

Housing Formation and Unemployment Rates: Evidence from 1975–2011

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Abstract This paper investigates the impact of shocks in the unemployment rate on household formation. Prior research has shown that negative economic shocks reduce household formation, but does not inform how long the declines in household formation will persist. Using time series data from 1975 to 2011, we examine how households respond to unemployment rate shocks and estimate the length of time it takes for households to return to its original level in a vector autoregressive model. The results demonstrate that household formation falls in the quarter after unemployment increases, and that it can take up to 10 quarters to return its previous level. While this is a substantial length of time, one implication of these results is that even a permanent increase in the unemployment rate will not permanently affect housing formation in the long run.

Keywords Housing formation · Housing demand · Unemployment · Vector autoregressive (VAR)

Introduction

It is well appreciated that the current economic downturn was precipitated by a collapse in the housing finance system that caused a severe dampening in housing demand. The resulting downturn in the real economy served to exasperate the decline in housing demand as jobs losses multiplied. One of the ways that housing demand has fallen is evident in the reduction in household formation. Recent research (e.g., Lee and Painter, 2013) demonstrates that young adults are less likely to leave their homes during periods of high unemployment and recession. Further, households that lose their homes or jobs are likely to combine living arrangements with others.

Housing demand has slowed substantially since the beginning of the housing market crisis, only recently showing some signs of recovery. According to the survey by the

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Pew Research Center (2009), 10 % of the respondents in the age between 18 and 34 have moved back in with their parents following the recession, while 12 % of those within this age category moved in with a roommate. Even among those older than 35, 1 % have moved back in with their parents and 3 % moved in with a roommate. Furthermore, the changes in the share of people who live alone dropped 0.6 % among those between 18 and 29, from 2007 to 2009. The Pew Research Center (2010) also found that the number of people living in multi-generational households increased by 2.6 million from 2007 to 2008.

Although it is evident that the recent crisis has dampened housing formation, what is unknown is how long it takes for the number of new households in the economy to increase back to normal levels after the worst of the downturn has ended. This study uses a vector autoregressive (VAR) model to estimate the relationship between household formation, unemployment rates, house prices and housing starts from 1975 to 2011. The model allows for these variables to endogenously determine the other variables, while controlling for other macroeconomic influences such as population, incomes and mortgage interest rates. Using impulse response functions, the model is also able to display the long term impact of shocks to the endogenous variables on household formation, which enables a prediction of how quickly housing demand may recover after a recession. In addition, we investigate how the impact of endogenous shocks changes over time using a variance decomposition technique.

The results suggest that in the short run, a permanent increase in the unemployment rate lowers the total number of households that are formed, and that the number of households returns back to its original level in the long run. Impulse response functions demonstrate that one standard deviation increase in the unemployment rate will cause the number of households to decline for 4–5 quarters before beginning to increase again. Only after the 10th quarter does the number of households return to previous levels. These results are largely confirmed in the variance decomposition. We find that the contribution of unemployment to the volatility of housing formation grows significantly during the first five quarters and continues to show marginal growth until the 20th quarter.

Literature on Housing Formation

Many studies of housing demand focus on the factors that influence the decision to own. However, focusing only on the homeownership rate will lead to an incomplete picture of the factors that influence housing demand. As Haurin & Rosenthal (2007) note, the homeownership rate is the number of households that own homes divided by the total number of households in the population. Thus, the rate is not only affected by the propensity of owning among those who have formed independent households but also is influenced by the propensity of forming an independent household. In response to a negative economic shock, young adults may delay the period of moving out from their parental households. People may also change their living arrangement by moving back with their parents or sharing residence with other households, which changes the denominator in the homeownership rate.

There is much less literature on household formation, especially in the United States. The extant literature on household formation suggests that age and other life-time events are the primary drivers in a person's decision to leave home. When young adults come to certain age most of them naturally move out from their parents and form their

own household (Billari & Liefbroer, 2007). This is closely related to events such as employment, graduation and marriage (Goldscheider & Goldscheider 1993). Murphy and Wang (1998) also find that females are more likely to leave home earlier than males, while Goldscheider and Da Vanzo (1989) suggest that ethnicity affects timing and tendency of leaving home and report that Asians have higher probability of remaining with their parents compared to other ethnic groups.

Since the crash of the housing market, many studies have examined whether the decline in the housing market affects the labor market (e.g. Farber, 2012; Coulson and Grieco 2013; Demyanyk et al. 2013). However, only few studies have begun to investigate how the negative economic conditions affect household decisions like household formation. For example, Lee and Painter (2013) show that the annual increase in the number of households fell to nearly zero from 2008–2010. Even more striking were the declines in the household formation of young adults (younger than age 35). The rate of young adult men living at home has grown rapidly from 14 % to 19 % from the beginning of the recession until 2011. Mykyta and Macartney (2011) also find that the rate of “doubling up” climbed to over 6 % during the current recession compared to average rate of 2 %.¹

Using a variety of empirical models, Lee and Painter (2013) further find a strong relationship between household formation, recessions, and the unemployment rate. The study used simulations within a partial equilibrium framework and found that a 2 percentage point increase in unemployment rates reduces household formation by 1 percentage point. Kaplan (2009) examines how young adults dynamically adjust their living arrangements in response to labor market shocks. The result of the duration model shows that a switch from employment to non-employment increases the hazard of moving back home by 64 % for males and 72 % for females after controlling for non-labor market factors such as marriage, childbirth and parental circumstances. Other recent work has found a relationship between labor market risk and living at home (Kaplan, 2010), foreclosures and household formation (Molloy and Shan, 2013), and unemployment and household composition (Weimer 2011).

However, in none of these previous studies has research explicated the dynamic relationship between shocks in the unemployment rate and household formation. Whether unemployment has a permanent or temporary impact on the housing formation is a critical question to ask, especially in a period where the labor market shows a slow recovery. This study will fill this important gap in the literature by estimating how long the unemployment shock affects the rate of household formation.

