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The Role of Real Estate Uncertainty in Predicting US Home Sales Growth: Evidence from a Quantiles-Based Bayesian Model Averaging Approach

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Abstract

This paper investigates the role of real estate-specific uncertainty in predicting the conditional distribution of US home sales growth over the monthly period of 1970:07 to 2017:12, based on Bayesian Model Averaging (BMA) to account for model uncertainty. After controlling for standard predictors of home sales (housing price, mortgage rate, personal disposable income, unemployment rate, building permits, and housing starts), and macroeconomic and financial uncertainties, our results from the quantile BMA (QBMA) model show that real estate uncertainty has predictive content for the lower and upper quantiles of the conditional distribution of home sales growth.

Keywords: Home Sales, Real Estate Uncertainty, Quantile Regression, Bayesian Model Averaging
JEL Codes: C11, C22, C53, R31

1. Introduction

Housing represents a large share of the total economy of the United States (US),[1] hence, from a macroeconomic perspective, movements in the housing sector spill over to the entire economy through new constructions, renovations of an existing property, and the volume of home sales. At the same time, from the microeconomic level, performances of financial institutions and real estate firms depend crucially on housing market activities. Hence, timely and accurate prediction of home sales is of paramount importance to policymakers, financial institutions, and real estate professionals, as well as, housing market participants. Given this, there exists a relatively large literature which has aimed to forecast US home sales at the aggregate- and regional-levels based on macroeconomic, financial and behavioural predictors (see for example, Dua and Smyth (1995), Dua and Miller (1996), Dua et al. (1999), Gupta et al. (2010), Baghestani et al. (2013), Baghestani and Kaya (2016), Baghestani (2017), Hassani et al. (2017)).

More recently, in the wake of the "Great Recession", large number of studies have attempted to measure uncertainty (a latent variable) using various methods, and have also analysed the impact of the same on the general macroeconomy and the financial sector (see, Chuliá et al., (2017) and Gupta et al., (2018) for detailed reviews in this regard). Building on this line of research, and given the role of the housing sector in the global financial crisis, Nguyen-Thanh et al., (2018) has recently developed a real estate-specific measure of uncertainty. Using a vector autoregressive (VAR) model, these authors showed that the real estate uncertainty index

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[1] Based on the Financial Accounts data of the US corresponding to the fourth quarter of 2018 (https://www.federalreserve.gov/releases/z1/20190307/z1.pdf), residential estate represents about 82.39% of total household non-financial assets, 26.30% of total household net worth and 22.79% of household total asset.

has a significant negative impact on housing market related variables, such as housing prices and starts, and construction employment, but the impact on home sales was not analyzed.[2] Given this, the objective of our paper is to analyze for the first time, the role of the real estate-specific measure of uncertainty of Nguyen-Thanh et al., (2018), in predicting growth of aggregate US home sales. In the process, we aim to add to the above-mentioned literature of home sales prediction in the US, by incorporating the role of real estate uncertainty (along with metrics of macroeconomic and financial uncertainties), over and above the standard predictors used in the studies mentioned above. Along the lines of Bernanke (1983), who dealt with general economic uncertainty, increase in real estate uncertainty is expected to lead to postponement of consumption and investment decisions associated with housing-related activities and hence, (negatively) affect home sales.

As far as the econometric framework is concerned, instead of a conditional mean-based (estimated using ordinary least squares (OLS)) predictive regression model, we use a quantiles-based framework augmented with Bayesian Model Averaging (BMA) to account for model uncertainty. In the process, we are able to predict the entire conditional distribution of home sales growth, which in turn, corresponds to its various regimes, i.e., bear (lower quantiles), normal (median) and bull (upper quantiles) market phases.[3] The remainder of the paper is organized as follows: Section 2 outlines the basics of the quantile BMA (QBMA) model, while Section 3 discusses the data and results, with Section 4 concluding the paper.

