0.743***	0.900***	0.958***	0.771***	0.619***

The symbols '***', '**', '*' and represents level of significance at 1%, 5% and 10% level respectively.The lag length for US is 0, and 1 for the Midwest, Northeast, West and the South.

reasons why housing starts may display this type of error-correction property. The literature has provided different reasons for why housing start tends to follow building permit and not the other way round. For example, there are factors that only affect the housing start and not building permit. Residential construction cost has been suggested to be one of the most important drivers of why housing start tends to adjust for disequilibrium. According to Somerville (1999), residential construction costs and housing starts are negatively correlated, whereas this cost does not have a very strong relationship with building permits. Housing start and completions are also related through a process of inventory management; and this being the key control variable of the builders (Coulson, 1999; Falk and Lee, 2004). Or in other words, the housing start involves long horizon production, large inventory-carrying costs and illiquid outputs Croce and Haurin (2009). It can also be argued that the entire process of bringing raw land into developed use or redeveloping

existing sites is not a single step, but a series of irreversible investments (Somerville, 2001). This is one of the reasons why housing start plays a disproportionate role when it comes to error-correction. The unseasonable weather can also be thought of as a factor which only affects the housing start since during the colder months in the year, the speed of the housing construction slows down (Cammarota, 1989). Apart from all these factors, monetary policy also plays a role in affecting housing starts. For example, change in the supply of mortgage credit (Guttentag, 1961), fixed interest rate (Alberts, 1962), final demand and inventory change, short term interest rate, the cost-of-capital effect felt by the builders and consumers and the monetary base (Huang, 1973) also play a very important role in determining the number of housing to be started in a given year. It should also be noted that the impact of interest rate on housing start may be affected by the presence of Usury law of 1966 as pointed out by Yandle and Proctor (1978). In the presence of the Usury law, interest rate goes up and an incentive gets created for the people to move the funds out of the mortgage market and invest in other high-yielding assets if monetary policy is too tight. This can have an adverse effect on the housing starts.

Along with these supply side factors, demand side factors also play an important role in the behavior of housing starts. The expected future price can play a very important role in the builder's decision to start a housing (Jud and Winkler, 2003). A builder may decide to postpone the housing project if the economic conditions may lead to a fall in house prices. Therefore, it is not surprising to find that housing start tends to correct for any short-run disequlibrium in the long-run relationship between housing start and building permit.

2.6 Robustness Check

2.6.1 Structural Break Test

The housing market in the U.S. has witnessed dramatic changes over the last few decades. This was especially evident during the financial crisis of 2007-08. To address the possible instability in our model, we examine if there is a structural break in our model specification. To address structural break, we use Bai and Perron (1998) multiple structural break point test and apply it to our VECM specification. In particular, our structural break model has the following specification,

$$\left.\begin{aligned} lnp_t &= \beta_{01} + \beta_{11} lns_t + \epsilon_t \quad \forall t = 1, 2, \cdots, \tau \\ lnp_t &= \beta_{02} + \beta_{12} lns_t + \epsilon_t \quad \forall t = \tau+1, \tau+2, \cdots, T \end{aligned}\right\} \tag{5}$$

For parsimony, our representation above shows a single break. In practice, we allow for multiple breaks and use Bai and Perron (1998) structural break test to examine the following hypotheses,

$$H_0 : \beta_{01} = \beta_{02} \ \ and \ \ H_0 : \beta_{11} = \beta_{12}$$

$$H_1 : \beta_{01} \neq \beta_{02} \ \ and \ \ H_1 : \beta_{11} \neq \beta_{12}$$

If the null hypotheses are rejected, then that infers the presence of a structural break. Not surprisingly in our analysis, the results do reject the null hypotheses which implies the existence of structural break. The identified break dates are very close to the financial crisis for the US and all regions[11]. Once the break dates are identified, we examine if the nature of error correction has changed across time. It turns out that the effect of break is mostly on the point estimate and the qualitative results that housing start plays a major role in error-correction still holds.

Table 6 shows the VECM results for the permit variable when we allow for break in the sample based on the structural break test. The top panel shows the results for the first sample period and the bottom panel reports the estimated results for the second sample period for the U.S., as well as all four regions. The results in this table show that the error correction coefficient of the permit variable is negative and significant only for the Northeast, West and the South region for the first sample period. And for the second sample period, it is significant with a negative sign only for the Northeast and West reg-

Table 6: VECM Results for Building Permits Based on Structural Break

Dep Var :	Δlnp_t				
	US	Midwest	Northeast	West	South
			1st Sub Sample		
Intercept	0.001	-0.000	0.026*	-0.001	-0.005
Δs_{t-1}			-0.163		
Δp_{t-1}			-0.328**		
α_1	-0.127	0.009	-0.373**	-0.234	-0.165**
			2nd Sub Sample		
Intercept	0.000	0.002	0.023	0.010	0.008
Δs_{t-1}		-0.072		-0.175**	-0.057
Δp_{t-1}		-0.358***		-0.108	-0.540***
α_1	-0.043	-0.094	-0.260**	-0.257**	0.048

The symbols '***', '**', '*' and represents level of significance at 1%, 5% and 10% level respectively. The first sub sample is 1994-2007 for the US and the Midwest, 1994-2008 for the Northeast and the West, 1994-1997 for the South. The second sub sample is 2008-2019 for the US and the Midwest, 2009-2019 for the Northeast and the West, 1997-2019 for the South. The lag lengths are chosen based on Schwarz information criterion.

[11]The break date correspond to the U.S. and the Midwest is July, 2007. For Northeast and the West, the break date is March,2008. The break date in south is identified in April, 1997.

Table 7: VECM Results for Housing Starts Based on Structural Break

Dep Var :	Δlns_t				
	US	Midwest	Northeast	West	South
			Time Range: 1st Sub-Sample		
Intercept	0.008·	-0.001	-0.055***	0.023·	0.001
Δs_{t-1}			-0.022		
Δp_{t-1}			-0.263*		
α_2	0.518***	1.192***	0.888***	1.001***	0.607***
			Time Range: 2nd Sub-Sample		
Intercept	-0.042***	-0.058***	-0.075***	-0.036***	-0.031***
Δs_{t-1}		0.041		-0.091	-0.092
Δp_{t-1}		-0.236		-0.218*	-0.097
α_2	1.001***	0.991***	0.918***	0.828***	0.914***

The symbols '***', '**', '*' and represents level of significance at 1%, 5% and 10% level respectively. The first sub sample is 1994-2007 for the US and the Midwest, 1994-2008 for the Northeast and the West, 1994-1997 for the South. The second sub sample is 2008-2019 for the US and the Midwest, 2009-2019 for the Northeast and the West, 1997-2019 for the South. The lag lengths are chosen based on Schwarz information criterion.

ion. This result is qualititatively the same as shown in the baseline VECM in Table 4. This implies that even if we allow for a break in the the VECM parameters, building permit does not show any evidence of error correction for the U.S. and the Midwest region. And this result also implies that the behavioral pattern of the dynamic adjustment of the permit variable remains the same over different sample periods.

Table 7 shows the result for the housing starts if we split the sample based on Bai and Perron structural break test. The results clearly suggest that the error correction property of housing starts remains robust to different sample periods, only the magnitude tends to differ. For example, for the U.S. and the South, the value of α_2 increased from 0.518 to 1.001 and from 0.607 to 0.914 respectively; whereas the level of significance remained the same.

To do so, we add lags of four widely used covariates for housing market and real economic activity: consumer sentiment index, yield spread, excess bond premium and change in unemployment rate. We perform the analysis only at the national level since regional level data for these controls are not available.

2.6.2 Inclusion of Additional Controls

Given the robustness of the dynamic relationship of the housing starts and building permits in the presence of structural break, the next step in our analysis is to examine if our results are robust to the inclusion of additional controls in the VECM specification.

Table 8: VECM Results with Additional Controls for Building Permits

Dep Var : Δlnp_t

	Baseline Model	**Additional Controls**
Intercept	0.001	-0.116
α_1	-0.063	-0.052
Consent		0.024
Spread		0.004
ΔUnemployment		-0.030
EBP		-0.000

The symbols '***', '**', '*' and '.' represents level of significance at 0.1%, 1%, 5% and 10% level respectively. The lag length is 0, and it is chosen based on Schwarz information criterion.

Yield spread and excess bond premium are two measures of credit spread that have been found to have predictive power for real economic activity. Yield spread is the difference between yield on 10-year bond and 2-year treasury constant maturity. Excess bond premium (EBP) is the difference between the yield on an index of non-financial corporate bonds and a similar maturity government bond, where the latter is adjusted to eliminate default risk. The underlying idea is to have a pure measure of the excess return that is not confounded by expectations of default. Gilchrist et al. (2009); Gilchrist and Zakrajšek (2012) have shown that GZ credit spread and, in particular, excess bond premium have significant predictive power for future movements in real economic activity[12]. On the other hand, the consumer sentiment and the change in unemployment represent the demand side of the housing market. A change in the unemployment rate in any region affects the income level of that region. As a result, the demand for investment in the housing asset also gets affected. In the same fashion, a change in the consumer sentiment also changes the tastes and preferrences towards the residential investment.[13]

Table 9: VECM Results with Additional Controls for Housing Starts

Dep Var : Δlns_t

	Baseline Model	**Additional Controls**
Intercept	-0.017***	-0.317*
α_2	0.743***	0.759***
Sentiment		0.064*
Spread		0.005
ΔUnemployment		0.003
EBP		-0.000

The symbols '***', '**', '*' and '.' represents level of significance at 0.1%, 1%, 5% and 10% level respectively. The lag length is 0, and it is chosen based on Schwarz information criterion.

[12] Faust and Wright (2013) have shown that this predictive power is robust to the inclusion of wide range of financial indicators in the forecasting model of real economic activity. See Kishor (2019) for recent forecasting application of this variable.

[13] See Carroll et al. (1994) for the role of sentiment in predicting consumer spending.

Table 8 and 9 show the results for this exercise for building permits and housing starts respectively. The first column shows the results for the baseline model and the second column shows the results for the model with additional controls. The error correcting coefficient of building permits (α_1) is insignificant in both the models and significant for housing starts (α_2) in both the models. For housing starts, the values of α_2 are also very close to each other for different models, i.e. 0.743 and 0.759. This implies that the VECM results obtained in the previous section are robust to the inclusion of additional controls in our baseline model specification.

2.7 Forecasting Changes in Housing Starts and Building Permits

The results reported in the previous sections clearly established the existence of a common long term trend between housing starts and building permits. The VECM analysis also shows that housing starts adjusts to correct for any short-run disequilibrium. In this section, we examine if this long term relationship between housing starts and building permits can be used to improve the forecasting performance of the two variables. In order to do so, we perform a recursive out of sample forecast of the housing start and building permit variable using three different forecasting models. Our baseline model is a parsimonious AR(1) model.

$$\Delta lnp_t = c_1 + \phi_1 \Delta lnp_{t-1} + u_{1t} \tag{6}$$

$$\Delta lns_t = c_2 + \phi_2 \Delta lns_{t-1} + u_{2t} \tag{7}$$

Equations 6 and 7 represent two AR(1) processes for the permit and the start variable respectively which we use as a benchmark model to compare our forecasts with. We then compare the forecasts from AR(1) model with a bivariate VAR model that includes building permit and housing start, and a VECM model that includes the disequilibrium error from the cointegrating relationship as an additional predictor in the VAR model.

$$\left.\begin{aligned} \Delta lnp_t &= \mu_1 + \phi_{11}^1 \Delta lnp_{t-1} + \phi_{12}^1 \Delta lns_{t-1} + \cdots + u_{1t} \\ \Delta lns_t &= \mu_2 + \phi_{21}^1 \Delta lnp_{t-1} + \phi_{22}^1 \Delta lns_{t-1} + \cdots + u_{2t} \end{aligned}\right\} \tag{8}$$

$$
\left.\begin{aligned}
\Delta lnp_t &= \mu_1 + \phi_{11}^1 \Delta lnp_{t-1} + \phi_{12}^1 \Delta lns_{t-1} + \cdots + \pi_1 \epsilon_{t-1} + u_{1t} \\
\Delta lns_t &= \mu_2 + \phi_{21}^1 \Delta lnp_{t-1} + \phi_{22}^1 \Delta lns_{t-1} + \cdots + \pi_2 \epsilon_{t-1} + u_{2t}
\end{aligned}\right\} \tag{9}
$$

Equation 8 represents our second model of forecasting which is a VAR system comprised of building permits and housing starts. And finally Equation 9 represents our third forecasting model where we have included the lagged cointegrated residual (ϵ_{t-1}) as an exogenous variable (VECM).

The recursive out-of-sample forecast involves following steps. In the first step, we have selected an initial estimation sample, which is from January, 1994 through December, 2008. In the second step, we forecast growth rate of starts and permits from the above model up to 12 months ahead, (i.e. from January, 2009 to December, 2009). In the third step, we add one more observation to the estimation sample, (i.e. from January, 1994 to January, 2009) and then again perform the forecast up to 12 months ahead; and then we continue this excercise until we reach the end of our sample. We calculate the root mean squared errors (RMSEs) of the forecast errors starting from the initial estimated sample through the final estimated sample for each forecast horizon (i.e. 1-month, 2-month and upto 12-months). We calculate the RMSEs for all the three aforementioned forecasting models.

Table 10: VECM vs AR(1) for Building Permits

	1-month	2-months	4-months	6-months	12-months
US National	1.014	1.009	1.010	1.010	1.009
Midwest	0.908	0.993	0.996	0.996	0.999
Northeast	1.001	0.989	0.981	0.984	0.985
West	0.934	0.988	0.992	0.989	0.993
South	0.872	0.976	1.000	1.000	1.000

The number in this table is the $\frac{RMSE_{VECM}}{RMSE_{AR(1)}}$ for the permits variable. The forecast sample is 2009:m01-2019:m07.

Finally, for the comparison between the VECM and the AR(1) model, we utilize the ratio of the RMSEs of the VECM and AR(1) model respectively over different forecast horizons, i.e. $\frac{RMSE_{VECM}}{RMSE_{AR(1)}}$. Ratio less than one implies superiority of VECM over AR(1) model. Similar ratios have been calculated for other models in this exercise as well.

Table 10 reports the forecasting results for building permits. The estimated ratio for the U.S. is close to unity for all forecasting horizons. The same pattern is evident for the Northeast as well. For the Midwest, the ratio is the smallest for 1-month ahead forecast (i.e. 0.908). Only for one-month ahead forecast in the South region we observe a reduction in RMSE by about 12 percent. Consistent with the findings reported earlier where building permits do not participate in error-correction, the results from out-of-sample show

similar behavior.

Table 11 shows the ratio of the RMSE of the VECM and the AR(1) model for housing starts. The ratio of the RMSE for the U.S. for 1-month forecast horizon is 0.761. For the Midwest and the Northeast, the estimated numbers are 0.778 and 0.736. For 12-month

Table 11: VECM vs AR(1) for Housing Starts

	1-month	2-months	4-months	6-months	12-months
US National	0.761	0.782	0.777	0.778	0.776
Midwest	0.778	0.780	0.783	0.769	0.780
Northeast	0.736	0.787	0.760	0.757	0.757
West	0.797	0.819	0.815	0.825	0.825
South	0.759	0.787	0.784	0.784	0.786

The number in this table is the $\frac{RMSE_{VECM}}{RMSE_{AR(1)}}$ for the starts variable. The forecast sample is 2009:m01-2019:m07.

forecast horizon the ratio is 0.776 for the U.S. On average the ratio hovers between 0.75-0.8. This suggests that the model with the cointegrating residual from the last period is able to reduce the RMSE of a univariate model by around 20-30 percent. This result is consistent over different forecast horizon as well. This is a significant improvement in the forecasting performance.

Table 12 displays the out-of-sample forecasting results for the VECM and the VAR models for building permits. This helps us in answering the question about the relative

Table 12: VECM vs VAR for Building Permits

	1-month	2-months	4-months	6-months	12-months
US National	1.003	1.004	1.005	1.006	1.003
Midwest	1.002	1.002	0.996	0.995	0.997
Northeast	1.004	0.979	0.979	0.984	0.985
West	0.986	0.986	0.992	0.989	0.990
South	1.004	1.006	0.999	0.998	0.996

The number in this table is the $\frac{RMSE_{VECM}}{RMSE_{VAR}}$ for the permits variable. The forecast sample is 2009:m01-2019:m07.

usefulness of cointegrating residual as an additional explanatory variable in the VAR model. The relative performance of the VECM and the VAR models are very close to each other with RMSE ratio hovering around unity. The VECM model slightly outperforms the VAR model for only the West region. Even in this case, the reduction is only around 1 to 2 percent. This is consistent with the error-correction estimates from the VECM models, where we do not find any evidence of permits adjusting to correct for the disequilibrium

from the last period.[14]

Table 13 reports the same results for the VECM and the VAR models for housing starts. For 1-month forecast horizon, the VECM model reduces the RMSE by nearly 20 percent for all the regions. For the forecast horizons higher than 1-month, the performance of the VECM model improves further for all the regions except the West. For the U.S., the ratio for 1-month and 12-months ahead forecasting is 0.893 and 0.774 respectively. For the Midwest, the ratios are 0.849 and 0.780 respectively. But for the West, the relative performance of the two models remains more or less the same as the ratio for 1-month and 12-months ahead is 0.896 and 0.825 respectively.