Data and Methods

In order to examine how changes in household formation over time vary with other variables, we collected national economic data from 1975 to 2011. Although the primary focus of this study is how the unemployment rate influences household formation, we include house prices, housing starts, population, income and mortgage rates to control for other factors which may also affect changes in the number of households. These variables are suggested by Painter and Redfearn (2002) in their study on measuring the impact of

¹ Mykyta and Macartney (2011) define a household as doubling up if it adds an adult that is not the householder, spouse or cohabiting partner of the householder.

interest rates on homeownership and housing stock.² Following this approach, we choose endogenous and exogenous variables to identify factors which influence the long-run fluctuation in the number of households. The four endogenous variables are the changes in the number of households, unemployment rate, house prices, and changes in the number of housing starts which accounts for the supply side of the market. The exogenous variables included in the model are the changes in population, 30 year fixed mortgage rate, and median household income.³ Households are likely to react to these exogenous variables, but it is less likely that housing formation will have a direct impact on these variables. Table 1 presents list of variables and the data sources.

Six variables are collected at monthly intervals, including the number of households and the unemployment rate. The monthly variables are averaged across 3 months and transformed into quarterly data. Household income is collected annually and thus we smoothed the data using linear interpolation to match our periodicity of the other variables in the analysis.

Figure 1 displays the times series for household formation over the sample period. Noticeably, there are jumps in the first quarters of 1982 and 2002. This is because the Current Population Survey/Housing and Vacancy Survey (CPS/HVS) revises the household estimates every 10 years incorporating the new information from the Decennial Census.⁴ Thus, the data is discontinuous between the last month before the year of revision and the first month of the year of revision. In order to adjust for this revision, we drop the first two quarters of 1982 and 2002 when calculating the change in the number of households. The second graph displays the change in the number of households, which is the key dependent variable in the analysis. This series has become more volatile over time, with the largest fluctuations since the housing crisis.

The remaining analysis variables are displayed in Fig. 2. The unemployment rate follows the business cycle closely over the past 35 years and has risen more than 5 % during the current recession. Similarly, housing starts plummeted in the most recent recession, and track all but one of the business cycles in the past 35 years. Trends in other variables displayed are well known. Population and median income have steadily increased over time until the most recent recession. Since then, the trend in median income has flattened and even decreased slightly.

Model

We use a vector autoregressive model to investigate the relationship between household formation, unemployment rates, house prices and housing starts. Vector autoregressive models possess a well known structure that enables the researcher to capture linear

² Painter and Redfeam (2002) used homeownership rate, housing starts, house prices and mortgage rates as endogenous variable, and median income, unemployment and population as exogenous variables. Since the focus of the paper was to look at the changes in homeownership rates and housing starts in response to interest rate shocks, their model treated the interest rate as endogenous and the unemployment rate as exogenous.

³ The change in the number of households is likely to have a proportional relationship with the changes in the population and housing starts. Thus both the first difference of the population and housing starts (which is already in changes) are included in the model. All other variables are in levels.

⁴ During our estimation period, the data has been revised in 1982, 1993 and 2002. However, there is almost no difference between the revised and the non-revised monthly estimates in 1993, and thus we drop only the change in the number of household estimates in the first quarter of 1982 and 2003. The discontinuous line change in the number of household graph in Fig. 1 reflects this adjustment.

Table 1 Summary of data files

Data series	Time range	Periodicity	Source
Number of households	1975:1–2011:12	Monthly	Census bureau: CPS/HVS
Census division HPI	1975:1Q-2011:4Q	Quarterly	OFHEO
Unemployment rate	1975:1–2011:12	Monthly	Bureau of labor statistics
Population by state	1975–2011	Monthly	Census bureau
Household income	1975–2011	Annual	Census bureau
Mortgage rate (30 yrs fixed)	1971:4–2012:1	Monthly	Federal reserve system
Treasury note rate (10 yrs)	1975:1–2011:12	Monthly	Federal reserve system
Housing starts	1975:1–2011:12	Monthly	Census bureau

OFHEO Office of Federal Housing Enterprise Oversight

interdependencies among the endogenously related time series variables (Hamilton, 1994, pp. 257–259). The specification of the main VAR model used in this paper is as follows:

$$Y_{it} = \alpha + \phi_1 \sum_1^n Y_{it-1} + \beta_{it} X_{it} + \epsilon_{it}$$

where *Y* represent the four endogenous variables (the change in the number of households, unemployment rates, house prices and housing starts) and *X* that controls for exogenous variables (population, mortgage rate and median income) which could have an effect on the number of households.

An alternative to estimating the VAR model is to estimate a Vector Error Correction Model (VECM) (Engle and Granger, 1987; Johansen, 1991; Granger, 1983). A VECM is appropriate when all variables are difference stationary. To determine whether a variable is stationary, we used an augmented Dickey Fuller test to determine whether each endogenous variable has a unit root. The null hypothesis is that there exists a unit root. The results show that the number of households, the HPI, and the unemployment rate contains a unit root. As for the first difference, the null hypothesis is rejected at 1 % significant level for changes in the number of households and unemployment rate, while the null is rejected at 5 % significance level for the change of HPI. On the other hand, housing starts is stationary at