2. Methodology

We consider the following model:

$$y_t = x_t'\beta_p + \varepsilon_t \tag{1}$$

where x_t is a n x 1 vector of explanatory variables, and β_p is a vector of coefficients dependent on the p-th quantile of the random error term ε_t which is defined as the value q_p for which $\Pr(\varepsilon_t < q_p) = p$. For standard quantile regression, the distribution of ε_t is left unspecified (i.e., it is a nonparametric distribution F_p), and estimation of β_p is the solution to the following minimization problem:

$$\min_{\beta} \sum_{t=1}^{T} \rho_p(\varepsilon_t), \tag{2}$$

where the loss function is $\rho_p(u) = u(p - I(u < 0))$ and $I(A)$ is an indicator function which takes value one if event A is true, and zero otherwise.

Following Korobilis (2017) we represent the error distribution ε_t using the form:

$$\varepsilon_t = \theta_{z_t} + \tau\sqrt{z_t u_t}, \tag{3}$$

where $z_t \sim Exponential\ (1)$, and u_t is distributed standard normal. In this formulation, $\theta = (1-2p)/p(1-p)$, and $\tau^2 = 2/p(1-p)$, for a given quantile $p \in [0,1]$. Replacing (3) into (1) gives the new quantile regression of the form:

$$y_t = x_t'\beta_p + \theta z_t + \tau\sqrt{z_t u_t}, \tag{4}$$

And the conditional density of y_t given the Exponential variates z_t is Normal and is of the form:

[2] In fact, Strobel et al., (2017) had shown that aggregate macroeconomic uncertainty actually does not affect home sales.

[3] Note that, unlike the Markov-switching and the smooth threshold models, we do not need to specify number of regimes of home sales growth in an ad hoc fashion with the quantiles-based approach. At the same time quantile regression estimates are known to be more robust against outliers in the dependent variable.

$$f(y|\beta(p),z) \propto \left(\prod_{i=1}^{T} z_t^{-\frac{1}{2}}\right) \times exp\left\{-\frac{1}{2}\sum_{i=1}^{T}\frac{\left(y_t - x_t'\beta_p - \theta z_t\right)^2}{\left(\tau\sqrt{z_t}\right)^2}\right\},$$

where $y = (y_1, \dots, y_T)'$ and $z = (z_1, \dots, z_T)'$.

Given this likelihood formulation we can now define prior distributions as follows:

$$\beta_{i,p} \sim N\left(0, \gamma_{i,p}\delta_{i,p}^2\right),$$
$$\delta_{i,p}^{-2} \sim Gamma(a,b),$$
$$\gamma_{i,p} \sim Bernoulli(\pi_0),$$
$$\pi_0 \sim Beta(c,d).$$

Posterior computation is relatively simple, with us needing to sequentially sample from the posteriors of each unknown quantity, namely $\left(\beta_p, z_t, \delta_p^{-2}, \pi_0\right)$ conditional on all the other ones. These conditional posterior can be sampled using the Gibbs sampler algorithm, details of which can be found in Korobilis (2017).

3. Data and Results

Our data set covers the monthly period of 1970:07 to 2017:12, with the start and end date being purely driven by the availability of the real estate uncertainty (*REU*) index developed by Nguyen-Thanh et al., (2018), whose methodological framework for the construction of the *REU* measure follows that of Jurado et al., (2015). Specifically speaking, the macroeconomic uncertainty (*MU*) and financial uncertainty (*FU*) measures of Jurado et al., (2015) and Ludvigson et al., (2019), is the average time-varying variance in the unpredictable component of 134 macroeconomic and 148 financial time-series respectively, i.e., it attempts to capture the average volatility in the shocks to the factors that summarize real and financial conditions.[4] Given this, Nguyen-Thanh et al., (2018) link uncertainty directly to the predictability of 40 housing market variables.[5] The various uncertainty indices are available for three forecasting horizons of one-, three-, and twelve-month-ahead, i.e., $x1$, $x3$, $x12$, with $x = REU, MU, FU$.

Besides using the indices measuring various types of uncertainties, the other variables used include: sales of new and single-family houses, median sale prices of new and single-family houses, 30-year conventional mortgage rate, real disposable personal income (in chained 2009 dollars), civilian unemployment rate, new private housing units authorized by building permits, and new privately owned housing units started. Data on home sales and prices are obtained from the Census Bureau of the US, while the other variables are derived from the FRED database of the Federal Reserve Bank of St. Louis. All the variables are in their seasonally adjusted-form. Following Korobilis (2017), we ensure that all variables are approximately mean-reverting which, in turn, requires us to use growth rates of home sales and prices, and that of real disposable personal income. The data has been summarized in Table A1 in the Appendix of the paper. The non-normality of the home sales growth variable as indicated by the overwhelming rejection of the null hypothesis of Jarque-Bera test (due to negative skewness and excess kurtosis), provides motivation to prefer a quantiles-based approach over a conditional mean (OLS) model. Figure A1 in the Appendix plots the variables used in the analysis.