To summarize, our results show that the information in the long-run relationship between building permits and housing starts can be exploited to improve the forecasting performance of housing starts at almost all forecasting horizons. In case of building permits, not much gain in forecasting performance is observed if one uses the cointegrating residual as a predictor. These results seem to suggest that conditional on the information from the bivariate model of building permits and housing starts, most of the movements in building permit is permanent since we do not observe any tendency to error correct. Housing starts on the other hand displays significant degree of error correction, which in turn implies out of sample predictability and significant transitory component.

Table 13: VECM vs VAR for Housing Starts

	1-month	2-months	4-months	6-months	12-months
US National	0.893	0.777	0.775	0.775	0.774
Midwest	0.849	0.747	0.787	0.768	0.780
Northeast	0.834	0.745	0.755	0.755	0.757
West	0.896	0.805	0.824	0.824	0.825
South	0.883	0.769	0.777	0.783	0.784

The number in this table is the $\frac{RMSE_{VECM}}{RMSE_{VAR}}$ for the starts variable. The forecast sample is 2009:m01-2019:m07.

2.8 Conclusions

Using monthly data from 1994-2019 we have showed that building permits and housing starts in the U.S. and its four census regions move together in the long run. If there is a disequilibrium in this long-run relationship, only housing starts adjust to correct for the short-term error. We use this property in the forecasting context to show that a model that contains the information from the past disequilibrium error can

[14] We also perform robustness test of the forecasting results for different sub-samples based on structural break in the previous section. The results are qualitatively similar to the full sample and are reported in the appendix.

be used to make significant improvements in forecasts of changes in housing starts. The forecasts that utilize the information from this long-run comovement significantly outperform the forecasts from the univariate AR model and the bivariate VAR models. However, unlike housing starts, we do not find consistent improvement in the forecasting performance for building permits. Our results are robust to structural breaks, as well as the inclusion of additional controls that includes unemployment rate, consumer sentiment index and different measures of spread.

Appendix: Robustness Check for the Forecasting Results

Table A1, A2, A3 and A4 report the robustness of these results in the presence of structural break. Table A1 and A3 show that when forecasting for housing start, the VECM outperforms both the AR(1) and VAR model in all the forecast horizons and for all the regions. Table A2 shows that for the forecasting of building permit, the VECM performs better than the AR(1) only when the forecast horizon is 1-month ahead for all the regions, except Northeast. For Northeast, however the VECM model dominates the AR(1) model over all the horizons. Similarly, the results in Table A4 imply that the relative performance of both the models are very close to each other over all the forecast horizons except Northeast and South when it comes to the forecasting of building permit. For Northeast, once again the VECM outperforms the VAR in every aspect. And in South, the same happens over all the forecast horizons only for the first sub sample.

Table A1: VECM vs AR(1) for Start with Structural Break

Table A.1: VECM vs AR(1) for Start

	1-month	2-months	4-months	6-months	12-months
			U.S.		
1st Sub Sample	0.640	0.847	0.957	0.966	0.956
2nd Sub Sample	0.685	0.690	0.692	0.704	0.709
			Midwest		
1st Sub Sample	0.552	0.671	0.708	0.720	0.738
2nd Sub Sample	0.818	0.825	0.840	0.842	0.938
			Northeast		
1st Sub Sample	0.487	0.672	0.742	0.736	0.832
2nd Sub Sample	0.761	0.823	0.786	0.776	0.761
			West		
1st Sub Sample	0.604	0.559	0.476	0.549	0.772
2nd Sub Sample	0.774	0.794	0.778	0.801	0.810
			South		
1st Sub Sample	0.614	0.821	0.897	0.890	0.907
2nd Sub Sample	0.704	0.734	0.769	0.780	0.787

The first sub sample is 1994-2008 for the US, Midwest, Northeast and the West, 1994-1997 for the South. The second sub sample is 2009-2019 for the US, Midwest, Northeast and the West, 1998-2019 for the South.

Table A3: VECM vs VAR for Start with Structural Break

	1-month	2-months	4-months	6-months	12-months
			US National		
1st Sub Sample	1.061	0.944	0.959	0.964	0.958
2nd Sub Sample	0.855	0.697	0.683	0.698	0.705
			Midwest		
1st Sub Sample	0.847	0.738	0.727	0.722	0.737
2nd Sub Sample	0.817	0.796	0.849	0.843	0.939
			Northeast		
1st Sub Sample	0.864	0.718	0.741	0.735	0.832
2nd Sub Sample	0.833	0.746	0.781	0.776	0.761
			West		
1st Sub Sample	0.704	0.552	0.461	0.549	0.775
2nd Sub Sample	0.868	0.781	0.783	0.799	0.809
			South		
1st Sub Sample	0.971	0.870	0.909	0.890	0.900
2nd Sub Sample	0.841	0.713	0.756	0.774	0.786

The first sub sample is 1994-2008 for the US, Midwest, Northeast and the West, 1994-1997 for the South. The second sub sample is 2009-2019 for the US, Midwest, Northeast and the West, 1998-2019 for the South.

Table A2: VECM vs AR(1) for Permit with Structural Break

	1-month	2-months	4-months	6-months	12-months
			US National		
1st Sub Sample	0.932	1.007	1.003	1.006	1.011
2nd Sub Sample	0.971	1.047	1.040	1.042	1.031
			Midwest		
1st Sub Sample	0.844	1.039	1.015	1.012	1.013
2nd Sub Sample	0.902	1.020	1.017	1.019	0.994
			Northeast		
1st Sub Sample	0.130	0.253	0.685	0.907	0.981
2nd Sub Sample	0.967	1.006	0.980	0.968	0.971
			West		
1st Sub Sample	0.762	1.262	1.179	1.136	1.281
2nd Sub Sample	0.934	1.009	1.016	1.002	0.998
			South		
1st Sub Sample	0.907	0.957	0.974	0.980	1.003
2nd Sub Sample	0.694	0.948	1.027	1.010	1.004

The first sub sample is 1994-2008 for the US, Midwest, Northeast and the West, 1994-1997 for the South. The second sub sample is 2009-2019 for the US, Midwest, Northeast and the West, 1998-2019 for the South.

Table A4: VECM vs VAR for Permit with Structural Break

	1-month	2-months	4-months	6-months	12-months
			U.S.		
1st Sub Sample	1.014	1.017	1.004	1.003	1.014
2nd Sub Sample	1.013	1.014	1.017	1.021	1.010
			Midwest		
1st Sub Sample	1.007	1.008	1.015	1.011	1.010
2nd Sub Sample	1.019	1.018	1.018	1.019	0.992
			Northeast		
1st Sub Sample	0.995	0.931	0.929	0.929	0.980
2nd Sub Sample	1.022	1.008	0.969	0.969	0.971
			West		
1st Sub Sample	0.871	1.205	1.150	1.122	1.277
2nd Sub Sample	0.996	0.997	1.013	0.998	0.993
			South		
1st Sub Sample	0.995	0.986	0.972	0.967	0.982
2nd Sub Sample	1.001	1.002	1.025	1.011	1.004

The first sub sample is 1994-2008 for the U.S., Midwest, Northeast and the West, 1994-1997 for the South. The second sub sample is 2009-2019 for the US, Midwest, Northeast and the West, 1998-2019 for the South.

* * *

Chapter 3

Decomposing Housing Demand into Consumption and Investment Motives

3.1 Introduction

Housing is one of the most important assets held by households across the globe. It affects the economy not only through the residential investment channel but also through its effects on consumer wealth. A severe drop in the residential investment can cause a recession throughout the economy because of the residential investment's relationship to the Gross Domestic Product (GDP) and the financial markets.[15] As pointed out by Leamer (2007), of all the components of the GDP, residential investment offers, by far, the best early warning sign of an oncoming recession. Evidently, a significant share of an economy's aggregate demand coming from the housing asset, supports this argument. Not surprisingly, the current average home ownership rate in the US is 65.8%. Also the National Income data of the United States documents that the average share of the residential asset in the total fixed asset to be 35.14%, thereby making it the most dominant component in the total asset.

One of the interesting aspects of housing asset is that unlike other financial assets, it serves a dual purpose. And hence, the demand for housing is comprised of two motives: A *consumption motive* and an *investment motive*. The *consumption motive* represents the desire for the utility an individual gets from the shelter provided by a house. On the other hand, the *investment motive* is the willingness to buy a house for the purpose of reselling at a future higher price (Henderson and Ioannides, 1983).

In macroeconomics, these two motives were first formally modelled by Henderson and Ioannides (1983). They provided a rationale behind housing tenure choices with the difference in these two motives. Following the similar idea, Ioannides and Rosenthal (1994), Arrondel and Lefebvre (2001) and Arrondel et al. (2010)

[15] The expansion following the 2001 recession was, in part stimulated by a boom in housing market investments (Joseph and Larrain, 2012).

empirically studied the housing markets of the US, France and Spain, respectively. These dual motives also play a central role in the recent literature on optimal portfolio choice of households.[16] Researchers in the area of portfolio choices have also looked into the implications of optimal portfolio allocation in the presence of housing as an asset.[17] While exploring housing asset from a production-side approach, another branch of literature modelled the home production through a preference over a home and a market-produced good (Benhabib et al., 1991; Greenwood et al., 1995; McGrattan et al., 1997). Although, there is a vast amount of literature that addresses the asset aspect of housing, no attempt has been made to decompose the demand for housing into consumption and investment motives. This decomposition is important for policymaking as well as portfolio allocation, as the relative importance of these motives not only shed light on the underlying causes of homeownership, but also explain the relative strength of the housing market. Therefore, in this paper, I attempt to address this gap by proposing a methodology which decomposes the total housing demand into consumption and investment motives.

The decomposition exercise is composed of three steps. First, I set up a dynamic optimization problem in a CAPM (Capital Asset Pricing Model) framework with housing entering both the utility function and the budget constraint. This yields an optimal inter-temporal relationship between the non-durable consumption and the consumption motive of housing demand. Recognizing that the two separate motives of the housing demand are unobserved, in the second step, I use the information from the Euler equations of the CAPM model and the observed total housing demand to estimate consumption and investment motives. To do so, I apply an unobserved component (Clark, 1987) (UC, hereafter) model and assume a parsimonious dynamic specification for consumption and investment motives. Finally, in the third step, this UC model is estimated using the maximum likelihood estimation (MLE, hereafter) via the Kalman filter (Kalman, 1960). The robustness of the proposed methodology is checked by decomposing the total housing demand into a trend and a cycle by applying the Hodrick-Prescott (HP, hereafter) filter (Hodrick and Prescott, 1997). To check if the estimated motives have any meaningful economic intuition, a simple linear regression model is specified with the lagged growth rate of selected macro-economic indicators as the regressors and the current growth rate of consumption and investment motives as the regressands.[18]

The findings of this study suggest that the steady-state share of the consumption motive in the total housing demand is 83% over the sample period of 1987:Q1 through 2019:Q4. The consumption motive is much less volatile than the investment motive for the sample period. I find that there was a drop in

[16] For details see Berkovec (1989), Brueckner (1997), Lin et al. (1999) and Ortalo-Magné and Rady (2002), Turner (2003), Dusansky and Koç (2007), Kraft and Munk (2011) and Yang et al. (2018).

[17] For example, Yamashita (2003), Piazzesi et al. (2007), Flavin and Nakagawa (2008), Zanetti (2014), Andréasson et al. (2017), Menzly et al. (2004), Cochrane et al. (2008), Flavin and Yamashita (2002) and Cocco (2005).

[18] The macro-economic indicators include *Mortgage Rate*, *Average House Price*, *Real GDP*, *S&P500 Return* and the *Unemployment Rate*.

consumption motive and a significant increase in investment motive before the Great Recession, specifically between 2003 and 2007. This result is consistent with the overall narrative that the housing market in the US was going through an episode of exuberance and a greater portion of the housing demand was due to the investment motives. A significant build-up in the investment motive before the 2008 crisis was followed by a steady decline post-2008 and continued on for almost 10 years. Comparing the results of this model with a simple HP decomposition of the total housing demand into a trend and a cycle with the implicit assumption that the cycle captures the investment motive, I do not find any consistent pattern in either of these motives. In fact, investment motive, as represented by the HP cycle, behaves like a white noise. I also find that the growth rate of consumption demand for housing is positively correlated with the growth rate of average house price, real GDP and S&P500 stock returns; and negatively correlated with that of unemployment rate. The results also suggest that the growth rate of investment demand is negatively correlated with the growth rate of mortgage rate, average house price, real GDP and S&P500 stock returns.

The rest of the paper is organized in six more sections. I discuss the existing literature in Section II, followed by introducing the model formulation in Section III. I explain the empirical strategy and the data sources in Section IV and V, respectively. The results of the empirical exercise is reported in Section VI and I have presented the conclusions in VII.

3.2 Literature Review

Housing has a longstanding presence in the research of consumer's optimal decisions. The dual motives of the housing asset were formally modelled for the first time in a paper by Henderson and Ioannides (1983). In their paper the factors behind different tenure choices were estimated using an ordered probit specification. They claim that a person decides to buy a house instead of renting, only if their investment demand for housing exceeds the consumption demand. By further empirically testing this idea in the US (Ioannides and Rosenthal, 1994), French (Arrondel and Lefebvre, 2001), and Spanish (Arrondel et al., 2010) housing markets, these researchers reported that the claim of the dual motive by Henderson and Ioannides (1983) is solely restricted to the US.

These dual motives also play a central role in the recent literature on optimal portfolio choice of households. A substantial amount of research been done on the implications of the dual motives on the household portfolio allocation using different methodologies. By incorporating the dual motives of the housing in a new tax policy regime, Berkovec (1989) estimated different portfolio choices of assets by a household. Considering the relative magnitude of consumption and investment demands for housing, he established a Walrasian

equilibrium by applying separate optimization rules for owners and renters. Addressing an identical research question in a Bellman dynamic optimization problem, Brueckner (1997) found that if the investment demand of housing exceeds the consumption demand, then people tend to over-invest in housing. This happens because besides being an asset, the housing provides utility as well. By introducing housing in a two-period model, Lin et al. (1999) estimated the elasticities for the consumption and investment demand for housing in Taiwan. In this paper, they have computed the income elasticity of the consumption demand for the renters, the share of consumption and investment demand for the primary home-owners and the income elasticity of the investment demand for the secondary home-owners. Using a game theoretic approach, Ortalo-Magné and Rady (2002) analyzed the rationale behind different modes of tenure in an environment where the household income and the costs of housing are uncertain. By specifying a binary choice model, Turner (2003) estimated how user costs and other controls affect the housing ownership decisions. Considering housing also as an investment asset, Dusansky and Koç (2007) used a two-period consumer optimization model and ascertained that the demand for owner-occupied housing goes up with the house prices. Additionally, by using a Brownian motion approach, Kraft and Munk (2011) posited that the consumption demand is higher than the investment demand only during the early and the late stage of life-cycle. In a latest study, Yang et al. (2018) re-examined, by controlling for the dual roles, the house prices and household consumptions in China. Using a Bellman value function approach in a dynamic programming set up, they concluded, that the demand for a second housing unit is strongly motivated by an increasing housing consumption demand over a pure investment need, for assessing portfolio choices.

In the context of portfolio choices, another direction of research has looked into the implications of optimal portfolio allocation in the presence of housing as an asset. This group of researchers have analyzed the effects of the housing asset on the household's optimal portfolio choices. Among them, Yamashita (2003) investigated the link between housing investment and stock holdings and found if an individual holds some amount of housing stock, then it acts as a buffer against the uncertainty intertwined with financial investments. Piazzesi et al. (2007) introduced the housing asset in a standard CAPM framework and showed that due to the presence of a housing in the portfolio there could arise a different type of risk—a *composition risk*. In their work, Flavin and Nakagawa (2008) analyzed the effect of housing in a person's portfolio where there is an adjustment cost attached to housing. Zanetti (2014) showed that as there is a utility attached to a housing, it can be used as a pledge against unexpected shocks. Using the real residential fixed investment data, a new formula to calculate the coefficient of relative risk aversion was derived in this paper when there is a housing asset present in the portfolio. In a very recent work, using data from the Household Expenditure Survey (HES) from the Australian Bureau of Statistics, Andréasson et al. (2017) developed an expected utility model to explain the retirement behaviour in the decumulation phase of the retirees. In

further modification of these works, researchers have introduced the housing service in a standard CAPM framework by featuring multiple trees and maintaining the one-good assumption. In doing so, they used both substitutable and non-substitutable utility functions.[19] Alternatively, several studies on home production modelled a non-separable preference over a home and a market-produced good to capture the effects of the housing asset from a producer's point of view.[20]

Within the existing literature, I find it noteworthy that no attempt has been made to decompose the total housing demand into the consumption and the investment motive. Thus, in this paper, I propose a methodology which decomposes the total housing demand into these two motives. This can not only shed light on the underlying causes of homeownership but also explain the relative strength of the housing market.