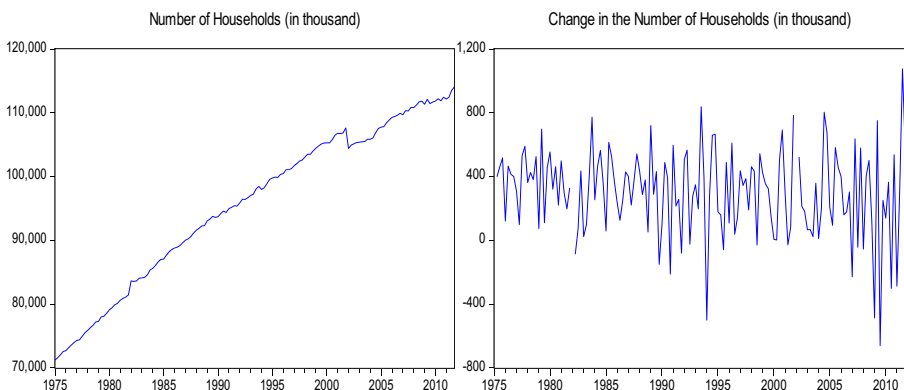


Fig. 1 Changes in household formation (1975–2010)

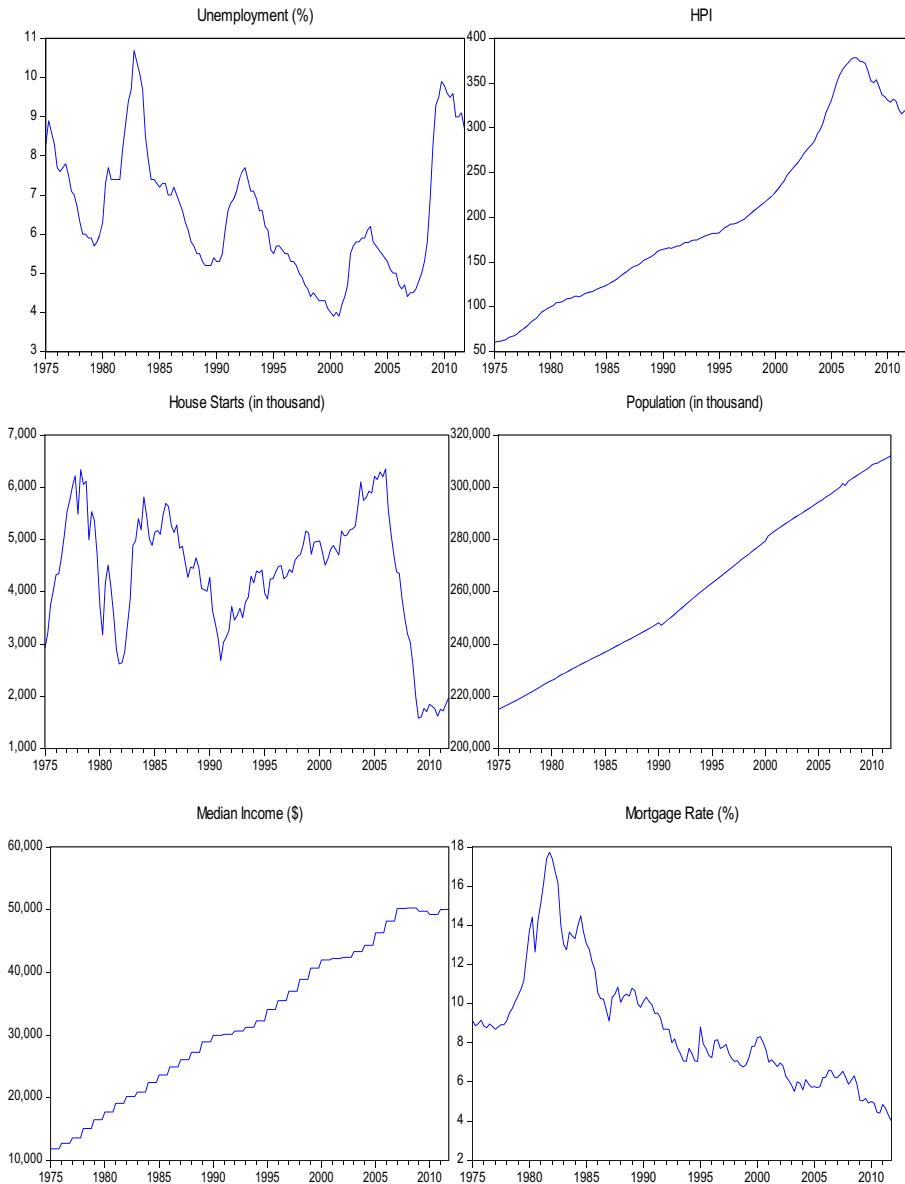


Fig. 2 Changes in analysis variables (1975–2010)

the 5 % significance level although it is still possible to argue that housing starts is difference stationary when evaluated at the 1 % significance level. Unfortunately, we are not able to estimate the VECM model due to the discontinuity in the data for the number of households.⁵

⁵ We can estimate the VECM model prior to the most recent revision. The results are qualitatively similar to the VAR results. The primary difference is that the impact of the unemployment rate on the number of households is greater and more persistent. Results of the Vector Error Correction Model and the Johnson tests are presented in Appendix Table 7 and 8.

Because of the discontinuity in the number of households data series, we use the change in the number of households as one of the endogenous variables, and housing starts, HPI, and the unemployment rate as the others. We chose not to difference the HPI and unemployment to make them stationary. Sims et al. (1990) argue that differencing reduces the precision of the estimates, and the model will perform better even if some variables are non-stationary.⁶

An additional issue with the VAR model is that the ordering of the variables in the model can also affect the results. In theory, the variable which does not have a contemporaneously impact on the following variables while being contemporaneously affected by the other variables should be placed at the top. The second variable should only affect the first variable while being affected by the ones below it. The same logic holds for the rest of the variables. Unfortunately, there is no empirical test to determine the best approach. Thus, we chose to place the variables in the following order: unemployment, change in the number of households, housing starts and then HPI. This allows the economy to affect housing demand, and then housing demand and housing starts to affect the price. The housing supply variable does not need to follow the housing demand variable, but the results are similar when we switched the order between the change in the number of households variable and the housing starts variable.