We estimate three models using the QBMA approach with the growth of home sales (*HSG*) as the dependent variable. In all of these three models, the common predictors are growth rates of prices (*HPR*) and disposable income (*DIG*), then we have the levels of the mortgage rate (*MIR*),

[4] The *MU* and *FU* indices are available for download from: https://www.sydneyludvigson.com/data-and-appendixes.

[5] The *REU* index is downloadable from: https://sites.google.com/site/johannespstrobel/.

unemployment rate (*UNEMP*), building permits (*PERMITS*), and housing starts (*STARTS*). We also include in this list of common predictors, one lag of the home sales growth based on the Bayesian Information Criterion (BIC). In addition to this variable, the first model includes *MU1*, *FU1,* and *REU1*. In the second and third models, we basically replace these three measures of uncertainties with their corresponding values at the forecasting horizons of three- and twelve-month-ahead.

The estimated coefficient of *REU1*, *REU3*, and *REU12* along with their significance for the quantiles range of 0.05 to 0.95 have been reported in Table 1. But it is essential to point out at the onset that, the coefficients corresponding to *REU1*, *REU3*, and *REU12* from the OLS estimation of the three models based on Newey and West (1987) heteroscedasticity and autocorrelation adjusted (HAC) standard errors were found to be negative, but statistically insignificant.[6] Turning back now to the QBMA results, we find that, predictability is particularly strong with *REU1* at both the lower (0.05-0.30) and upper (0.90) quantiles, as well as around the median (0.50 and 0.65). For *REU3* and *REU12*, predictability is stronger at the upper quantiles, i.e., 0.85-0.95, and 0.80, 0.85 and 0.95 respectively, with the lowest quantile of 0.05 also included under *REU3*.[7, 8] Interestingly, while the impact of real estate uncertainties is mostly negative at the lower quantiles and hence, is in line with common intuition, the effect switches sign at the upper quantiles. The positive impact of uncertainty on home sales growth when the housing sales are booming, is possibly an indication that the initial levels of real estate uncertainty from which it has increased were in fact low,[9] and hence optimistic economic agents consider this to be a temporary change. Alternatively, their decision to keep increasing home sales could be due to the fact that they believe real estate uncertainty will increase further in the future, and hence, it is a rational choice to invest more into housing now. This is because, home-buying is considered as a safer asset relative to other liquid financial investments (Aye et al., forthcoming), which in turn are likely to be affected due to the spillover of real estate uncertainty on to the general macroeconomy and financial markets, given the strong correlation across the measures of uncertainties (Nguyen-Thanh et al., 2018). This latter line of reasoning seems to be corroborated by the fact that real-estate uncertainties at medium- and long-horizons positively affect home sales growth, primarily at its upper quantiles. Moreover, real estate uncertainty shocks may influence adversely housing prices but not the quantity of houses sold reflecting that real estate investors are becoming highly selective rather than postponing their investments, especially when the market is performing well. This reasoning is in line with the

[6] While *REU1* and *REU3* were weakly significant at the 10% level, *REU12* was not significant even at the 10% level. Complete details on the OLS estimation results are available upon request from the authors.

[7] Note that, we also applied the bivariate causality-in-quantiles test of Jeong et al., (2012), and found that *REU1*, *REU3*, and *REU12* predicted home sales growth over its entire conditional distribution. But this causality test being based on a bivariate framework is likely to suffer from omitted variables bias, and hence, we cannot put too much reliance on these results, complete details of which are however, available upon request from the authors.

[8] As far as the predictability of the other predictors are concerned, we found that unemployment and macroeconomic uncertainty captures predictive information for home sales growth. While unemployment has statistically significant predictive power consistently for all quantiles, except at some moderately low quantiles and around the median, macroeconomic uncertainty is particularly influential at only lower quantiles of home sales growth. As the focus here is on real estate uncertainty, we have presented the results of the other predictors in Table A2 in the Appendix of the paper.