3.3 The Model

For holding it from the existing literature, a salient feature of any housing asset is the dual motives. When an individual spends money on a house, it exibits two inherrent motives behind it: a *Consumption motive* and an *Investment motive*. The consumption motive is the desire to get utility from a house when considered solely as a shelter. Contrarily, the investment motive considers housing as a financial asset purchased in expectation of selling at a higher future price. Therefore, the total housing demand (h_t) can be represented in terms of consumption (h_t^C) and investment motive (h_t^I), respectively (as shown in Equation 10).

$$h_t = h_t^C + h_t^I \tag{10}$$

Housing is one of the basic necessities in life. However, when it comes to the inter-temporal choices, apart from the housing expenditure, there are several other expenditures that an individual needs to take into account. As Equation 11 shows, at any point in time, the total asset in period (t+1) can be written as the sum of an interest accrued asset from period t ($(1 + r_t)a_t$) and a monetary income (y_t) minus the expenditures on the non-durable good (c_t) and the total housing demand (h_t). The value of the housing stock from the previous period also plays a very important role in determining the optimal choices in the current period. In order to take that into consideration, the depreciated value of the housing stock from the previous period is also introduced in Equation 11 through the depreciation rate δ.[21]

[19]For details, see Menzly et al. (2004), Cochrane et al. (2008), Flavin and Yamashita (2002), Cocco (2005).
[20]For details, see Benhabib et al. (1991), Greenwood et al. (1995) and McGrattan et al. (1997).
[21]This asset equation is motivated from the work of Piazzesi et al. (2007). In another research, Henderson and Ioannides

$$a_{t+1} = (1 + r_t)a_t + y_t - c_t - h_t + (1 - \delta)h_{t-1} \tag{11}$$

It is important to understand that the gain yielding from the expenditures on consumption and investment motives of housing is different in nature. For example, from the consumption motive of housing, an individual gets a utility which comes from the shelter that a house provides. For this reason, along with the non-durable consumption, the consumption motive of housing also enters the utility function of an individual at any point in time. On the other hand, the investment motive of housing earns an individual a monetary benefit when the house is resold in the future at a higher price. Hence, the presence of the investment motive can only be observed in the asset equation of that individual. Equation 12 is a representation of this idea where both the housing motives play an important role in the optimal decision of an agent by yielding different types of gains. It shows that at time period t, an individual maximizes a value function, subject to some dynamic asset equations

$$\left.\begin{aligned} &max\ u(c_t, h_t^C) + \beta E_t[V(a_{t+1}, h_t^C, h_t^I)] \\ &s.t.\ \ a_{t+1} = (1 + r_t)a_t + y_t - c_t - h_t + (1 - \delta)h_{t-1} \\ &\qquad h_t = h_t^C + h_t^I \end{aligned}\right\} \tag{12}$$

where the value function is comprised of a utility function for period t, and a value function for period (t+1). The value function for period (t+1) depends on the asset for period (t+1); consumption motive; and investment motive for period t. On the other hand, the t^{th} period utility function has two elements: the non-durable consumption (c_t) and the consumption motive of housing (h_t^C).

$$u(c_t, h_t^C) = \frac{\left[\left(c_t^{\frac{\epsilon-1}{\epsilon}} + h_t^{C\,\frac{\epsilon-1}{\epsilon}}\right)^{\frac{\epsilon}{\epsilon-1}}\right]^{1-\frac{1}{\sigma}}}{1 - \frac{1}{\sigma}} \tag{13}$$

The utility obtained from the non-durable consumption and the consumption demand for housing

(1983), Lin et al. (1999) and Berkovec (1989) used similar versions of asset equations for owners and renters. Arrondel et al. (2010), Yang et al. (2018) and Arrondel and Lefebvre (2001) introduced the risk associated to housing in the asset equation. The asset equation used by Brueckner (1997) and Yamashita (2003) also takes into account the role of financial asset returns.

follows a Constant Elasticity of Substitution (CES) and a Constant Relative Risk Aversion (CRRA) specification.[22] Also, as the type of utility provided by these two elements are different from each other in nature, it is highly plausible to expect a very low degree of substitutability between them. Equation 13 represents the utility at time t that depends on the consumption of a non-durable good (c_t) and the consumption motive of housing (h_t^C) at time t.

$$\beta E_t \left[(1 + r_{t+1}) \left(\frac{c_{t+1}}{c_t} \right)^{-\frac{1}{\epsilon}} \left(\frac{c_{t+1}^{\frac{\epsilon-1}{\epsilon}} + {h_{t+1}^C}^{\frac{\epsilon-1}{\epsilon}}}{{c_t}^{\frac{\epsilon-1}{\epsilon}} + {h_t^C}^{\frac{\epsilon-1}{\epsilon}}} \right)^{\frac{\sigma-\epsilon}{\sigma(\epsilon-1)}} - 1 \right] = 0 \tag{14a}$$

$$E_t \left[\left(\frac{h_t^C}{c_t} \right)^{-\frac{1}{\epsilon}} + \beta(1-\delta) \left(\frac{c_{t+1}}{c_t} \right)^{-\frac{1}{\epsilon}} \left(\frac{c_{t+1}^{\frac{\epsilon-1}{\epsilon}} + {h_{t+1}^C}^{\frac{\epsilon-1}{\epsilon}}}{{c_t}^{\frac{\epsilon-1}{\epsilon}} + {h_t^C}^{\frac{\epsilon-1}{\epsilon}}} \right)^{\frac{\sigma-\epsilon}{\sigma(\epsilon-1)}} - 1 \right] = 0 \tag{14b}$$

At any point in time in the life-cycle, an individual derives certain rules for inter-temporal consumption that optimize their utility. In a standard dynamic optimization problem these rules are known as the *optimal rule of inter-temporal substitution* or the *consumption-Euler equation*. When a housing asset is involved in the utility function of an individual, there can exist more than one such rules. Equation 14a represents the first consumption-Euler equation in this case. This equation equates the marginal utility from an additional unit of non-durable good at period t with the same at period t+1. Similarly, Equation 14b gives the second optimal rule of the inter-temporal substitution. It states that the marginal utility from an additional unit of housing in period t is equal to a direct benefit from that housing plus an indirect expected discounted gain that the additional housing stock brings into period t+1 for the remaining $(1-\delta)$ fraction.[23]

$$h_t^{C^*} = c_t \left(\frac{1 + r_{t+1}^e}{\delta + r_{t+1}^e} \right)^{\epsilon} \tag{15}$$

Besides determining the optimal rule of inter-temporal substitution, the consumption-Euler equations of a dynamic optimization problem can, furthermore, lead to an optimal rule of substitution between the

[22]This type of utility function in the presence of housing asset is used by Zanetti (2014). Here, ϵ and σ are the intra and inter-temporal elasticity of substitution respectively. And, the coefficient of relative risk aversion is $\frac{1}{\sigma}$. Other forms of utility function (Cobb-Douglas specification) in this literature can be found in the work of Brueckner (1997), Lin et al. (1999) and Yang et al. (2018). In the utility function used by Arrondel and Lefebvre (2001), Flavin and Nakagawa (2008) and Arrondel et al. (2010), the adjustment cost associated with the housing is factored into. Berkovec (1989), Henderson and Ioannides (1983) and Ioannides and Rosenthal (1994) designed a seperate utility function for the owners and renters. Dusansky and Koç (2007) introduced a two-period utility function with the housing in it, and Yamashita (2003) introduced the financial asset returns in the utility function.

[23]The derivation is given in Appendix-A. Here, $r_{t+1}^e \equiv E_t[r_{t+1}]$.

elements that yield a utility to any individual. In the macroeconomic literature, this rule of substitution is called *Policy Equation*. In this model, Equation 15 represents such a policy rule between the non-durable consumption (c_t) and the consumption demand for housing (h_t^C). It shows that the ratio between c_t and h_t^C depends on three components: the ex-ante real rate of interest (r_{t+1}^e); the intra-temporal elasticity of substitution (ϵ); and the depreciation rate of housing stock (δ). An interesting property of this equation is that—despite being a single equation—it captures the variation in both the consumption-Euler equations (i.e., Equation 14a and Equation 14b). Thus, I consider this policy equation as the main tool in estimating the consumption and investment motives by decomposing the total housing demand.

3.4 Empirical Methodology

There are two benefits of using the derived policy equation in the decomposition exercise. Along with estimating the decomposed motives, this equation also estimates the structural parameters of the model. However, using this policy equation is, evidently, problematic as consumption and investment motives are unobserved in real life. Therefore, to address this issue, an UC model (Clark, 1987) is applied using the information present in the policy equation and the observed variable of total housing expenditure.

The UC model is comprised of two parts. In the first part, a set of equations are used to represent the observed variables in terms of the unobserved variables. These equations are called *Measurement Equations*. In the second part, I specify the dynamics of the unobserved variables through another set of equations. These specifications are assumed based on the degree of parsimony of the unobserved variables and the past trend in the corresponding observed variables. This set of equations is known as *Transition Equations*.

To construct the first measurement equation of this framework, a log-linearized version of the policy equation is used (as shown in Equation 16). In this equation, log of c_t is represented in terms of α (an intercept), log of h_t^C, and r_{t+1}^e. For the derivation of this equation a Taylor approximation rule has been applied after taking a log on both sides of Equation 15 (see Appendix-B.1.)[24]

$$logc_t = \alpha + log{h^C}_t + \gamma r_{t+1}^e \tag{16}$$

Along with the non-durable consumption (c_t), the total demand for housing (h_t) is also observed in real life. Thus, to incorporate the variation of h_t into the framework, I use a log-linearized version of Equation 10

[24] Here, $\alpha = -3.21\epsilon$, $\gamma = 24\epsilon$ and the approximating intercept is normalized to zero.

and consider it as the second measurement equation. This equation is derived by taking a log on both sides of Equation 10 followed by the application of a Taylor approximation rule and is represented by Equation 17 (see Appendix-B.2.). In this equation, log of h_t is represented in terms of log of h_t^C and log of h_t^I. Here, Λ_1 and Λ_2 represent the steady-state share of the consumption and investment motives in the total housing demand, respectively.

$$logh_t = \Lambda_1 logh_t^C + \Lambda_2 logh_t^I \tag{17}$$

Apart from h_t^C and h_t^I, the expected next period real interest rate (r_{t+1}^e) is also an unobserved variable in the UC model. Thus, the r_{t+1}^e can be represented in terms of the ex-post real interest rate (r_t) and a white noise (e_t^{re}). Equation 18, therefore, represents a rearrangement of this idea. This equation is also the third measurement equation in the framework.

$$r_t = r_{t+1}^e + e_t^{re} \tag{18}$$

In the second part of the UC model, I specify the dynamics of the unobserved variables through a set of transition equations. I assume a parsimonious random walk model for these unobserved variables. It is important to consider that during the post-recessionary years, substantial structural changes took place in the housing sector. Hence, it is highly likely for the unconditional mean in this sector to have significant variations across time. To factor those variations in, a framework by Clark (1989) is adopted where a time-varying drift parameter is introduced in the transitional equation for each unobserved variables. Following this idea, Equation 19a represents the dynamics of log of h_t^C where μ_t^C is a time-varying unconditional mean. Equation 19b gives the dynamics of μ_t^C which is also assumed to follow a simple random walk. Similarly, Equation 19c and Equation 19d give the same set of dynamics for log of h_t^I and μ_t^I, respectively. Finally, Equation 19e shows the dynamic specification of r_{t+1}^e.

$$logh_t^C = \mu_{t-1}^C + logh_{t-1}^C + e_{1t} \tag{19a}$$

$$\mu_t^C = \mu_{t-1}^C + e_{Ct} \tag{19b}$$

$$logh_t^I = \mu_{t-1}^I + logh_{t-1}^I + e_{2t} \tag{19c}$$

$$\mu_t^I = \mu_{t-1}^I + e_{It} \tag{19d}$$

$$r_{t+1}^e = r_t^e + e_{rt} \tag{19e}$$

The above-specified measurement and transition equations are represented by a particular framework, known as the *State-space framework* (see Appendix-C). Then, the structural parameters of this framework are estimated by using an MLE technique via the Kalman Filter. Finally, by using these parameter estimates, the series for the consumption and investment motives are obtained. Equation 20 shows the list of structural parameters estimated using the MLE. Here, Λ_1 is the steady-state share of the consumption motive in the total housing demand and ϵ is the elasticity of

$$\theta \in \{\Lambda_1, \epsilon, \sigma_1^2\,\sigma_2^2, \sigma_r^2, \sigma_{re}^2, \sigma_C^2, \sigma_I^2\} \tag{20}$$

intra-temporal substitution. The σ_1^2, σ_2^2, σ_{re}^2, σ_C^2 and σ_I^2 are the variances of the shock in the transition equations, i.e., for the h_t^C, h_t^I, r_{t+1}^e, μ_t^C and μ_t^I, respectively. On the other hand, σ_r^2 is the variance of the shock in the measurement equation for r_t.[25]

3.4 Data

The data used in this paper is of a quarterly frequency and it ranges from the first quarter of 1987 through the fourth quarter of 2019. Considering the current global scenario, it has been observed that the

[25] $e_{1t} \sim iid(0, \sigma_1^2), e_{2t} \sim iid(0, \sigma_2^2), e_{rt} \sim iid(0, \sigma_{re}^2), e_{Ct} \sim iid(0, \sigma_C^2), e_{It} \sim iid(0, \sigma_I^2), e_t^{re} \sim iid(0, \sigma_r^2)$.

COVID-19 pandemic is still active. It is reasonable to assume that it will take some time to gauge the full extent of this abnormal episode. Thus, to avoid the issue of outliers, the observations for the year 2020 is deliberately omitted. To measure the demand for the non-durable consumption, data on the Real Personal Consumption Expenditure on non-durable goods is used. For the total housing demand, Real Personal Consumption Expenditure on Housing and Utilities is used as a proxy. The source of these datasets are the NIPA tables of the Bureau of Economic Analysis. The nominal interest rate is represented by the 10-Year Treasury Constant Maturity; which is downloaded from the website of St. Louis Fed. This interest rate is converted to a real interest rate by normalizing it with an inflation index. The inflation index used for the purpose is the 10-Year-Ahead Inflation Forecasts from the Survey of Professional Forecasters obtained from the website of the Philadelphia Fed. All these variables are used in the UC model. For the regression analysis, I use important and relevant macroeconomic indicators. Among them Average House Price and 30-Year Fixed Rate Mortgage are obtained from the website of St. Louis Fed. I get data on S&P500 Stock Return from the historical dataset maintained by the Yahoo Finance. Data on Real GDP is collected from the website of the Bureau of Economic Analysis. And finally, Unemployment data has been sourced from the Bureau of Labor Statistics.

3.5 Results

I categorize the results obtained from the decomposition exercise into four sections. In the first section, I present the MLE estimates of the structural parameters of the model. After that, I plot the evolution of the estimated consumption and investment motives. These plots are followed by a robustness analysis where an HP filter is applied to decompose the total housing demand into a trend and a cycle. Finally, to check the economic interpretation of the estimated motives, I report the regression coefficients of the growth rates of the two motives on the lagged growth rate of selected macro-economic indicators.

Table 14 reports the MLE estimates of the structural parameters of the model[26]. It suggests that the steady-state share of the consumption motive in the total housing demand (i.e., Λ_1) is 83.8% over the sample period.[27] This estimate is significant at 5% level of significance and has a tight confidence interval with a standard error of 0.074. It implies that, in the steady-state, the consumption motive dominates the investment motive in the total housing demand. A probable reason for this high value of Λ_1 is motivated by the fact that, unlike the investment motive, the consumption motive for the housing demand stems from basic necessity by providing a shelter. Whereas, the investment motive comes into play only after the fulfillment

[26]For the purpose of identification, the shocks in the transition equations are assumed to be uncorrelated to each other.

[27]This result is in contradiction to the findings of Lin et al. (1999), where the researchers estimated the share of consumption demand for the owners of primary houses in Taiwan to be 26%.

of the shelter criteria. The results further reveal the value of the intra-temporal elasticity of substitution (i.e., ϵ) to be 0.003. The value of this ϵ is consistent with the idea that although an individual gets a utility from both c_t and h_t^C, yet the type of utility provided by them are very much

Table 14: Estimates of the Parameters

Parameters	Estimates	Std. Errors
Λ_1	0.838	(0.074)
ϵ	0.003	(0.001)
σ_1^2	0.004	(0.003)
σ_2^2	0.005	(0.004)
σ_r^2	0.12	(0.008)
σ_{re}^2	0.004	(0.021)
σ_C^2	0.001	(0.003)
σ_I^2	0.001	(0.001)
Log likelihood	1181.332	

different from each other.[28] Therefore, it is highly implausible to think if the cost of one element goes up, then that can be substituted with the other. The variances of the shock in consumption (σ_1^2) and investment motives (σ_2^2) are 0.004 and 0.005, respectively. This means, the investment motive is more volatile to any shock than the consumption motive. The risk associated to the investment motive can be a factor behind this. The variances of the shock in the time-varying drift parameter of consumption (σ_C^2) and investment (σ_I^2) motives are both 0.001. One interpretation of this result can be—although there are substantial structural changes in the unconditional mean of these variables, yet the overall influence of those changes are very low. Finally, the variance of the shock in the ex-ante (σ_{re}^2) real interest rate is less than that of the ex-post(σ_r^2) real interest rate where the former and the later are 0.004 and 0.12, respectively. This is also consistent with the findings in the literature that expected values of a variable tend to be much smoother than the realized outcomes.