Finally, the optimal number of lags in the endogenous variables needs to be chosen. We chose the number of lags based on the Akaike information criterion (AIC) which suggests how many lags should be included in the VAR model capturing the tradeoff between the uncertainty in the model and the number of parameters.⁷

Impulse response functions can then be used to determine how changes in the number of households and house prices are influenced by a standard deviation shock in the unemployment rate. We investigate both the current and accumulate impact of an unemployment rate shock on the household formation over 30 quarters. Finally, we use variance decomposition to investigate which factors influence the volatility in household formation among the four endogenous variables.

Results

Vector Autoregressive Model

Table 2 presents the VAR results for our analysis sample. The models include four endogenous variables (change in the number of households, the unemployment rate, the HPI, and change in housing starts) and three exogenous variables (change in population, median income and mortgage rates). Four lags are included based on the AIC. The AIC results are presented in the Appendix Table 5

⁶ We have also implemented the VAR after differencing the HPI and the unemployment rate. While the results do not show a noticeable difference from what is presented in this paper, it is more difficult to interpret the impulse response function for the change in the unemployment rate.

⁷ The AIC was first proposed by Akaike (1973). The AIC for a given model is the difference between the maximized log-likelihood (L) and the number of estimable parameters (K): $AIC = -2 \log(L) + 2K$. The optimum number of lags is chosen at the minimum AIC value. The main advantage of the AIC is that it rewards goodness of fit through the likelihood ratio, while penalizes the increase in the number of variables.

Table 2 VAR for the changes in the number of households and house prices

	Δ Households	HPI
Unemployment (-1)	111.190 (114.941)	0.813 (0.832)
Unemployment (-2)	-365.021** (179.902)	-0.469 (1.302)
Unemployment (-3)	63.699 (172.788)	0.271 (1.251)
Unemployment (-4)	183.952* (101.533)	-0.239 (0.735)
Δ Households (-1)	-0.357*** (0.093)	0.0009 (0.00067)
Δ Households (-2)	-0.367*** (0.100)	0.0012* (0.00072)
Δ Households (-3)	-0.380*** (0.105)	-0.00022 (0.00076)
Δ Households (-4)	0.014 (0.100)	-0.00029 (0.00072)
Δ Housing start (-1)	0.042 (0.079)	-0.0002 (0.0006)
Δ Housing s (-2)	0.019 (0.103)	0.002 (0.00074)
Δ Housing start (-3)	-0.124 (0.103)	-0.00012 (0.00074)
Δ Housing start (-4)	0.060 (0.07428)	-0.00009 (0.00054)
HPI (-1)	25.065** (11.428)	1.668*** (0.083)
HPI (-2)	-47.108** (21.584)	-1.164*** (0.156)
HPI (-3)	33.712 (22.879)	1.001*** (0.166)
HPI (-4)	-10.671 (12.882)	-0.539 (0.093)
C	744.484 (461.903)	-5.885*** (3.344)
Δ Population	0.047 (0.085)	0.00036 (0.00062)
Mortgage	12.955 (14.020)	-0.161 (0.101)
Median income	-0.013 (0.011)	0.00020*** (0.00008)
No. of observation	133	133
Adj. R-squared	0.192	0.999

(Table 5).⁸ We display the results for the equations estimating the change in the number of households and the HPI because we will create impulse response functions for those variables. Results for the other two equations are presented in Table 6.

The results in Table 2 demonstrate that lags in the change in household formation predict this period's change, and that lags in the unemployment rate have a negative effect two quarters hence and a positive effect four quarters ago. This suggests it takes some time for the negative effect of a negative unemployment rate shock to impact household formation. The previous two quarters of the HPI have contradictory impacts on household formation leaving it difficult to interpret the impact of HPI shock on the change in the number of households using only the estimates themselves. The change in housing starts does not have a statistically significant effect. Among the exogenous variables, none of the three have a concurrent influence on the change in the number of households although the impact may exist through their impacts on the other endogenous variables.

With respect to house prices, the lag of house prices has a significant relationship with the current HPI suggesting a strong momentum effect. While other variables do not have much impact, the coefficient on the second lag of the change in the number of households has a statically significant relationship with the current HPI, indicating that house prices are influenced by the change in the number of households. This result is consistent with a shift in the demand curve; that is, we observe that housing demand increases when the number of households increases.

Impulse Response Functions

The primary focus of this study is to determine how quickly the rate of household formation changes in responses to a negative economic shock. This is best illustrated through impulse response functions derived from the VAR models (Enders, 2009, pp. 307–311). In the impulse response functions, we present estimates for the impact of a one standard deviation increase (1.679 percentage points) in the unemployment rate on the number of households in the long run. Figure 3 displays the response in household formation to the unemployment shock on the left panel and accumulated response to the shock on the right panel.⁹ We find that an increase of 1.679 percentage points of the unemployment rate will lead to a slight increase of the number of households in the first two quarters (although this increase is not statistically significant), but by the third quarter, the number of households is reduced by 60,000 and will continue to fall until the fifth quarter. Based on the accumulated response to the shock, we find that the number of households falls in the second quarter and gradually starts to increase. The number of households returns to its previous level by the 10th quarter. The results demonstrate two important facts. The shock impacts household formation for a long duration. At the same time, even without changes in the economic environment, household formation will return back to its original level.

Figure 4 demonstrates the impact of an unemployment shock on the HPI. The results show that the unemployment rate shock has almost no significant influence on the house prices (Left panel). However, when estimating the impact of a one standard deviation in

⁸ We tested additional criteria to determine the number of lags. All other approaches also suggested that four lags were optimal except for the Schwarz Criterion, which suggested two lags to be optimum. We also estimate the model with two lags based on the Schwarz Criterion, and the results are invariant to the reduced number of lags.

⁹ The red dotted lines show the confidence interval at 95 % band.