[9] To validate this point, we analysed the cross-quantilogram (as developed by Han et al., (2016)) between home sales growth and the three real estate measures of uncertainty in turn. Note that, the cross-quantilogram measures quantile dependence and is a model-free test of directional predictability between two time series involved in the system. Based on the cross-quantilogram, we observed that changes in real estate uncertainty from its lower quantiles tend to have a stronger positive impact on home sales growth around the upper end of its conditional distribution, when compared to the same changes of real estate uncertainty from its upper quantiles. Complete details of these results are available upon request from the authors.

Valencia (2017), who finds that real estate loans do not react to uncertainty shocks as strongly as the business and consumer loans. Finally, the lack of predictability around the conditional median of home sales growth, especially from the medium- and long-horizons-based metrics of uncertainty suggests that real estate uncertainty does not have a role to play in predicting home sales growth during its normal phase.[10]

[INSERT TABLE 1]

4. Conclusion

We analyze the role of real estate-specific uncertainty in predicting the conditional distribution of aggregate US home sales growth, by controlling for model uncertainty through Bayesian Model Averaging (BMA). The quantile BMA (QBMA) predictive regression model contains information on price of homes, mortgage rate, real personal disposable income, unemployment rate, building permits authorized and housing starts, macroeconomic and financial uncertainties, besides lagged home sales growth itself. When the model is estimated over the monthly period of 1970:07 to 2017:12, we find that real estate uncertainty has predictive content for home sales growth primarily at the lower and upper conditional quantiles of home sales growth. Our results imply that housing market participants (financial institutions and real estate professionals), can benefit from the information content of real estate uncertainty in designing their investment strategies involving home sales growth, especially during bearish and bullish-regimes of the housing market. Given that the housing market is known to lead the US business cycle (Leamer, 2007, 2015), the ability of real estate uncertainty in predicting the future path of home sales growth, is of paramount importance to policymakers. In particular, our results tend to suggest that real estate uncertainty in general, is likely to reduce home sales growth, especially when the housing market is performing weakly, and this might lead to or deepen the ongoing recession. However, if the housing market is booming, increase in real estate uncertainty by enhancing home sales might delay the recession, that is likely result from the spillover of real estate uncertainty on to macroeconomic and financial uncertainty. Clearly, using this information, policymakers can decide on the size and timing of their policy choices.

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[10] Ludvigson et al., (2019) has developed a narrower index of macroeconomic uncertainty based on 73 variables related to real activity, which they call real uncertainty (*RU*), and is downloadable from the link in Footnote 4. Replacing the *MU* index at horizons of one-, three-, and twelve-month-ahead, with *RU1*, *RU3*, and *RU12*, we re-estimated the QBMA three models. We found that using this sub-index of macroeconomic uncertainty, the coverage of quantiles for which predictability is observed for home sales growth, due to *REU1*, *REU3* and *REU12*, increases, though the pattern of the sign remains the same. These findings clearly suggest that the information content regarding macroeconomic uncertainty in the *MU*s are, not surprisingly, greater than in the *RU*s. Complete details of these results are available upon request from the authors.

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Table 1. Predictive Performance of QBMA Models:

		Quantile (p)																		
Model	β_p	0.05	0.10	0.15	0.20	0.25	0.30	0.35	0.40	0.45	0.50	0.55	0.60	0.65	0.70	0.75	0.80	0.85	0.90	0.95
1	*REU1*	-9.29***	-10.06***	-4.27*	-4.35*	-6.94***	-4.61*	0.15	0.95	-2.12	-8.09***	-1.18	-2.53	-4.90*	0.10	2.70	-0.28	-1.17	7.54***	2.43
2	*REU3*	-6.93***	-1.20	-1.84	-3.97	-3.10	-1.61	-1.12	-3.47	4.28	-4.28	0.08	0.77	2.55	-1.80	-0.60	3.61	4.93*	4.49*	13.40***
3	*REU12*	-1.56	-4.11	0.03	1.12	-1.60	-0.76	-0.69	-2.04	-2.30	-2.22	-3.22	-1.43	-0.31	1.88	4.15	4.98*	4.63*	2.81	13.76***