The parameter estimates reported in Table 14 are used in the Kalman filter to estimate consumption and investment motives from the total housing demand. Figure 2 shows the result of this exercise. The top panel shows the observed total demand for housing.[29] The bottom left and the bottom right panel represent the consumption and investment motives, respectively. These plots manifest a couple of interesting patterns in these variables. First, the bottom two panels show that, over the sample period, the investment motive is much more volatile than the consumption motive. This pattern of the two motives can be supported by

[28]Using a GMM estimation, Piazzesi et al. (2007) found the value of ϵ to be very low as well. According to them, $\epsilon \to 0$ implies both the goods are complementary.

[29]Proxied by the total real expenditures on housing and utilities.

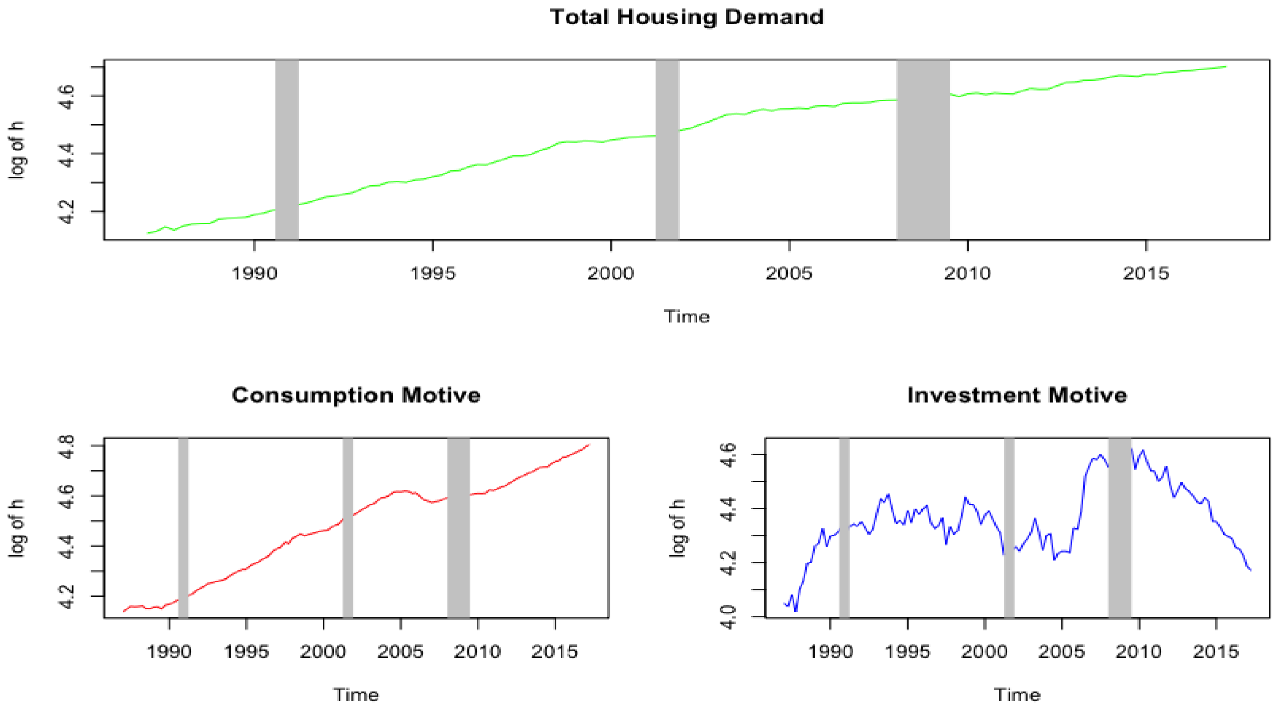


Figure 2: Kalman Filter Decomposition of Housing

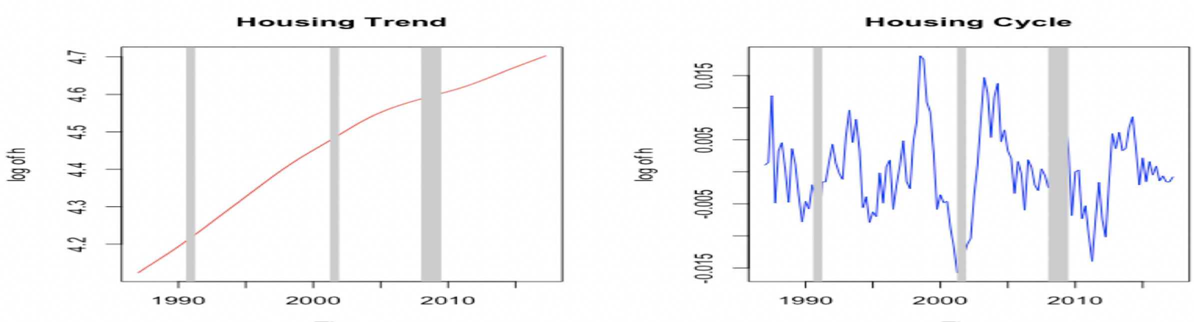


Figure 3: Hodrick-Prescott Filter Decomposition of Housing

the relative magnitude of the σ_1^2 and σ_2^2 from Table 14. Secondly, it can be noticed that there was a drop in the consumption motive and a significant increase in the investment motive before the great recession, specifically for 2003-2007.

This result is consistent with the overall narrative that, during that time, the housing market in the U.S. was not only going through an episode of exuberance, but also, a greater portion of the housing demand was due to the investment motives. The plots further reveal that the significant build-up in the investment

motive before the 2008 crisis was followed by a steady and big decline after 2008 and then continued on for almost 10 years. Additionally, a strong resemblance of the consumption motive with the total housing demand can also be observed in these figures. This is not surprising since the consumption motive accounts for 83.8% of the total housing demand.

$$logC_t = \tau_t^C + \eta_t^C \tag{21a}$$

$$logh_t = \tau_t^h + \eta_t^h \tag{21b}$$

$$logr_t = \tau_t^r + \eta_t^r \tag{21c}$$

I use a multivariate structural model to decompose housing demand into consumption and investment motive. The underlying idea is to use economic theory to perform the decomposition. It would also be an interesting exercise to compare the structural decomposition with an atheoretical decomposition of total housing demand into a trend and a cycle. For this purpose, I use the widely used Hodrick-Prescott (HP), Baxter-King (BK) and a Christiano-Fitzgerald (CF) method to perform a univariate decomposition of total housing demand into a trend and a cycle. As the investment motive is mainly driven by an incentive to earn monetary benefits, hence, it is implicitly assumed that a temporary cycle will be a representation of this motive. On the other hand, the consumption motive can be manifested through the trend component of this decomposition. Along with that, I also fit an atheoretical UC model where the non-durable consumption, housing demand and interest rate is decomposed into a trend and a cycle. Equations {21a - 21c} represent the measurement equations of the atheoretical UC model.[30] And, Equation {22a - 22i} represent the transition equations of this model.[31]

Figure 3 shows the results of this decomposition where the bottom left and the bottom right panel represent the trend and the cycle, respectively. By comparing these diagrams with those in Figure 2, I do not find any consistent pattern in consumption and investment motive. In fact, the investment motive behaves like a white noise throughout the sample period. Not only it fails to show the pre-recessionary housing boom, but also, it does not follow any expected pattern during the post-recessionary period. Along with that, Figure 4 plots the trend and cycle of the total housing demand obtained through the atheoretical UC model. In this plot as well, the cyclical component fails to follow any pattern that is consistent with the existing narrative of the housing market. The similar comment can also be made for the Baxter-King and

[30] τ and η are the corresponding trends and cycles.
[31] ρ is the time-varying drift parameter.

$$\tau_t^C = \rho_{t-1}^C + \tau_{t-1}^C + \psi_{1t} \tag{22a}$$

$$\tau_t^h = \rho_{t-1}^h + \tau_{t-1}^h + \psi_{2t} \tag{22b}$$

$$\tau_t^r = \rho_{t-1}^r + \tau_{t-1}^r + \psi_{3t} \tag{22c}$$

$$\rho_t^C = \rho_{t-1}^C + \psi_{ct} \tag{22d}$$

$$\rho_t^h = \rho_{t-1}^h + \psi_{ht} \tag{22e}$$

$$\rho_t^r = \rho_{t-1}^r + \psi_{rt} \tag{22f}$$

$$\eta_t^C = \phi^C \eta_{t-1}^C + \psi_{4t} \tag{22g}$$

$$\eta_t^h = \phi^h \eta_{t-1}^h + \psi_{5t} \tag{22h}$$

$$\eta_t^r = \phi^r \eta_{t-1}^r + \psi_{6t} \tag{22i}$$

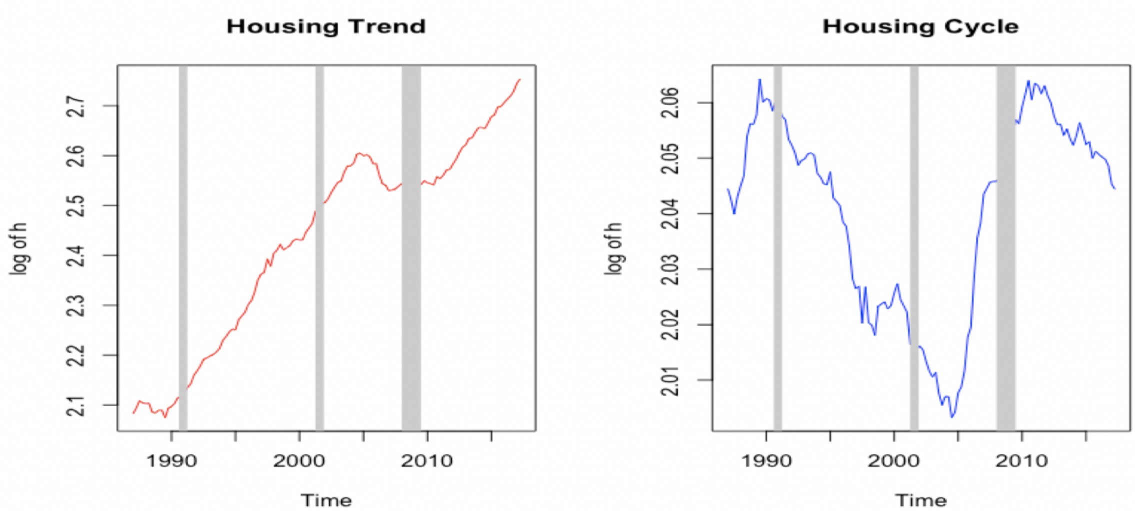


Figure 4: Atheoretical Kalman Filter Decomposition of Housing

Christiano-Fitzgerald filter decompositions (see Figure B.1 and Figure B.2 in Appendix-D). This failure of the total housing demand to explain the housing market all alone supports the methodology I propose in

this paper.

In addition to these atheoretical decompositions through different filters, I also check if the estimated motives have any meaningful economic interpretation. I specify a simple linear regression model with the lagged growth rates of selected macro-economic indicators as the regressors and the current growth rate of consumption and investment motives as the regressands.[32] Equation 23a and 23b represent the regression equation for the consumption and the investment motive, respectively.[33]

$$\Delta log h_t^C = \beta_{01} + \beta_{11} \Delta log X_{t-1} + \xi_{1t} \tag{23a}$$

$$\Delta log h_t^I = \beta_{02} + \beta_{12} \Delta log X_{t-1} + \xi_{2t} \tag{23b}$$

Table 15 shows the relationship between the growth rate of consumption motive with the other variables. The results suggest that higher house prices are positively associated with the consumption component of housing expenditure. If average house price increase by 1%, then consumption motive of housing also increases by 0.003%. The growth rate of consumption motive is positively related to the growth rate of real GDP and S&P500 stock returns. The regression coefficients for these variables are 0.002 and 0.037, respectively. This relationship hinges deeply on the logic that as the economy of a country grows over time, people living in that country look for a superior house. Finally, these results also reveal that the growth rate of unemployment has a negative impact on the next period growth rate of consumption motive. A 1% rise in

Table 15: Regression Results for Consumption Demand

Dependent Variable:	$\Delta log h_t^C$				
	(1)	(2)	(3)	(4)	(5)
Intercept	0.005***	0.004***	0.005***	0.004***	0.005***
Mortgage	0.019*				
House Price		0.003***			
RGDP			0.002***		
S&P500				0.037***	
Unemployment					-0.072***
R^2	0.021	0.273	0.086	0.139	0.273

The signs (***), (**) and (*) represents 1%, 5% and 10% level of significance. The degrees of freedom is 119. The control variables are in the form of percentage change lagged by one period.

[32]The macro-economic indicators include *Mortgage Rate*, *Average House Price*, *Real GDP*, *S&P500 Return* and the *Unemployment Rate*.

[33]X_{t-1} are the lagged macroeconomic control variables.

unemployment rate pulls down the consumption motive by a 0.072% in the next period.

Table 16 reports the relationship of investment motive of housing with other variables. It shows that mortgage rate and average house price are negatively related to the growth rate of investment motive[34]. That means, if mortgage rate goes up, it creates a disincentive for an individual to take a home loan. Therefore, the investment motive goes down in the next period. On the other hand, a negative relationship of investment motive with average house price can be explained by the law of demand. The results further suggest an inverse relationship of real GDP with investment motive. A 1% rise

Table 16: Regression Results for Investment Demand

Dependent Variable: $\Delta log h_t^I$					
	(1)	(2)	(3)	(4)	(5)
Intercept	-0.005	0.003	0.008	0.005	0.002
Mortgage	-0.177**				
House Price		-0.001***			
RGDP			-0.025***		
S&P500				-0.241***	
Unemployment					0.329***
R^2	0.047	0.082	0.171	0.132	0.122

The signs (***), (**) and (*) represents 1%, 5% and 10% level of significance. The degrees of freedom is 119. The control variables are in the form of percentage change lagged by one period.

in real GDP reduces the investment motive by 0.025%. Lastly, a negative regression coefficient between investment motive and S&P500 stock returns implies, as the returns from the financial assets go up, it discourages an individual to invest in the housing (The regression coefficient is -0.241).

3.6 Conclusion

In this paper, I propose a methodology to decompose the total housing demand into consumption and investment motives. For that purpose, I set up a dynamic optimization problem in a CAPM framework and factor the housing into both the utility function and the budget constraint. To address the issue of non-identifiability of the two motives in the resulting consumption-Euler equations, an unobserved component (UC) model is proposed. Using data from 1987 through 2019, this model is estimated by applying the MLE technique via a Kalman filter. The results of this exercise suggest the steady-state share of consumption motive in the total housing demand to be 83.8% over the sample period. Furthermore, it shows the intra-temporal elasticity of substitution to be very low, i.e. 0.003. The plots of the two motives reveal that

[34] The regression coefficients are -0.177 and -0.001 respectively.

the consumption motive is much less volatile than the investment motive. Moreover, there is a drop in consumption motive and a significant increase in investment motive before the Great Recession, specifically between 2003 and 2007. A significant build-up in the investment motive before the 2008 crisis can also be noticed which was followed by a steady decline post-2008. By comparing the results with a simple HP filter decomposition of total housing demand into a trend and a cycle with the implicit assumption that the cycle captures the investment motive, I do not find any consistent pattern in the two motives. By regressing the growth rates of the consumption and investment motives on the lagged growth rate of selected macroeconomic indicators, I find that consumption motive is positively correlated with average house price, real GDP and S&P500 stock returns; and negatively correlated with unemployment rate. The regression results also state that investment motive, is negatively correlated with mortgage rate, average house price, real GDP growth and S&P500 stock returns.