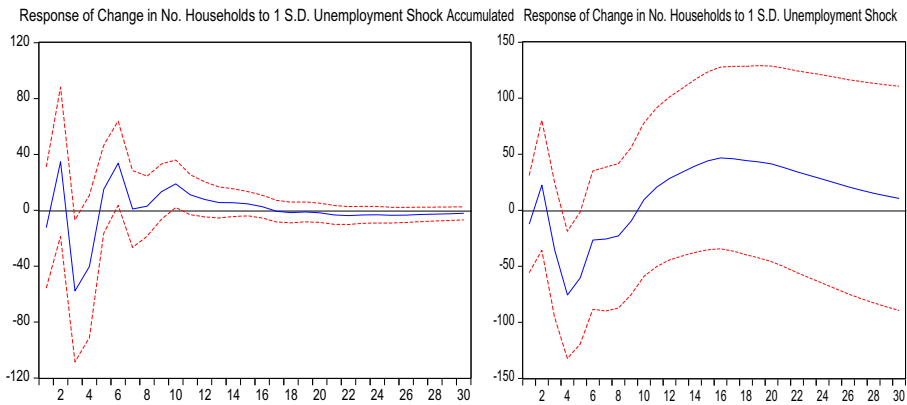


Fig. 3 Impulse response: change in the number of households to an unemployment rate shock: multivariate

the number of households (Right panel), we find that there is a significant impact in demand that is long lasting. Because the unemployment rate affects household formation the result suggests that the increase in the unemployment rate may have indirect impact on the HPI through the reduction in the number of households. As shown in Fig. 4, one standard deviation decrease in the change in the number of households has a negative effect on HPI in all periods of estimation.

Multivariate: Variance Decomposition

Variance decomposition is used to complement the interpretation of the VAR model once the model has been fitted. In the housing literature, variance decomposition has been used to determine factors which affect the housing market variables. For example, Campbell et al. (2009) find that while real interest rates, housing premia and rent growth all contribute to the variation in the rent-price ratio, the housing premium is the principal source of this variation. Jarociriski and Smets (2008) use variance decomposition to find the fraction which monetary policy contributes to the variance in both housing investment and house prices and show that the contribution increases over the time horizon.

Table 3 presents the variance decomposition for the change in the number of households. It suggests that the variance in the change in the number of households

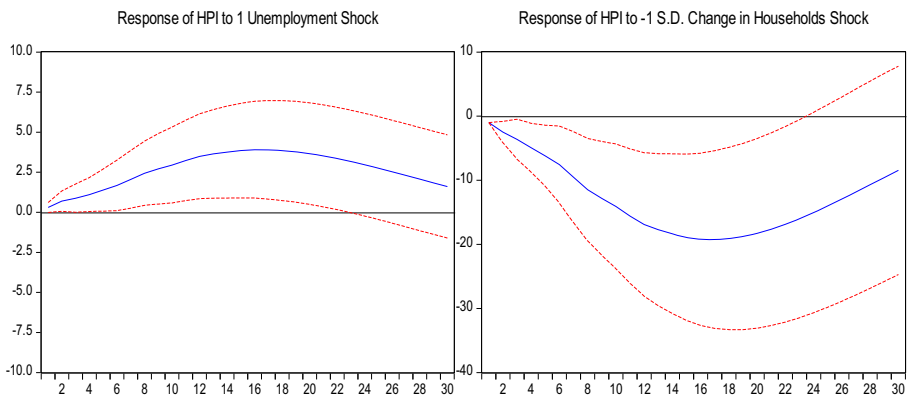


Fig. 4 Impulse response of HPI to unemployment rate shock & change in households

Table 3 Variance decomposition for the changes in the number of households

Period	S.E.	Unemployment	Δ Households	Δ Housing start	HPI
1	0.231	0.244	99.756	0.000	0.000
2	0.383	1.834	95.092	0.423	2.651
3	0.499	5.792	90.728	0.389	3.091
4	0.596	7.504	88.550	0.590	3.356
5	0.663	7.381	87.509	0.929	4.181
10	0.792	8.890	84.098	1.034	5.978
20	0.959	9.118	83.541	1.067	6.273
30	1.195	9.204	83.385	1.113	6.297

is mostly explained by its own lags, with small contributions by unemployment, HPI and housing starts. The largest contribution among the other three variables is from unemployment shocks, which confirms the VAR results suggesting that households are more responsive to unemployment shocks than to house price shocks in the short run. However, while the contribution of unemployment shock does not increase measurably after the 5th quarter, the contribution of HPI grows continuously, catching up with the contribution of the unemployment rate. The results show that in the long run, the unemployment rate and the HPI together account for approximately a 15 % contribution to volatility in the change in the number of households. However, the change in housing starts contributes little to the volatility in the change in the number of households, indicating that households are less responsive to the supply of housing.

The results in Table 4 suggest that although the HPI initially contributes to the 90 % variance of HPI in the short run, over the long term, the impact of the other three variables substantially increases. The contribution to the variance of unemployment and the change in housing starts is larger than that of the change in the number of households.

Additional Results

We also tested the sensitivity of the estimates to the most recent financial crisis (Table 9). Ideally, one would estimate the VAR model before and after the financial crisis. However, one has insufficient data after the great recession to estimate a model. Instead, we exclude the years from 2007 and then estimate the VAR model and impulse response functions to determine if the financial crisis changes our estimated behavioral responses in the patterns of household formation.¹⁰ From 1975 to 2006, one standard deviation of unemployment is 1.447, 0.232 lower than that of the total sample period, reflecting the substantial increase of unemployment rate since 2007. Because the size of the shock is smaller, the coefficients on the lag unemployment in Table 9 are slightly smaller in size compared to the numbers shown in Table 2. However, the signs and the patterns of the estimates are similar. The impulse response function displays similar results while excluding the post crisis period (Fig. 5). While the reduction in the number of households is smaller (around 30,000), the recovery period is similar (10th quarters) to the results shown in Fig. 3. This suggests that the households' response to the

¹⁰ Two lags are included based on AIC.