Note: Entries are coefficients corresponding to real estate uncertainties at horizon 1, 3 and 12, i.e., *REU*1, *REU3* and *REU12* respectively, with ***, and * indicating significance at 1% and 10% levels respectively. Model 1 includes one lag of home sales growth, housing returns, growth of disposable personal income, mortgage interest rate, unemployment rate, housing permits, housing starts, macroeconomic uncertainty (*MU*) and financial uncertainty (*FU*) at horizon 1, i.e., *MU1* and *FU1* respectively, along with *REU1*. Model 2 and 3 has the same variables as Model 1, except that REU1, MU1 and FU1 are replaced by *REU3*, *MU3*, and *FU3*, and *REU12*, *MU12*, and *FU12* respectively.

APPENDIX:

Table A1. Summary Statistics:

Statistic	*HSG*	*HPR*	*DIG*	*MIR*	*UNEMP*	*PERMITS*	*STARTS*	*MU1*	*FU1*	*REU1*	*MU3*	*FU3*	*REU3*	*MU12*	*FU12*	*REU12*
Mean	0.05	0.47	0.24	8.17	6.32	1393.03	1440.35	0.67	0.91	0.82	0.81	0.95	0.92	0.93	0.99	0.96
Median	0.09	0.69	0.26	7.74	5.90	1412.00	1479.00	0.64	0.88	0.80	0.78	0.93	0.91	0.91	0.99	0.96
Maximum	23.71	12.73	5.61	18.45	10.80	2419.00	2494.00	1.07	1.55	0.98	1.21	1.42	1.06	1.21	1.13	1.02
Minimum	-41.02	-11.02	-5.93	3.35	3.80	513.00	478.00	0.55	0.64	0.73	0.68	0.73	0.84	0.85	0.91	0.92
Std. Dev.	7.22	3.78	0.76	3.15	1.54	417.10	433.75	0.09	0.17	0.05	0.10	0.13	0.05	0.07	0.05	0.03
Skewness	-0.33	-0.09	-0.20	0.81	0.72	-0.05	-0.11	1.59	0.82	0.62	1.61	0.68	0.61	1.74	0.39	0.33
Kurtosis	4.99	3.08	22.07	3.56	2.84	2.43	2.58	5.75	3.47	2.58	5.54	3.12	2.65	5.75	2.48	2.36
Jarque-Bera	104.72	0.95	8639.67	69.24	50.39	7.82	5.34	419.50	68.77	41.21	399.38	44.73	38.39	469.04	21.05	20.26
***p*-value**	0.00	0.62	0.00	0.00	0.00	0.02	0.07	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Observations	570															