Appendix-A: The Derivation of the Euler Equations

The dynamic problem is,

$$\left.\begin{aligned} &max\ u(c_t, h_t^C) + \beta E_t[V(a_{t+1}, h_t^C, h_t^I)] \\ &s.t.\ \ a_{t+1} = (1+r_t)a_t + y_t - c_t - h_t + (1-\delta)h_{t-1} \\ &\qquad h_t = h_t^C + h_t^I \end{aligned}\right\} \tag{24}$$

The FOCs are,

$$[c_t] : u_c(c_t, h_t^C) \;=\; \beta E_t[V_a(a_{t+1}, h_t^C, h_t^I)] \tag{25a}$$

$$[h_t^C] : u_{h^C}(c_t, h_t^C) \;=\; \beta E_t[V_a(a_{t+1}, h_t^C, h_t^I)] + (1-\delta)\beta E_t[V_{h^C}(a_{t+1}, h_t^C, h_t^I)] \tag{25b}$$

By putting Equation 25a into Equation 25b, I get,

$$u_{h^C}(c_t, h_t^C) = u_c(c_t, h_t^C) + (1-\delta)\beta E_t[V_{h^C}(a_{t+1}, h_t^C, h_t^I)] \tag{26}$$

The application of the Envelope theorem along with the use of Equation 26 yield the two following consumption-Euler equations,

$$1 = \beta E_t \left[(1+r_{t+1}) \left(\frac{u_c(c_{t+1}, h_{t+1}^C)}{u_c(c_t, h_t^C)} \right) \right] \tag{27a}$$

$$1 = \left[\frac{u_c(c_t, h_t^C)}{u_{h^C}(c_t, h_t^C)} \right] + (1-\delta)\beta E_t \left[\frac{u_{h^C}(c_{t+1}, h_{t+1}^C)}{u_{h^C}(c_t, h_t^C)} \right] \tag{27b}$$

By using the explicit form of the utility function given in Equation 13, the following final form of the consumption-Euler equations can be obtained,

$$\beta E_t \left[(1+r_{t+1}) \left(\frac{c_{t+1}}{c_t} \right)^{-\frac{1}{\epsilon}} \left(\frac{c_{t+1}^{\frac{\epsilon-1}{\epsilon}} + h_{t+1}^{C\,\frac{\epsilon-1}{\epsilon}}}{c_t^{\frac{\epsilon-1}{\epsilon}} + h_t^{C\,\frac{\epsilon-1}{\epsilon}}} \right)^{\frac{\sigma-\epsilon}{\sigma(\epsilon-1)}} - 1 \right] = 0 \tag{28a}$$

$$E_t \left[\left(\frac{h_t^C}{c_t} \right)^{-\frac{1}{\epsilon}} + \beta(1-\delta) \left(\frac{c_{t+1}}{c_t} \right)^{-\frac{1}{\epsilon}} \left(\frac{c_{t+1}^{\frac{\epsilon-1}{\epsilon}} + h_{t+1}^{C\,\frac{\epsilon-1}{\epsilon}}}{c_t^{\frac{\epsilon-1}{\epsilon}} + h_t^{C\,\frac{\epsilon-1}{\epsilon}}} \right)^{\frac{\sigma-\epsilon}{\sigma(\epsilon-1)}} - 1 \right] = 0 \tag{28b}$$

Finally, by solving Equation 28a and Equation 28b, I derive the following policy equation,[35]

$$h_t^{C*} = c_t \left(\frac{1+r_{t+1}^e}{\delta + r_{t+1}^e} \right)^{\epsilon} \tag{29}$$

[35] In the literature, the $(1+r_{t+1})$ and $\left[\left(\frac{c_{t+1}}{c_t} \right)^{-\frac{1}{\epsilon}} \left(\frac{c_{t+1}^{\frac{\epsilon-1}{\epsilon}} + h_{t+1}^{C\,\frac{\epsilon-1}{\epsilon}}}{c_t^{\frac{\epsilon-1}{\epsilon}} + h_t^{C\,\frac{\epsilon-1}{\epsilon}}} \right)^{\frac{\sigma-\epsilon}{\sigma(\epsilon-1)}} \right]$ are assumed to be uncorrelated for the purpose of identification.

Appendix-B: BK and CF Filter Decomposition

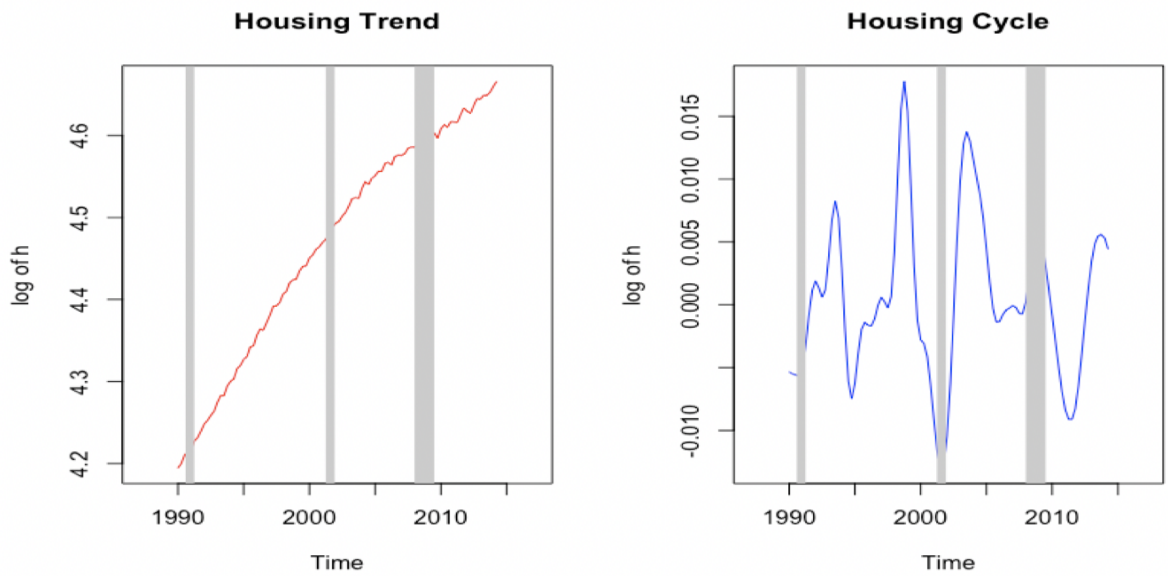


Figure B.1: Baxter-King Decomposition of Housing

Figure B.2: Christiano-Fitzgerald Decomposition of Housing

Appendix-C: The Derivation of the Measurement Equations

C.1: The Derivation of the First Measurement Equation

The policy equation is,

$$h_t^C = c_t \left(\frac{1 + r_{t+1}^e}{\delta + r_{t+1}^e} \right)^{\epsilon} \tag{30}$$

Taking log on both sides, I get,

$$logh_t^C = logc_t + \epsilon log(1 + r_{t+1}^e) - \epsilon log(\delta + r_{t+1}^e) \tag{31}$$

Considering $\delta = 0.04$ and by taking Maclaurin approximation rule on $(1 + r_{t+1}^e)$ and $(\delta + r_{t+1}^e)$, the following equation is obtained[36],

$$logc_t = \alpha + logh^C{}_t + \gamma r_{t+1}^e \tag{32}$$

C.2: The Derivation of the Second Measurement Equation

The decomposition of housing is,

$$h_t = h_t^C + h_t^I \tag{33}$$

By taking log on both sides,

$$logh_t = log(h_t^C + h_t^I) = log\left(1 + \frac{h_t^C}{h_t^I}\right) + logh_t^I \tag{34}$$

Again, $log\left(1 + \frac{h_t^C}{h_t^I}\right)$ can be written as,

[36] Here, $\alpha = -3.21\epsilon$, $\gamma = 24\epsilon$ and the approximating intercept is normalized to zero.

$$log\left(1+\frac{h_t^C}{h_t^I}\right)=log(1+e^{\overline{logh_t^C-logh_t^I}}) \tag{35}$$

Finally, by using Maclaurin approximation rule on $log(1+e^{(logh_t^C-logh_t^I)})$, the following can be written,[37]

$$logh_t=\Lambda_1 logh_t^C+\Lambda_2 logh_t^I \tag{36}$$

Appendix-D: The Design of the State-Space Framework

The measurement equations are,

$$\left.\begin{aligned}
&logc_t=\alpha+logh^{C*}_t+\gamma r_{t+1}^e\\
&logh_t=\Lambda_1 logh_t^C+\Lambda_2 logh_t^I\\
&r_t=r_{t+1}^e+e_t^{re}
\end{aligned}\right\}$$

The transition equations are,

$$\left.\begin{aligned}
&logh_t^C=\mu_{t-1}^C+logh_{t-1}^C+e_{1t}\\
&\mu_t^C=\mu_{t-1}^C+e_{Ct}\\
&logh_t^I=\mu_{t-1}^I+logh_{t-1}^I+e_{2t}\\
&\mu_t^I=\mu_{t-1}^I+e_{It}\\
&r_{t+1}^e=r_t^e+e_{rt}
\end{aligned}\right\}$$

[37]Here, $\Lambda_1=\frac{\overline{h^C}}{\overline{h}}$ and $\Lambda_2=\frac{\overline{h^I}}{\overline{h}}$.

In the State-space framework, the measurement equations can be written as,

$$
\begin{bmatrix} logc_t \\ logh_t \\ r_t \end{bmatrix} = \begin{bmatrix} \alpha \\ 0 \\ 0 \end{bmatrix} + \begin{bmatrix} 1 & 0 & \gamma & 0 & 0 \\ \Lambda_1 & \Lambda_2 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \end{bmatrix} \begin{bmatrix} logh_t^C \\ logh_t^I \\ r_{t+1}^e \\ \mu_t^C \\ \mu_t^I \end{bmatrix} + \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & e_t^{re} \end{bmatrix} \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}
$$

And the transition equations as,

$$
\begin{bmatrix} logh_t^C \\ logh_t^I \\ r_{t+1}^e \\ \mu_t^C \\ \mu_t^I \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} logh_{t-1}^C \\ logh_{t-1}^I \\ r_t^e \\ \mu_{t-1}^C \\ \mu_{t-1}^I \end{bmatrix} + \begin{bmatrix} e_{1t} \\ e_{2t} \\ e_{rt} \\ e_{Ct} \\ e_{It} \end{bmatrix}
$$

The variance-covariance matrix of the measurement equations is,

$$
\Omega = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & \sigma_{re}^2 \end{bmatrix}
$$

The variance-covariance matrix of the transition equations is,

$$
\Sigma = \begin{bmatrix} \sigma_1^2 & 0 & 0 & 1 & 0 \\ 0 & \sigma_2^2 & 0 & 0 & 1 \\ 0 & 0 & \sigma_r^2 & 0 & 0 \\ 0 & 0 & 0 & \sigma_C^2 & 0 \\ 0 & 0 & 0 & 0 & \sigma_I^2 \end{bmatrix}
$$

* * *

Chapter 4

Time Varying Effects of House Price on Tradable and Non-tradable Employment

4.1 Introduction

The housing market plays a very important role in many business activities in an economy through various channels of consumer demand. Being one of the most important factors behind the Great Recession of 2008, the impact of the housing market on macroeconomy is still a highly studied topic in the world of academia. The channels through which the housing market affects the economy have received widespread attention not only from researchers, but also from policymakers during the post-recessionary periods. The ensuing volume of research exploring the nexus between the housing market and consumer demand is strong evidence of this fact.

Among many such channels, in the most recent literature, the link between the housing market and the employment sector of an economy has gained a high degree of importance. Some of the pioneering studies in this area that explore the nexus between housing market and employment are done by Mian et al. (2013) and Mian and Sufi (2014). According to these studies, the employment sector in an economy can be divided into two groups: Tradable employment and Non-tradable employment. Tradable employees are those who work in industries that do trade on a global scale. Contrarily, non-tradable employees are those who are employed in industries that do trade on a much more local scale. The main assertion in these studies is that if there appears to be a shock in consumer demand through the channel of housing net worth, then the response of the tradable employment will be much lower than the non-tradable employment. They further posit that in general, since industries with a large number of tradable employees trade on a global scale, they can easily transmit the effect of a shock to any other location as compared to the local industries. Using cross-section recessionary period data of the U.S. counties they showed that reduced housing net worth led to significant job losses in the non-tradable sector but not in the tradable sector. In a similar research,

Giroud and Mueller (2017) used micro-level data from the U.S. Census Bureau and finds that the correlation between employment and local house prices is significantly stronger among establishments of more highly levered firms that are in the non-tradable sector. In a more recent paper, Kishor et al. (2022) extended the work of Mian and Sufi (2014) in a dynamic framework with a hand-constructed time-series data. By using a sample that includes both the boom and the bust period, they find that house prices do a better job in forecasting non-tradable employment than the tradable employment for most of the U.S. states.

In this paper, we perform an exploratory analysis to verify the hypothesis of Mian and Sufi (2014) across 45 states of U.S. We use Kishor et al. (2022) data to examine the time-varying response of tradable and non-tradable employment due to a shock in house price. To do so, we use a *Time-Varying Parameter VAR model with a Stochastic Volatility (TVP-VAR-SV)*.[38] It is a simple multivariate stochastic volatility modelling strategy where both the coefficients and the entire variance covariance matrix of the shocks are allowed to vary over time. This particular type of modelling is very crucial in capturing many characteristics of the housing market in the U.S. For example, the type of time-varying relationship that the housing market has had with the other macroeconomic indicators during the period of high booms & busts in the first decade of the 21^{st} century can appropriately be simulated by the TVP-VAR-SV model. The drifting coefficients of the TVP-VAR-SV model have the ability to explain any possible non-linearities or time variation in the lag structure of the model. Not only that, there is also an intrinsic multivariate stochastic volatility property of the TVP-VAR-SV model that can explain any probable heteroscedasticity of the shocks and non-linearities in the simultaneous relations among the variables of the model. This property of the model can be very useful in analyzing various demand and supply side channels of the housing market that has experienced a significant number of shocks since the Great Recession of 2008-09. According to Primiceri (2005), among many characteristics required for an econometric model, the two most important of a TVP-VAR-SV model are that: 1) It can measure any policy changes and implied shifts in the private sector behavior through its time varying parameters; 2) It can explain the mechanism through which changes in policy can affect the rest of the economy by its multiple equation framework. Finally, this model can also distinguish the two main sources of time variation in any framework: The size of the exogenous shock and the changes in the transmission mechanism.

Further, to evaluate the posterior distributions of the parameters of interest, a Gibbs sampling technique is used. Gibbs sampling technique is an algorithm that is used in Bayesian econometrics. It is a particular variant of Markov chain Monte Carlo (MCMC) methods that consists of drawing from lower dimensional conditional posteriors as opposed to the high dimensional joint posteriors of the whole parameter set.

To report the results of the TVP-VAR-SV model, we examine the time-varying impulse responses

[38] Introduced by Primiceri (2005).

for both the tradable and non-tradable employment for 45 U.S. states.[39] Additionally, to evaluate the performance of the TVP-VAR-SV model, we also compare the responses of the two types of employment by running a simple *VAR* in the data. The results we obtain show that for only 16 out of 45 states, the response to non-tradable employment is higher than the tradable employment. Those states are Alabama, Arizona, Arkansas, California, Connecticut, Florida, Idaho, Kentucky, Massachusetts, Michigan, Missouri, Montana, New Mexico, South Dakota, Tennessee and Vermont. These results are consistent with the findings of Mian and Sufi (2014). On the other hand, for the other 29 states, either the tradable employment is higher than the non-tradable employment, or they are equal to each other for the entire horizon. Our findings further reveal that the impulse responses obtained through bivariate VAR hover around zero. That means, when it comes to the representation of the impulse response of the two types of employment, the TVP-VAR-SV model performs better than the VAR model. Finally, our Granger-causality test results report that there are only 15 states where the growth rate of the house price Granger-causes both the tradable and the non-tradable employment. And among them, there are only 6 states where the response of non-tradable employment is higher than that of tradable employment. The results of the TVP-VAR-SV model for these states are not consistent with the results in Mian and Sufi (2014). In our opinion, there might exist some other probable underlying factors that need further attention and are open to future research.

The rest of the paper is organized as follows. We discuss the existing literature in Section II, followed by the specification of the empirical strategy in Section III. We describe the data sources in Section IV. The results of the empirical exercise are reported in Section V and we present the conclusions in Section VI.

4.2 Literature Review

The importance of the movements in employment and disparities in the labor market conditions is getting acknowledged in the academic literature for a very long time. There is a great volume of research that have explored the field of regional unemployment differentials through the lens of different perspectives.[40] Some of the important factors of regional unemployment identified in the existing literature are *vacancy rate* (through Beveridge curve), *natural unemployment rate* (through cyclical sensitivity model), *migration*, *inflation rates of unemployment* (through Phillips curve), *own lags of employment* and *housing market conditions*.

Among all the plausible factors, especially after the recession of 2008, the housing market conditions attracted a lot of attentions as the connection between the housing market and labor market conditions came

[39] The horizon of impulse response is up to 12 periods ahead.

[40] See Holzer (1993), Pehkonen and Tervo (1998), Layard et al. (2005), Payne (1995), Kerr et al. (1998), Mian et al. (2013) and Halleck Vega et al. (2016) for details.

to light. It has been revealed in studies that a deteriorating housing market condition adversely affects the consumer demands; and that eventutally affects the employment sectors in the economy. Using this idea, Rapach and Strauss (2009) investigate the forecasts of state-level real housing price growth for the period 1995–2006. They find that autoregressive models, and especially models that incorporate information from numerous economic variables, often provide relatively accurate housing price forecasts for a number of interior states during pre-recessionary periods. In a similar research, Barnichon et al. (2012) present a forecasting model of unemployment based on the current labor force flows data. In a more recent study, Mian and Sufi (2014) divide the entire employment sector into a tradable (consisted of industries that trade globally) and a non-tradable (consisted of industries that trade locally) employment. By using a cross-sectional approach they show that the effects of a shock in the housing net worth affects the two different types of employment in a completely different yet significant manner. In another study, Kishor et al. (2022) extend this research by using a time series framework on a hand constructed time-series data for a sample that includes both the boom and the bust period. They find that the house prices do a better job in forecasting the non-tradable employment than the tradable employment for most of the U.S. states.