Table 4 Variance decomposition for the HPI

Period	S.E.	Unemployment	Δ Households	Δ Housing Start	HPI
1	0.231	2.784	0.098	1.763	95.355
2	0.383	4.560	0.160	1.400	93.880
3	0.499	6.027	1.265	2.169	90.538
4	0.596	7.356	1.473	4.017	87.154
5	0.663	8.279	1.080	5.568	85.073
10	0.792	16.555	1.750	11.051	70.645
20	0.959	31.300	3.295	17.966	47.438
30	1.195	36.187	3.923	20.082	39.807

unemployment shock may not be structurally different prior to the housing crisis, but the increased in the size of the shock itself lead to reduction in the total housing demand.

Further, we tested how this model predicts the actual change in the number of households over the period from 2008–2010 with an unemployment shock that was similar to the actual loss in jobs. During this period, the actual number of households formed was 1.5 million, but the model predicts a cumulative change of 728,000 implying that the number of households formed was greater than the model would have predicted. Thus the surprise in the recent recession is that the number of households did not fall more than it did. Without the recession, the model would have predicted an additional 1.147 million households than were actually formed.

Finally, we simulated the impact of larger shocks to the unemployment rate because the recent crisis leads to a more than 5 % increase in the unemployment rate. Figure 6 displays the impact of a 2 standard deviation increase in unemployment on the number of households. The accumulated impulse response function suggests that the number of households drops to 500,000 below it's the original level by the second quarter. However, the recovery period does not increase, suggesting that households adjust to the permanent increase in the unemployment rates even when there is a much larger increase in the unemployment rate.¹¹

Conclusion

The current economic recession and depressed housing demand continues to be a source of concern to policy makers. However, despite the huge shock in the economy, U.S. homeownership only fell 4 % since the crisis. Comparing to the percentage of homeowners who are underwater,¹² the reduction in homeownership seems relatively small. Recent literature (Lee and Painter, 2013) suggests that this may be due to the

¹¹ We have also tried a 3 standard deviation unemployment rate shock which is similar to the increase of unemployment rate in the current regression. Although the number of households drops by a greater magnitude, the result from impulse response function shows a similar pattern: the number of households returns back to its original level by the 12th quarter. We also tried to analyze the impact of unemployment rate in the four regions and among different age groups. However, since the number of households for the subsample could only be obtained annually, the estimates were inaccurate to gain any meaningful interpretation.

¹² As of the fourth quarter in 2011, 11.1 million U.S. homeowners were underwater on their mortgages, accounting for 22.8 % of all residential properties with a mortgage. (Corelogic, 2011)

decrease in the housing formation. Because household formation is a foundational component of housing demand, it is critical to understand how quickly household formation can recover after economic shocks. This analysis has been the first to test for this in the context of a vector autoregressive model.

There are a few findings of note. First, even with a permanent increase in the unemployment rate, household formation rates eventually return to its original level. In the context of this model, we found that a permanent increase in the unemployment rate of 1.679 % lowers the rate of household formation by 60,000 in the third quarter, with continued reductions in household formation over the next 2–3 quarters. These reductions are then followed by a recovery period which lasts another 5–6 quarters before the number of household returns to its original level. This suggests that demographic factors will eventually dominate economic factors when households make a household formation decision.

Appendix

Table 5 VAR Lag order selection criteria

Lag	LR	FPE	AIC	SC	HQ
0	NA	6.25e+13	43.11689	43.48658	43.26704
1	1143.637	3.28e+09	33.26067	34.00005	33.56096
2	92.63236	1.83e+09	32.67530	33.78437*	33.12573
3	40.18565	1.63e+09	32.55704	34.03580	33.15762
4	52.70299*	1.27e+09*	32.29969*	34.14815	33.05042*
5	15.35829	1.42e+09	32.40582	34.62397	33.30669
6	17.41735	1.56e+09	32.48300	35.07084	33.53402
7	18.57883	1.67e+09	32.53871	35.49624	33.73988
8	12.23238	1.93e+09	32.65926	35.98649	34.01058

* indicates lag order selected by the criterion

** The above acronyms indicate the following: *LR*=Likelihood Ratio, *FPE*=Final prediction error, *AIC*=Akaike Information criterion, *SC*=Schwarz criterion, *HQ*=Hannan–Quinn criterion

Table 6 VAR for the changes in the number of households & HPI: multivariate

	Unemployment	ΔHousing start
Unemployment (−1)	1.240*** (0.106)	170.929 (133.605)
Unemployment (−2)	−0.240 (0.166)	−133.098 (209.115)
Unemployment (−3)	0.018 (0.160)	239.409 (200.845)
Unemployment (−4)	−0.120 (0.0939)	−146.008 (118.019)
ΔHouseholds (−1)	−0.000027 (0.00008)	0.021 (0.108)
ΔHouseholds (−2)	0.0002* (0.000092)	0.077 (0.116)

Table 6 (continued)

	Unemployment	Δ Housing start
Δ Households (-3)	0.00009 (0.000097)	0.088 (0.122)
Δ Households (-4)	0.000098 (0.000092)	-0.017 (0.116)
Δ Housing start (-1)	-0.00017*** (0.00007)	0.852*** (0.092)
Δ Housing start (-2)	0.00011 (0.000095)	0.033 (0.120)
Δ Housing start (-3)	0.00002 (0.00010)	-0.100 (0.119)
Δ Housing start (-4)	-0.00003 (0.000069)	0.224*** (0.08634)
HPI (-1)	0.005 (0.010)	14.770 (13.283)
HPI (-2)	-0.031 (0.020)	8.346 (25.089)
HPI (-3)	0.031 (0.021)	-24.530 (26.594)
HPI (-4)	-0.003 (0.012)	-4.040 (14.974)
C	1.064*** (0.427)	-277.820 (536.906)
Δ Population	-0.00012 (0.00008)	0.131 (0.099)
Mortgage	0.010 (0.013)	-78.559*** (16.297)
Median income	-0.000017 (0.00001)	0.028** (0.012)
No. of observation	133	133
Adj. R-squared	0.977	0.943