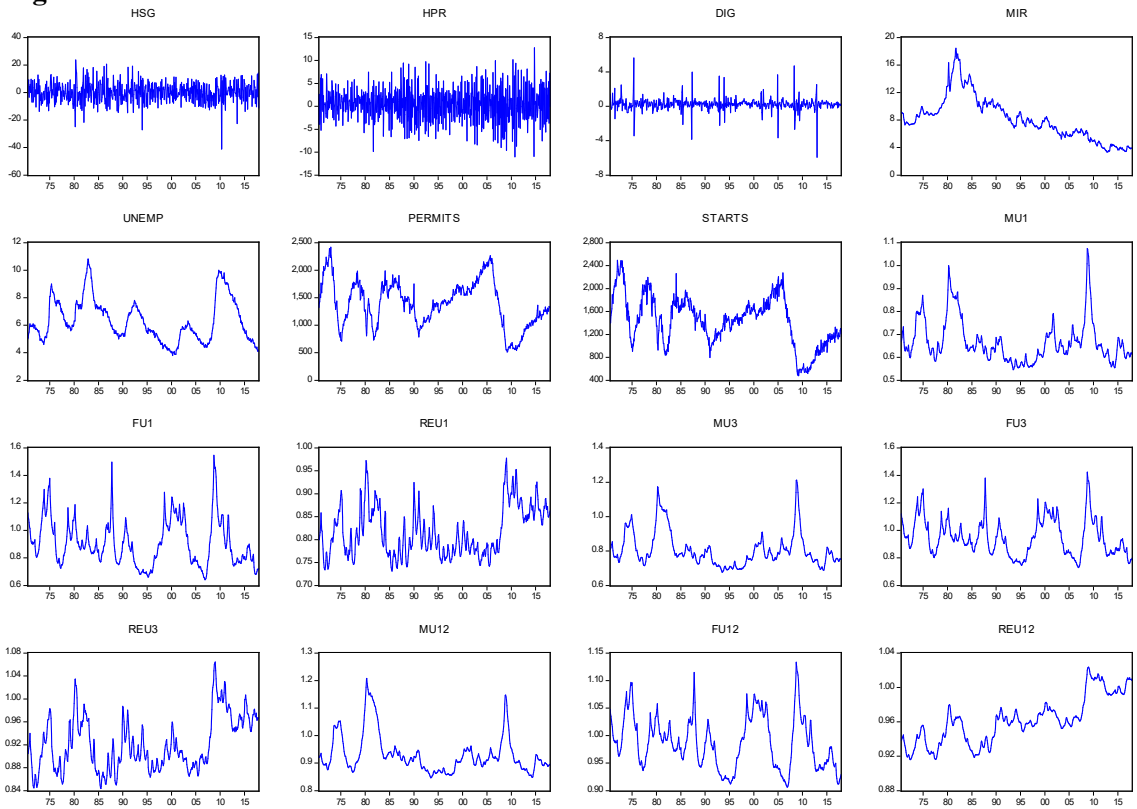
Note: *HSG*: Home sales growth of new and single-family houses; *HPR*: Median sales price returns of new and single-family houses; *DIG*: Real personal disposable income growth; *MIR*: 30-year conventional mortgage interest rate; *UNEMP*: Civilian unemployment rate; *PERMITS*: New private housing units authorized by building permits; *STARTS*: New privately owned housing units started; *MU1(3)[12]*: Macroeconomic uncertainty at forecast horizon of one-, three-, and twelve-month-ahead; *FU1(3)[12]*: Financial uncertainty at forecast horizon of one-, three-, and twelve-month-ahead; *REU1(3)[12]*: Real estate uncertainty at forecast horizon of one-, three-, and twelve-month-ahead; Std. Dev. stands for standard deviation, while probability is the *p*-value for the Jarque-Bera test, with the null hypothesis of normality.

Table A2. Predictive Performance of other Predictors in the QBMA Models:

	Quantile (p)																		
β_p	0.05	0.10	0.15	0.20	0.25	0.30	0.35	0.40	0.45	0.50	0.55	0.60	0.65	0.70	0.75	0.80	0.85	0.90	0.95
Panel A : Model 1																			
HSG(-1)	-0.16***	-0.20***	-0.16***	-0.17***	-0.16***	-0.27***	-0.20***	-0.18***	-0.21***	-0.19***	-0.15***	-0.26***	-0.23***	-0.19***	-0.20***	-0.23***	-0.25***	-0.20***	-0.18***
HPR	0.05	0.04	0.00	0.01	-0.04	-0.06	-0.14	0.06	-0.06	-0.01	0.09	-0.06	0.04	0.07	-0.02	0.02	-0.08	0.18*	0.16
DIG	-0.32	-0.32	-0.22	-0.18	-0.14	-0.32	0.75	-0.41	-0.70	-0.13	-1.07**	-0.24	-0.32	-0.36	-0.10	0.03	-1.45**	-0.95*	-0.48
UNEMP	0.54*	0.59**	0.60**	0.51*	0.38	0.46	0.19	0.65**	0.65**	0.80***	0.19	0.70**	0.89***	0.49*	1.12***	0.60**	1.10***	1.59***	1.01***
STARTS	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.01***
PERMITS	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01***
MIR	-0.12	0.03	0.00	0.05	0.07	-0.05	0.06	-0.01	-0.06	-0.01	0.04	-0.04	-0.09	0.07	-0.10	-0.05	-0.10	-0.03	0.19
FU1	-2.28	1.54	0.53	2.17	0.69	-2.40	1.50	0.02	0.61	0.89	-2.46	1.94	1.78	-0.89	-0.52	-0.89	3.75**	0.70	4.31**
MU1	0.20	-7.70***	-6.51**	-8.49***	-5.86**	0.77	-3.45	-7.33***	-6.50**	-5.14**	-2.78	-2.56	-2.61	-3.47	0.19	-4.01	-2.14	2.43	-2.77
Panel B : Model 2																			
HSG(-1)	-0.21**	-0.17**	-0.18**	-0.17**	-0.19**	-0.21**	-0.18**	-0.22***	-0.26***	-0.20**	-0.19**	-0.19**	-0.18**	-0.17**	-0.19**	-0.24***	-0.35***	-0.10	-0.24***
HPR	-0.05	0.03	0.06	0.06	0.02	0.06	0.03	0.04	0.18	0.02	0.06	-0.04	0.07	0.14	-0.02	0.00	0.17	-0.02	0.01
DIG	-0.27	-0.53	-0.23	-0.31	-0.29	-0.25	-0.35	-0.36	-0.30	-0.31	-0.25	-0.61	-0.39	-0.31	-0.13	0.37	-0.34	-1.29*	0.53
UNEMP	0.61	0.57	0.56	0.71*	0.68*	0.71*	0.47	0.76*	0.69*	0.68*	0.41	0.69*	0.88**	0.70*	0.86**	0.79**	0.83**	0.83**	2.29***
STARTS	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.01
PERMITS	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.02***
MIR	-0.17	0.02	0.01	-0.02	0.04	-0.15	0.04	0.05	0.12	-0.03	0.02	-0.01	0.02	-0.08	-0.09	-0.11	-0.21	-0.06	-0.14
FU3	-3.16	-1.16	-1.86	-0.20	4.28*	-0.20	0.91	-0.42	-2.83	0.17	0.12	2.41	-1.14	-0.96	-0.45	0.67	5.62**	2.09	4.79**
MU3	-4.96*	-5.24*	-3.46	-5.97**	-9.32***	-2.21	-5.62**	-4.33	-9.59***	-4.92*	-5.86**	-4.63*	-2.06	-3.25	-4.69*	0.11	0.28	-0.35	5.76**
Panel C : Model 3																			
HSG(-1)	-0.19***	-0.18***	-0.20***	-0.15*	-0.21***	-0.20***	-0.12**	-0.16***	-0.19***	-0.17***	-0.16***	-0.16***	-0.14**	-0.15***	-0.21***	-0.23***	-0.21***	-0.21***	-0.16***
HPR	0.04	-0.05	0.06	-0.03	0.06	0.02	0.02	-0.01	0.02	0.05	0.04	0.04	0.06	0.05	-0.07	0.13	0.09	0.08	0.06
DIG	-0.18	-0.53	-0.31	-0.44	-0.13	-0.69	-0.36	-0.50	-0.27	-0.19	0.12	-0.32	-0.54	0.11	-0.29	0.91*	-0.06	-0.68	-0.98*
UNEMP	0.55*	0.73**	0.65**	0.56*	0.71**	0.37	0.38	0.79***	0.59**	0.50*	0.88***	0.43	0.69**	0.40	0.88***	0.95***	0.73**	0.78***	0.72**
STARTS	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
PERMITS	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01*	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
MIR	0.09	-0.09	0.05	-0.03	0.11	0.00	0.02	-0.12	-0.01	0.01	0.10	-0.02	-0.04	-0.17	0.00	-0.30*	-0.10	0.06	0.05
FU12	5.27**	0.99	3.54	-1.79	-1.63	3.68	0.38	-2.64	3.03	3.57	-2.40	3.81	1.59	-0.46	1.93	4.88*	2.64	5.46**	6.45**
MU12	-11.40***	-6.19**	-7.59***	-3.99	-10.39***	-7.06***	-6.01**	-1.03	-8.00***	-8.75***	-3.49	-7.10***	-5.38**	-4.41*	-5.81**	2.83	-1.91	1.00	3.98

Note: See Notes to Table 1 and Table A1. Entries are coefficients corresponding to each predictors, with ***, ** and * indicating significance at 1%, 5% and 10% levels respectively.

Figure A1. Data Plot:



Note: See Notes to Table A1.