In this paper, we perform a simple exploratory analysis to verify the assertion of Mian and Sufi (2014) across different U.S. states. For this purpose, we use the hand constructed data from Kishor et al. (2022), fit a time varying structural VAR model with stochastic volatility and examine the impulse response functions for different horizons. To estimate the posterior distributions of the parameters of interest, we resort to a Bayesian methodology. We also examine the impulse response functions obtained through a simple OLS for all the U.S. states to compare the performance of the BVARSV model. Apart from that, we further check if our sample has any better in-sample predictive power over the others. For that purpose, we run a Granger-causality test on a standard bivariate VAR framework consisted of the tradable & non-tradable employment and house price (Granger, 1969, 1980). Our results suggest that apart from some of the states[41], the findings of Mian and Sufi (2014) is not robust in presence of time-varying parameters and stochastic volatility. There are still some probable underlying factors that require more in-depth research in this area.

4.3 Empirical Methodology

In this study, we use a *Time-Varying Parameter VAR model with a Stochastic Volatility (TVP-VAR-SV)*. It is a simple multivariate stochastic volatility modelling strategy introduced by Primiceri (2005) where both the coefficients and the entire variance covariance matrix of the shocks are allowed to vary over

[41]Those are Alabama, Arizona, Arkansas, California, Connecticut, Florida, Idaho, Kentucky, Massachusetts, Michigan, Missouri, Montana, New Mexico, South Dakota, Tennessee and Vermont.

time. The drifting coefficients in the model have the ability to capture any possible non-linearities or time variation in the lag structure of the model. Not only that, the multivariate stochastic volatility in this model can also capture the probable heteroscedasticity of the shocks and non-linearities in the simultaneous relations among the variables of the model. This particular type of modelling is very crucial in distinguishing the two main sources of time variation in any framework: Size of exogenous shock and Changes in the transmission mechanism. To evaluate posterior distributions of the parameters of interest, a Bayesian methodology is used. There are a couple of reasons for selecting the Bayesian methodology. The first reason can be attributed to the efficiency of this approach to deal with the unobservability of the hyper-parameters of the variance covariance matrix which is the source of the stochastic volatility. Moreover, it has been revealed in the existing literature that in the presence of high dimensionality and non-linearity, the classical approach sometimes results in likelihoods with multiple peaks, some of which are in uninteresting or implausible regions of the parameter space. Not only that, even though it is possible to write up the likelihood of the model, it is very difficult to maximize it over a high dimensional space. Bayesian methodologies, on the other hand deal with the high dimension of the parameter space and non-linearities with greater efficiency by splitting the original estimation problem in smaller and simpler ones. Hence, for posterior numerical evaluation of the parameters of interest, a Gibbs sampling is used. Along with these, we further check if our sample has any better in-sample predictive power over the others. For that purpose, we run a Granger-causality test on a standard VAR framework consisted of the tradable & non-tradable employment, and house price (Granger, 1969, 1980). In this regard, it is noteworthy that Granger-causality is not a causality statement. It only provides information about the in-sample predictive power of one sample over the other. In a bivariate framework, to establish a causal relationship, it is important to ensure that no other variable apart from the independent variable is affecting the target variable. In the framework of Granger-causality, that is not possible.

$$y_t = \alpha_t + \beta_{1,t} y_{t-1} + \beta_{2,t} y_{t-2} + \cdots + \beta_{k,t} y_{t-k} + u_t \qquad t = 1, ..., T \tag{38}$$

Equation 38 represents the time-varying structural VAR model used in this paper. y_t is a 2x1 vector of observed endogenous variables[42]; α_t is a 2x1 vector of time varying coefficients that multiply constant terms; $\beta_{i,t}, i = 1, ..., k$ are 2x2 matrices of time varying coefficients; u_t are heteroscedastic unobservable shocks with variance covariance matrix Ω_t. Furthermore, a triangular reduction of Ω_t is assumed without any loss of generality:

[42]In this case, Employment (Tradable & Non-tradable) and House Price.

$$B_t \Omega_t B_t' = \Sigma_t \Sigma_t' \tag{39}$$

Where the B_t is a lower triangular matrix and Σ_t is a diagonal matrix. From this conversion, it follows that,

$$y_t = \alpha_t + \beta_{1,t} y_{t-1} + \beta_{2,t} y_{t-2} + \cdots + \beta_{k,t} y_{t-k} + B_t^{-1} \Sigma_t \epsilon_t, \quad V(\epsilon_t) = I_n \tag{40}$$

By stacking in a vector β_t, all the coefficients in the R.H.S. of Equation 40 can be written as,

$$y_t = X_t' \beta_t + B_t' \Sigma_t \epsilon \tag{41a}$$

$$X_t' = I_n \otimes [1, y_{t-1}', ..., y_{t-k}'] \tag{41b}$$

where the symbol $\otimes$ denotes the Kronecker product. And, the modelling strategy consists of modelling the coefficient processes in Equation {41a - 41b} instead of Equation 38.

For the estimation of the model with drifting coefficients and multivariate stochastic volatility, a numerical evaluation of the posterior of the parameter of interest is required. And for that purpose, a Gibbs sampling technique is used in this paper. Gibbs sampling is a particular variant of Markov chain Monte Carlo (MCMC) methods that consists of drawing from lower dimensional conditional posteriors as opposed to the high dimensional joint posteriors of the whole parameter set. The priors for the hyperparameters of the time-varying coefficients are assumed to be distributed as independent inverse-Wishart; and the priors for the initial states of the time-varying coefficients are assumed to be normally distributed. The Gibbs sampling is replicated for 5000 times and to get rid of the effects of the initial values, the first 1000 observations are burnt-in.

For the purpose of identification, a particular strategy introduced by Primiceri (2005) is adopted.[43] The shocks associated to the ϵ_t in Equation 41a are assumed to be independent of any other innovations. This assumption is crucial for the interpretation of the effects of such shocks, besides the existence of other innovations in the system. Additionally, the current period shock in the y_t and X_t are assumed to be correlated within equation, but uncorrelated across equations. On the other hand, the shocks in the lagged X_t are allowed to be correlated across equations too. This assumption would allow the analysis of the impact

[43] According to this paper, the crucial difference between modelling time variation in a structural VAR as opposed to standard VAR is that, in a time-varying structural VAR there can be more than one sources of shocks.

of shocks to the X_t on the rest of the economy.

$$y_{1t} = c_1 + \phi_{11}^1 y_{1t-1} + \phi_{12}^1 y_{2t-1} + \phi_{11}^2 y_{1t-2} + \phi_{12}^2 y_{2t-2} + \cdots + \epsilon_{1t} \tag{42a}$$

$$y_{2t} = c_2 + \phi_{21}^1 y_{1t-1} + \phi_{22}^1 y_{2t-1} + \phi_{21}^2 y_{1t-2} + \phi_{22}^2 y_{2t-2} + \cdots + \epsilon_{2t} \tag{42b}$$

Equation {42a - 42b} represent the standard bivariate VAR framework used for the Granger-causality test. To check if y_{2t} Granger-cause y_{1t}, we check the following hypothesis,[44]

$$\begin{aligned} H_N &: \quad \phi_{12}^1 = \phi_{12}^2 = \cdots = 0 \\ H_A &: \quad \text{Not } H_N \end{aligned}$$

4.4 Data

The data used in this study is hand-constructed data on tradable and non-tradable employment, and house prices in a monthly frequency that runs from 2001:M1 through 2020:M06.[45] The credit of constructing the data goes to the work of Kishor et al. (2022). The main source of employment data is Current Employment Statistics (CES).[46] This data is also available at a monthly frequency for two-digit North American Industry Classification System, or NAICS industries.[47] All the 19

[44]The null hypothesis is "y_{2t} doesn't Granger-cause y_{1t}".

[45]The sample is for the 45 U.S. states. The states of Delaware, Hawaii, Maine, Rhode Island, and Wyoming are not included because of data unavailability.

[46]The CES is built on the back of the Quarterly Census of Employment and Wages (QCEW), pulling its survey sample from the QCEW universe, and benchmarking to QCEW every year. The primary difference between the two is that the survey-based estimates of CES allow for more timely data releases, with estimates published less than a month after the reference period, while QCEW's population data allow for much more granular geographic and industry data.

[47]The disaggregated time-series data at state level is available only at 2-digit level.

Table 17: Industry Classification

All Industries	Tradable	Non-tradable
11-Agriculture, Forestry, Fishing	✓	
21-Mining, Quarrying and Oil & Gas	✓	
22-Utilities		✓
23-Construction		✓
31-33 Manufacturing	✓	
42-Wholesale Trade	✓	
44-45 Retail Trade		✓
48-49 Transportation & Warehousing		✓
51-Information	✓	
52-Finance & Insurance	✓	
53-Real state-rental & Leasing		✓
54-Professional and Technical services	✓	
56-Administrative & Waste services		✓
61-Education services	✓	
71-Art, Entertainment reaction	✓	
72-Accommoation & Food services		✓

This table reports the classification of tradable and non-tradable industries. The source of this table is Kishor et al. (2022).

Table 18: Summary Statistics (Mean)

States	Tradable	Non-tradable
Alabama	13.29	13.39
Alaska	11.12	11.62
Arizona	13.68	13.67
Arkansas	12.77	12.88
California	15.45	15.46
Colorado	13.48	13.65
Connecticut	13.24	13.10
Florida	14.53	14.97
Georgia	14.03	14.20
Idaho	12.16	12.35
Illinois	14.46	14.48
Indiana	13.80	13.81
Kansas	12.96	12.98
Kentucky	13.20	13.36
Louisiana	13.11	13.46
lowa	13.14	13.09
Maryland	13.44	13.69
Massachusetts	13.93	13.82
Michigan	14.14	14.13
Minnesota	13.70	13.63
Mississippi	12.63	12.90
Missouri	13.60	13.72
Montana	11.55	11.99

States	Tradable	Non-tradable
Nebraska	12.57	12.65
Nevada	12.35	13.39
New Hampshire	12.22	12.29
New Jersey	13.99	14.09
New Mexico	12.15	12.55
New York	14.80	14.75
North Carolina	14.04	14.15
North Dakota	11.56	11.75
Ohio	14.34	14.36
Oklahoma	12.96	13.17
Oregon	13.18	13.26
Pennsylvania	14.42	14.41
South Carolina	13.21	13.50
South Dakota	11.67	11.80
Tennessee	13.63	13.84
Texas	14.98	15.17
Utah	12.85	13.02
Vermont	11.38	11.52
Virginia	13.89	14.03
Washington	13.77	13.76
West Virginia	12.06	12.38
Wisconsin	13.77	13.68

This table reports the mean of the log of tradable & non-tradable employment from 2001:M01 through 2020:M06 for 45 U.S. states. The states of Delaware, Hawaii, Maine, Rhode Island, and Wyoming are not included because of data unavailability.

Table 19: Summary Statistics (Variance)

States	**Tradable**	**Non-tradable**
Alabama	0.002	0.002
Alaska	0.006	0.001
Arizona	0.012	0.021
Arkansas	0.003	0.002
California	0.001	0.006
Colorado	0.004	0.005
Connecticut	0.002	0.001
Florida	0.003	0.007
Georgia	0.002	0.005
Idaho	0.004	0.009
Illinois	0.005	0.001
Indiana	0.002	0.002
Kansas	0.001	0.001
Kentucky	0.001	0.003
Louisiana	0.001	0.002
Iowa	0.001	0.001
Maryland	0.001	0.002
Massachusetts	0.001	0.003
Michigan	0.007	0.003
Minnesota	0.001	0.002
Mississippi	0.006	0.002
Missouri	0.001	0.001
Montana	0.003	0.003

States	**Tradable**	**Non-tradable**
Nebraska	0.001	0.001
Nevada	0.007	0.007
New Hampshire	0.001	0.001
New Jersey	0.002	0.002
New Mexico	0.001	0.001
New York	0.001	0.006
North Carolina	0.002	0.006
North Dakota	0.026	0.020
Ohio	0.003	0.002
Oklahoma	0.001	0.003
Oregon	0.002	0.006
Pennsylvania	0.001	0.001
South Carolina	0.002	0.005
South Dakota	0.003	0.002
Tennessee	0.003	0.005
Texas	0.006	0.013
Utah	0.015	0.014
Vermont	0.002	0.001
Virginia	0.001	0.001
Washington	0.019	0.010
West Virginia	0.004	0.001
Wisconsin	0.001	0.001

This table reports the variance of the log of tradable & non-tradable employment from 2001:M01 through 2020:M06 for 45 U.S. states. The states of Delaware, Hawaii, Maine, Rhode Island, and Wyoming are not included because of data unavailability.

Table 20: Summary Statistics

	Tradable	Non-tradable	House Price
Mean	13.27	13.42	4.91
Median	13.29	13.50	4.92
Variance	1.01	0.86	0.01
First Quartile	12.63	12.90	4.83
Third Quartile	13.93	14.03	5.02

This table reports the descriptive statistics of the log of tradable employment, non-tradable employment and house price across 45 U.S. states from 2001:M01 through 2020:M06.

two-digit industries in the private sector are considered as total employment. In this study, each industry is categorized tradable or non-tradable industry following the work of Mian and Sufi (2014)[48].

[48] Mian and Sufi (2014)use two different methods to classify industries. Based on the "retail and world trade" classification, industries are categorized as tradable, non-tradable, construction, and others. An industry is tradable if total exports plus imports are greater than $500M. Non-tradable industries include the retail sector and restaurants. Construction industries include construction, real estate, and land development, and the remainder industries are categorized as other. The second method - the "Geographical Concentration" classification - is based on geographical concentration. Mian and Sufi (2014) argue that the production of tradable goods should be more concentrated geographically, while non-tradable industries should be geographically dispersed.

Table 21: Results of the Granger Causality Test

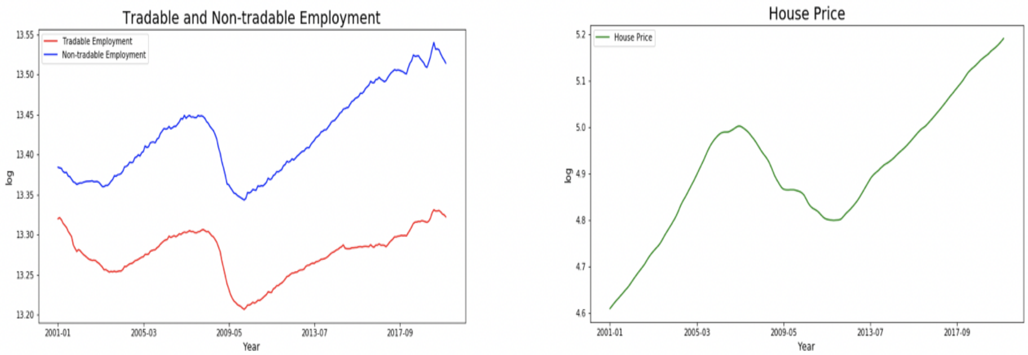
States	Tradable	Non-Tradable
Alabama	**0.01**	0.16
Alaska	0.87	0.57
Arizona	0.34	**0.01**
Arkansas	**0.01**	**0.10**
California	0.30	0.15
Colorado	**0.10**	**0.07**
Connecticut	0.57	0.99
Florida	**0.01**	**0.01**
Georgia	**0.01**	**0.02**
Idaho	**0.01**	**0.01**
Illinois	0.64	0.71
Indiana	0.48	0.95
Kansas	0.88	0.99
Kentucky	0.30	0.34
Louisiana	0.70	0.65
Iowa	0.33	0.58
Maryland	0.55	0.70
Massachusetts	**0.09**	0.73
Michigan	**0.10**	0.85
Minnesota	0.77	0.82
Mississippi	0.20	0.42
Missouri	0.15	0.30
Montana	**0.01**	**0.02**
Nebraska	0.74	0.90
Nevada	**0.01**	**0.04**
New Hampshire	0.91	0.37
New Jersey	0.78	0.68
New Mexico	**0.03**	**0.10**
New York	**0.10**	**0.09**
North Carolina	**0.01**	**0.08**
North Dakota	**0.01**	**0.01**
Ohio	0.76	0.97
Oklahoma	0.86	0.47
Oregon	**0.01**	**0.02**
Pennsylvania	0.25	0.24
South Carolina	0.29	0.37
South Dakota	**0.10**	0.67
Tennessee	**0.02**	**0.10**
Texas	0.21	0.27
Utah	**0.01**	**0.01**
Vermont	0.45	0.39
Virginia	0.20	0.26
Washington	0.65	**0.05**
West Virginia	**0.06**	**0.09**
Wisconsin	0.93	0.98

This table reports the p-values of the Granger-causality test. The null hypothesis is that the growth rate of house price does not Granger-cause the growth rate of tradable or the growth rate of non-tradable employment. The degrees of freedom are 1 and 458 respecitvely. The lag lengths are chosen based on Schwarz criteria. The bold numbers denote significant results.