Table 7 Johansen test

Hypothesized No. of CE (s)	Eigenvalue	Trace Statistic	0.05 Critical value	Prob.**
None *	0.398716	105.1943	47.85613	0.0000
At most 1 *	0.266035	56.36027	29.79707	0.0000
At most 2 *	0.223049	26.66806	15.49471	0.0007
At most 3	0.025095	2.439827	3.841466	0.1183

Trace test indicates 3 cointegrating eqn (s) at the 0.05 level

*Denotes rejection of the hypothesis at the 0.05 level

Table 8 Vector error correction model

Cointegrating Eq:	CointEq1	CointEq2	CointEq3	
Unemployment (-1)	1.000	0.000	0.000	
ΔHouseholds (-1)	0.000	1.000	0.000	
ΔHousing start (-1)	0.000	0.000	1.000	
HPI (-1)	-0.093*** (0.030)	-2.141 (2.517)	-10.604 (21.434)	
C	7.773	2.769	-2958.155	
Error correction:	D (Unemployment)	D (ΔHouseholds)	d (ΔHousing start)	D (HPI)
CointEq1	-0.105*** (0.032)	-22.852 (30.508)	240.743*** (43.438)	0.0143 (0.125)
CointEq2	0.00015 (0.00022)	-2.099*** (0.212)	0.469 (0.302)	0.002** (0.00087)
CointEq3	-0.00010** (0.00004)	0.074* (0.045)	-0.177*** (0.064)	0.0005*** (0.00018)
D (Unemployment (-1))	0.236** (0.103)	-25.395 (96.943)	169.691 (138.030)	0.410 (0.396)
D (Unemployment (-2))	0.069 (0.104)	-146.541 (98.257)	-67.809 (139.901)	0.385 (0.401)
D (ΔHouseholds (-1))	-0.00017 (0.00016)	0.753*** (0.154)	-0.325 (0.220)	-0.001** (0.00063)
D (ΔHouseholds (-2))	-0.0001 (0.00011)	0.314*** (0.100)	-0.120 (0.143)	-0.0004 (0.0004)
D (ΔHousing start (-1))	-0.00008 (0.00008)	-0.082 (0.074)	-0.163 (0.105)	-0.0008*** (0.00030)
D (ΔHousing start (-2))	-0.00003 (0.00007)	-0.048 (0.069)	-0.017 (0.098)	0.000145 (0.00028)
D (HPI (-1))	-0.027 (0.029)	-16.192 (27.720)	127.141*** (39.469)	0.327*** (0.113)
D (HPI (-2))	0.030181 (0.032)	-14.44416 (30.015)	81.936** (42.736)	0.056 (0.123)
C	1.703 (2.036)	-393.309 (1924.34)	-4535.010* (2739.92)	-3.437 (7.856)
Population	-0.0000007 (0.00001)	0.008 (0.010)	0.008 (0.014)	0.000016 (0.00004)
Mortgage	0.019 (0.013)	6.461 (12.722)	-81.256*** (18.113)	-0.079 (0.052)
Median income	-0.000064** (0.00003)	-0.056** (0.028)	0.104*** (0.040)	0.00005 (0.00011)
No. of observation	100	100	100	100
Adj. R-squared	0.430	0.636	0.326	0.418

Table 9 VAR for the changes in the number of households & HPI: multivariate prior to 2007

	Δ Households	HPI
Unemployment (-1)	-101.251 (94.197)	0.654 (0.509)
Unemployment (-2)	93.454 (88.670)	-0.500 (0.479)
Δ Households (-1)	-0.151 (0.093)	-0.00025 (0.0005)
Δ Households (-2)	-0.329*** (0.091)	0.0005 (0.0005)
Δ Housestart (-1)	-0.084 (0.071)	-0.00008 (0.00038)
Δ Housestart (-2)	0.094 (0.068)	0.00064* (0.00037)
HPI (-1)	24.420 (17.294)	1.510*** (0.093)
HPI (-2)	-24.695 (17.974)	-0.506*** (0.097)
C	685.086* (366.482)	-2.155 (1.980)
D Population	-0.055 (0.098)	-0.0004 (0.0005)
Mortgage	-0.988 (11.911)	-0.112* (0.064)
Median income	-0.006 (0.010)	0.00001 (0.00006)
No. of observation	119	119
Adj. R-squared	0.094	0.999

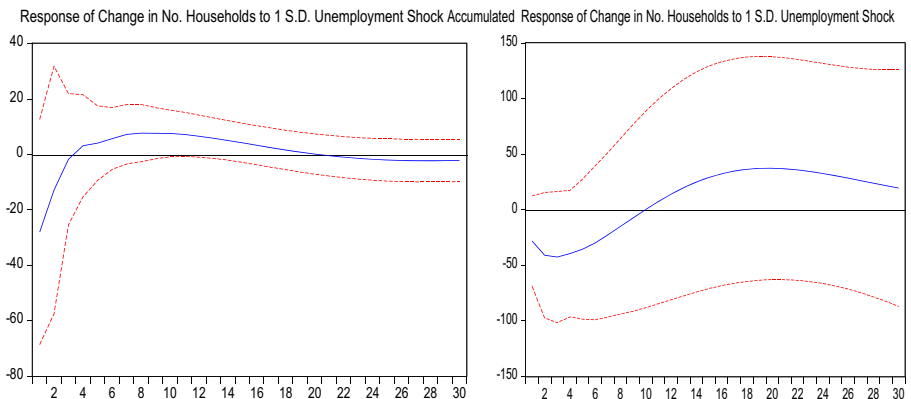


Fig. 5 Impulse response: change in the number of households from an unemployment rate shock: multivariate prior to 2007