Table 17 reports the industry classifications used in this paper. The state-level house price data is obtained from the Freddie Mac, and is also available at the Federal Reserve Bank of St. Louis' FRED database. The house price data is seasonally adjusted using the Census X-12 methodology and is deflated by the PCE price index. All our variables in this study are growth measures, i.e. a monthly percentage change.

Table 18 provides a summary of the means of the tradable and non-tradable employment overtime for the 45 U.S. states. It can be observed from this table that the means of the two types of employments are very close to each other. The average difference between the two types of employment for all the states is very small, i.e. -0.148. On the other hand, Table 19 reports a summary of the overtime variances of the tradable and non-tradable employment for the 45 U.S. The variances also follow a similar pattern

Figure 3: Employment and House Price



as the mean. The average of the difference in the variances between the two types of employment for all the states is just -0.0005. Not only that, the data further reveals that in an aggregate sense both the two types of employment and the house price are negatively and positively skewed respectively (see Table 20).[49]

Figure 3 plots the between group mean of the tradable & non-tradable employment and the house price over the time period of the data. It shows that all of these variables exhibit a very similar pattern in nature. There is a gradual increase in the house price followed by a sudden drop during 2006-07. Following a similar pattern, both the types of employment rose as well with a sudden drop during 2007-08. These drastic drops can be considered as the predecessor of the financial crisis of 2008-09. This feature of our variables raises the possibility of the existence of a Granger-causality within the model. Table 21 reports the coefficients of the Granger-causality test of tradable and non-tradable employment specified in Equation {42a - 42b}.[50][51] For each of the employment types, a standard bivariate VAR model is used with the house price as the other variable. The results from this exercise can be listed into three categories. In the first category, there are states where the lagged growth rates of the house price can only predict the growth rate of the tradable employment. Those states are Alabama, Massachussetts, Michigan and South Dakota. In the second category, the house price predicts only non-tradable employment. The states in this category are only Arizona and Washington. In the third category, there are 15 states where the house price Granger-causes

[49] The difference between the third quartile & median and median & first quartile, i.e. $(Q_3 - Q_2) - (Q_2 - Q_1)$ are -0.02, -0.07 and 0.01, respectively.

[50] $\phi_{12}s$ for the tradable and non-tradable employment. The lag lengths are chosen based on Schwarz criterion.

[51] Granger-causality is not a causality statement. It only provides information about the in-sample predictive power of one sample over the other.

both the tradable and non-tradable employment. Those states are Arkansas, Colorado, Florida, Georgia, Idaho, Montana, Nevada, New Mexico, New York, North Carolina, North Dakota, Oregon, Tennessee, Utah and West Virginia. For the rest of the states, the house price predicts neither the tradable employment nor the non-tradable employment.

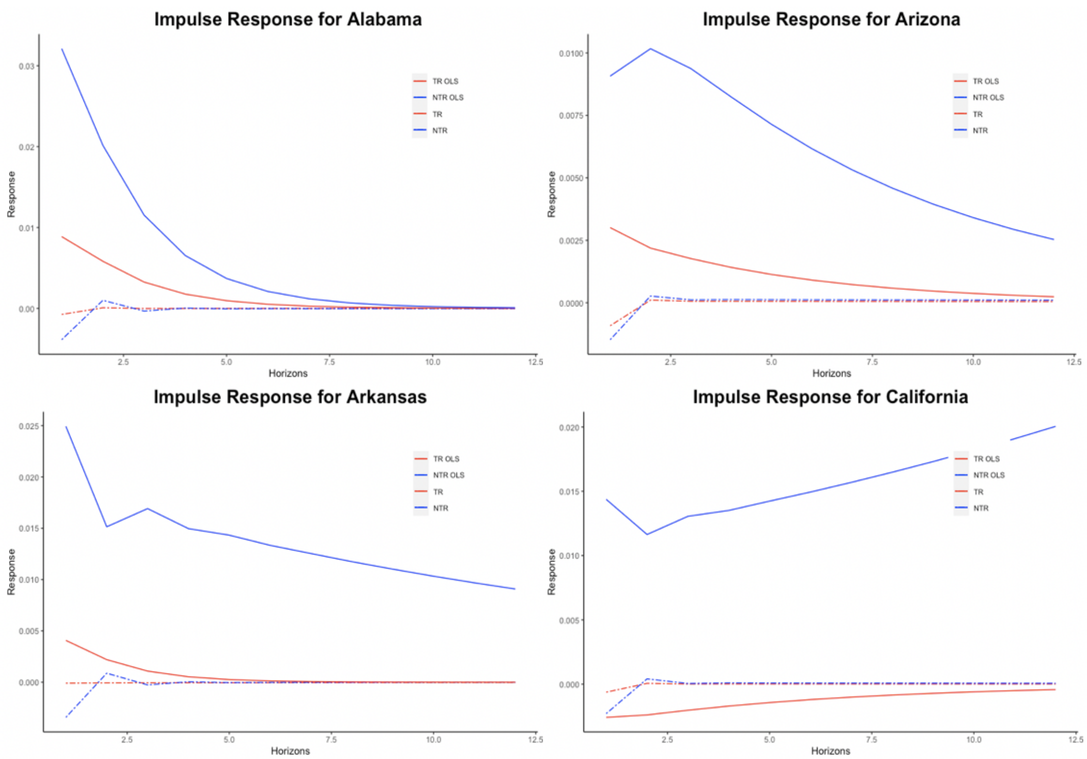
4.5 Results

Following the characteristics of the data presented in the last section, the current section provides the results of this study. This section starts with the following two types of econometric analysis: a *Time-varying Parameter Vector Auto Regression with Stochastic Volatility* (TVP-VAR-SV) and a simple *Bivariate VAR*. The time varying parameter VAR is a bivariate model comprised of the growth rate of the two types of employment and the growth rate of house prices. This model is used separately for the tradable and non-tradable employment; and for the purpose of estimation of the model parameters, a Gibbs sampling algorithm[52] is used. The MCMC algorithm is replicated 5000 times with a burning of 1000 observations. On the other hand, the bivariate VAR models are simple reduced-form VAR models of the growth rates of tradable and non-tradable employment regressed on the lagged growth rates of the same variables. Figure {4 - 10} represent the time-varying impulse responses of the growth of tradable and non-tradable employment when a shock in the growth of house price occurs[53]. The impulse response functions are for 45 U.S. states obtained through the TVP-VAR-SV models. The horizon chosen for this exercise is up to 12 periods ahead, where 1 to 3 periods can be considered short run and 8 to 12 as long run. The impulse response functions obtained through simple VAR are also shown in the plots to assess the relative performance of the Bayesian models[54].

The impulse responses of the tradable and non-tradable employments obtained through the TVP-VAR-SV models can be sorted into three broad categories. The responses shown in Figure {4 - 5} can be considered as the first category. The states that belong to this category are Alabama, Arizona, Arkansas, California, Connecticut, Florida, Idaho, Kentucky, Massachusetts, Michigan, Missouri, Montana, New Mexico, South Dakota, Tennessee and Vermont. In this category, the impulse response of non-tradable employment is prominently higher than its tradable counterpart. These results can further be categorized into two sub-groups. In the first sub-group the dominance of non-tradable employment is visible throughout the horizons.[55] In the second sub-group, the difference between the impulse response of the two types of employment gets

[52]It is a particular variant of Markov chain Monte Carlo (MCMC) methods.
[53]The bold lines.
[54]The dashed lines.
[55]The states in this category are Arizona, Arkansas, California, Florida, Idaho, Montana, Tennessee, and Vermont.

Figure 4: Impulse Response Comparison



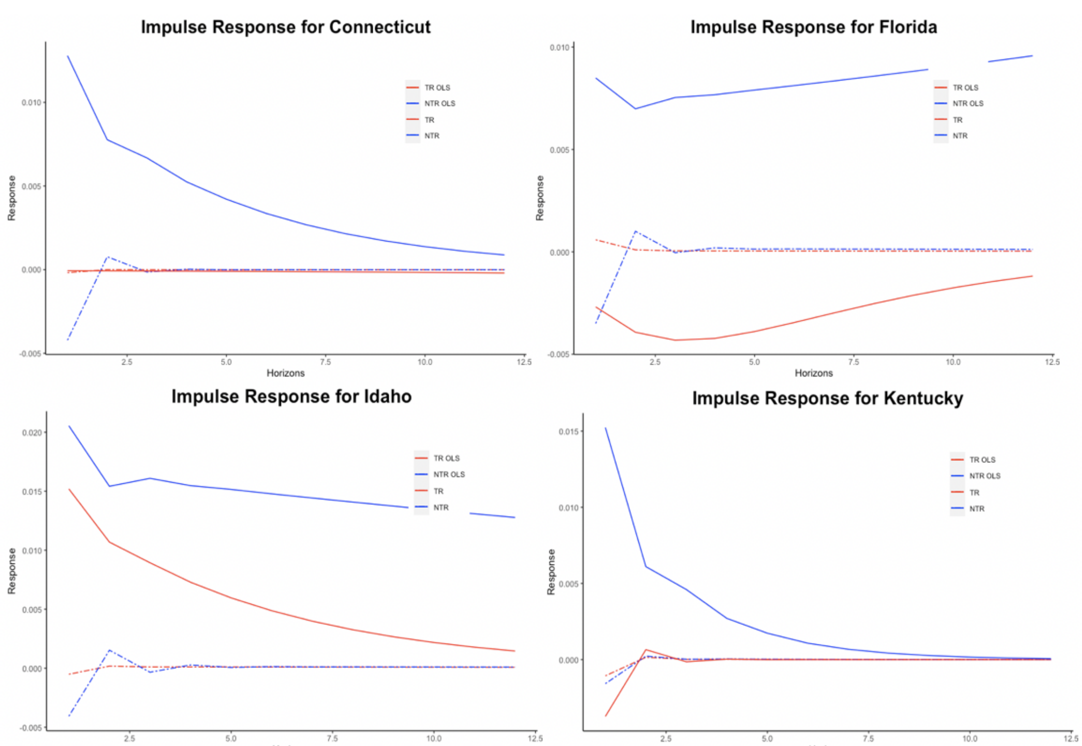


Figure 5: Impulse Response Comparison (contd.)

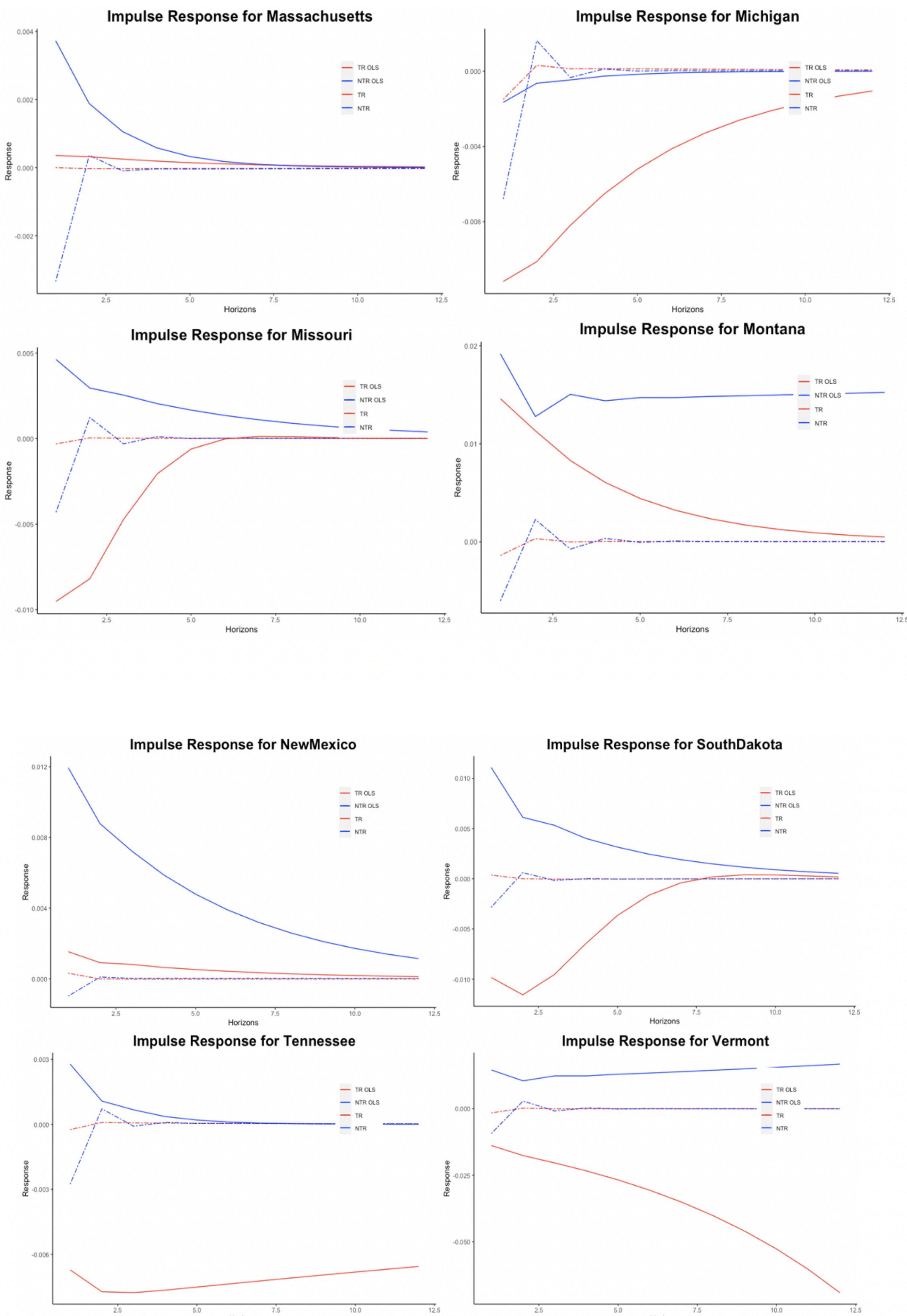


Figure 6: Impulse Response Comparison (contd.)