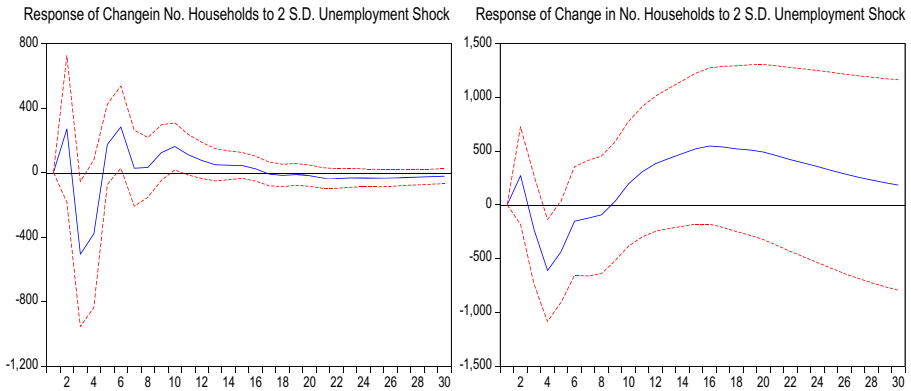


Fig. 6 Impulse response: change in the number of households from an unemployment rate shock 2 S.D. unemployment shock

References

- Akaike, H. (1973). *Information theory and an extension of the maximum likelihood principle* (in second international symposium on information theory, pp. 267–281). Budapest: Akademiai Kiado.
- Billari, F. C., & Liefbroer, A. C. (2007). Should I stay or should I go? The impact of age norms on leaving home. *Demography*, 44(1), 181–198.
- Campbell, S. D., Davis, M. A., Gallin, J., & Martin, R. R. (2009). What moves housing markets: a variance decomposition of the rent-price ratio. *Journal of Urban Economics*, 66(2), 90–102.
- Coulson, N. E., & Grieco, P. (2013). Mobility and mortgages: evidence from the PSID. *Regional Science and Urban Economics*, 43, 1–7.
- Demyanyk, Y., Hryshko, D., José Luengo-Prado, M., & Sørensen, B. E. (2013). Moving to a Job: The Role of Home Equity, Debt, and Access to Credit. *Federal Reserve Bank of Cleveland, Working Paper Series 13–05*.
- Enders, W. (2009). *Applied Econometric Times Series*. 3rd ed. Wiley.
- Engle, R. F., & Granger, C. W. J. (1987). Co-integration: representation, estimation and testing. *Econometrica*, 55(2), 251–267.
- Farber, H. S. (2012). Unemployment in the great recession: did the housing market crisis prevent the unemployed from moving to take jobs. *American Economic Review*, 102(3), 520–525.
- Goldscheider, F. K., & Da Vanzo, J. (1989). Pathways to independent living in early adulthood: marriage, semiautonomy, and premarital residential independence. *Demography*, 26, 597–614.
- Goldscheider, F. K., & Goldscheider, C. (1993). *Leaving home before marriage. ethnicity, familism and generational relationships*. Madison, WI: University of Wisconsin Press.
- Granger, C. W. J. (1983). Co-Integrated Variables and Error-Correcting Models. UCSD Discussion Paper 83–13.
- Hamilton, J. D. (1994). *Time Series Analysis*. Princeton University Press.
- Haurin, D. R., & Rosenthal, S. (2007). The influence of household formation on homeownership rates across time and race. *Real Estate Economics*, 35(4), 411–450.
- Jarocirski, M., & Smets, F. R. (2008). House prices and the stance of monetary policy. *Federal Reserve Bank of St. Louis Review*, 90(4), 339–365.
- Johansen, S. (1991). *Statistical Analysis of Cointegration Vectors*. In *Long-run Economic Relationship: Readings in Cointegration*. Oxford University Press: New York.
- Kaplan, G. (2009) Boomerang Kids: Labor Market Dynamics and Moving Back Home. Working Paper 675, Federal Reserve Bank of Minneapolis.
- Kaplan, G. (2010) Moving Back Home: Insurance Against Labor Market Risk, Working Paper 677, Federal Reserve Bank of Minneapolis.
- Lee, K. O., & Painter, G. (2013). What happens to household formation in a recession? *Journal of Urban Economics*, 76, 93–109.
- Molloy, R., & Shan, H. (2013). The post-foreclosure experience of U.S. households. *Real Estate Economics*, 41(2), 225–254.

- Murphy, M., & Wang, W. (1998). Family and sociodemographic influences on patterns of leaving home in postwar Britain. *Demography*, 35, 293–305.
- Mykyta, L., & Macartney, S. (2011). The Effects of Recession on Household Composition: “Doubling Up” and Economic Well-Being. SEHSD Working Paper, Number 2011–4 U.S. Census Bureau.
- Painter, G., & Redfearn, C. (2002). The role of interest rates in influencing long-run homeownership rates. *Journal of Real Estate Finance and Economics*, 25(2/3), 243–267.
- Pew Research Center. (2009) Home for the holidays... and every other day. Washington, DC. <http://pewsocialtrends.org/assets/pdf/home-for-the-holidays.pdf>.
- Pew Research Center. 2010. The Return of the Multi-Generational Family Household. Washington, DC. <http://pewsocialtrends.org/assets/pdf/752-multi-generational-families.pdf>.
- Sims, C., Stock, J., & Watson, M. W. (1990). Inference in linear time series models with some unit roots. *Econometrica*, 58, 113–144.
- Weimer, E.E. (2011). The Effect of Unemployment on Household Consumption and Doubling Up. *National Poverty Center Working Paper Series, WP#11-12*.