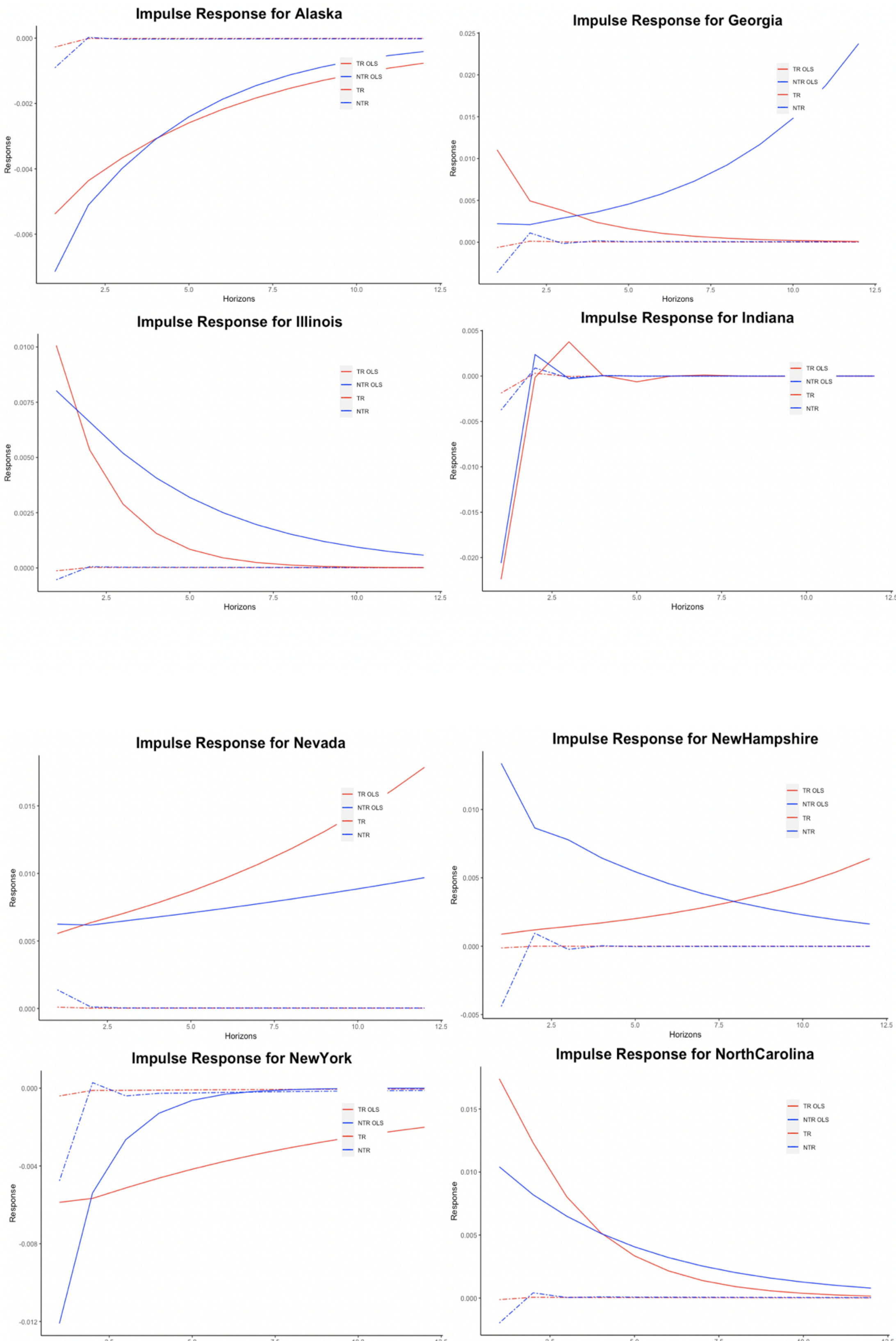
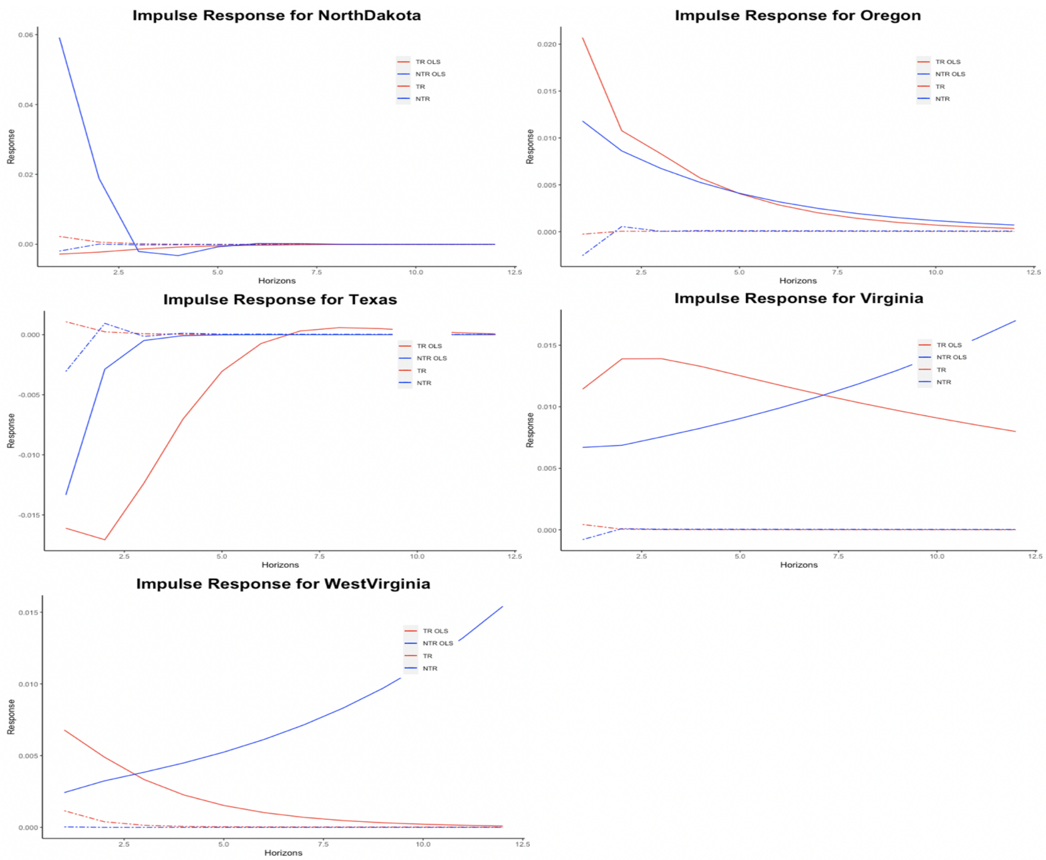


Figure 7: Impulse Response Comparison (contd.)



dampened over longer horizons.[56] The impulse responses obtained through the VAR, on the other hand, are not that clear.Throughout the entire horizons, impulse responses for the two types of employment are not clearly distinguishable. That means, when it comes to the representation of the impulse responses of the two employments, the TVP-VAR-SV duly does a better performance than the its VAR counterpart. These results are consistent to the hypothesis made by Mian and Sufi (2014) and Kishor et al. (2022).

[56]The states in this case are Alabama, Connecticut, Kentucky, Massachusetts, Michigan, Missouri, New Mexico and South Dakota.

Figure 8: Impulse Response Comparison (contd.)

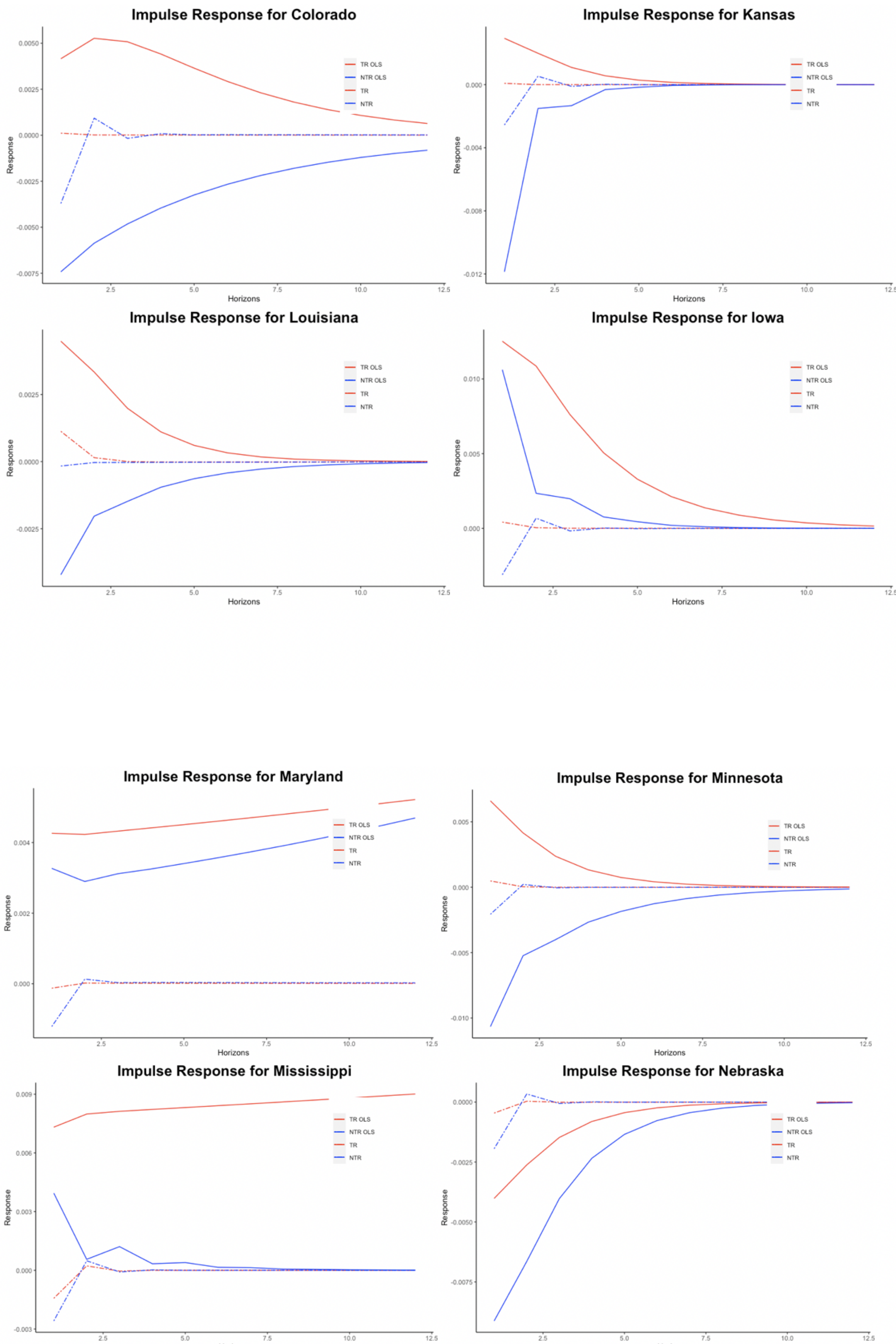
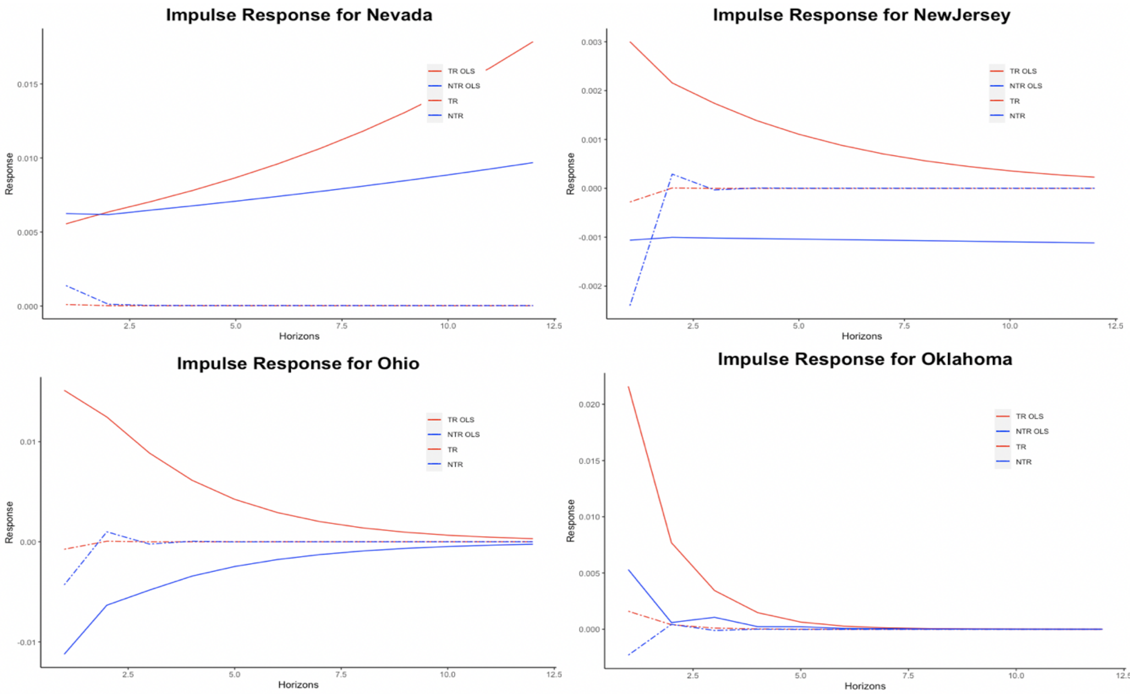


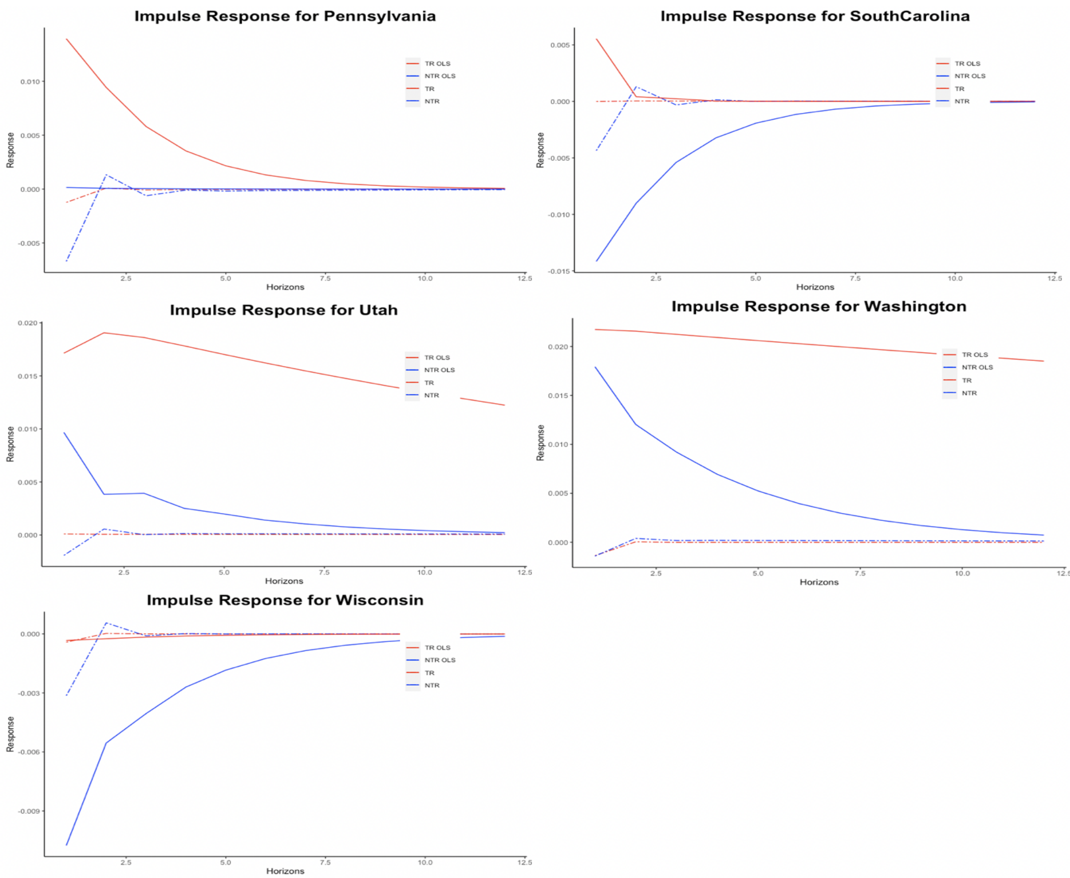
Figure 9: Impulse Response Comparison (contd.)



The results in the next category, however, show a different pattern. In this group, the impulse responses obtained through the TVP-VAR-SV for the two types of employment are by an large intertwined over different horizons (see Figure {6 - 7}). The states that belong to this class are Alaska, Georgia, Illinois, Indiana, Nevada, New Hampshire, New York, North California, North Dakota, Oregon, Texas, Virginia and West Virginia. In this category, there are two sub-groups as well. In the first sub-group, the impulse response of the tradable employment dominates the non-tradable employment in the short horizon; and then the relative magnitude of the impulse response gets reversed in the longer horizons.[57] Whereas, in the second sub-group, it is the non-tradable employment that dominates in the shorter horizons; and after that the degree of impulse responses of the two types of employments moves hand in hand over the longer horizons.[58]

[57] The states in this category are Alaska, Georgia, Illinois, New York, North Carolina, Oregon, Virginia and West Virginia.
[58] The states in this category are Indiana, New Hampshire, North Dakota, and Texas.

Figure 10: Impulse Response Comparison (contd.)



Finally, in the third category of results, there are some states where the impulse response of the tradable employment is higher than its non-tradable counterpart throughout the entire set of horizons (see Figure {8 - 10}). The U.S. states in this group are Colorado, Kansas, Louisiana, Iowa, Maryland, Minnesota, Mississippi, Nebraska, Nevada, New Jersey, Ohio, Oklahoma, Pennsylvania, South Carolina, Utah, Washington and Wisconsin. The higher degree of impulse response of the tradable employment in compare to its non-tradable counterpart somewhat shows a contradiction to the hypothesis of Mian and Sufi (2014) and Kishor et al. (2022). Finally, these plots also reveal that impulse responses obtained through a simple VAR by and large hover around zero. This feature of the VAR results can be considered a manifestation of the better performance of the Bayesian VAR to capture the responses of the employment sector that a shock in the house price brings about.

4.6 Conclusion

In this paper, we examine the impact of house price shocks on tradable and non-tradable employment in 45 U.S. states. This extends the work of Mian and Sufi (2014), where an increase in demand arising due to changes in housing net worth brings about a much lower response in the tradable employment as compare to the non-tradable employment. The data we use is a state-level panel data used in Kishor et al. (2022) and fit a time-varying parameter VAR model with stochastic volatility (TVP-VAR-SV). The use of TVP-VAR-SV model allows us to capture the time-variation in the relationship between employment & house prices as well as time-variation in the volatility of shocks. To estimate posterior distributions of the parameters of interest, we use a Gibbs sampling algorithm. Our results show that for only 16 out of 45 states, the impulse response of non-tradable employment is higher than that of the tradable employment. These results are consistent with the findings of Mian and Sufi (2014). On the other hand, for the other 29 states, either the tradable employment is higher than the non-tradable employment, or they are equal to each other for the entire horizon. Additionally, we run a Granger-causality test in a standard bivariate VAR framework with the tradable & non-tradable employment, and house price as its variables. From this analysis, we find that there are only 15 states where the house price Granger-causes both the tradable and non-tradable employment. Hence, in our opinion, there might exist some other probable underlying factors that need further academic attention and is open to future research.

* * *

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