University of Pretoria
Department of Economics Working Paper Series

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Working Paper: 2017-57
August 2017

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Abstract

This paper examines the spill over effect of economic uncertainty on the duration probability of housing market booms, busts and normal times of 12 OECD countries. Quarterly data from 1985 to 2012 were used. Based on a discrete-time duration (hazard) model, we find that the probability of exiting housing market busts increases with higher economic uncertainty in a statistically significant fashion. Uncertainty, however, is not found to influence the likelihood of leaving booms and normal times. Our results tend to suggest that housing serves as possible hedge against uncertainty.

Keywords: Housing Market Cycles, Uncertainty, Hazard Model.

JEL Codes: C41, E32, E51, E52, R31.

1. Introduction

The global economic and financial crisis from 2007 to 2009 which basically had its root in the housing sector has heightened interest in this sector among researchers, investors, policy makers and other stakeholders. Real estate is the most prone to booms and busts among the financial assets. This may be due to positive demand shocks, inelastic and lagging supply that leads to price increases which with adaptive expectations can become self-fulfilling (Wachter, 2011). The consequences of boom-bust cycles of the housing market can be grievous. Booms are usually associated with fast credit growth and sharp upsurges in leverage. However, as bust sets in, debt overhang and deleveraging can create downward spirals by threatening financial and macroeconomic stability (Crowe et al., 2012). The association between real estate boom-busts and economic activity extends beyond financial crises, to normal times, hence, in most advanced economies, house price cycles tend to lead credit and business cycles (Igan et al., 2009). Post war recessions in the US, for instance has

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been associated with shocks in the housing sector, given that as Leamer (2007) noted eight out of ten recessions were preceded by the housing sector shocks.

Since housing price shocks are likely to attract the attention of policy makers, it is not unusual to attribute fluctuations in the housing market to increased policy uncertainty (Su et al, 2016). Uncertainty about economic policy could deter investment decisions in the real estate market given that it can reduce demand for capital, and hence affect housing returns (Calcagnini and Saltari, 2000; Hirata et al. 2013; Burnside et al. forthcoming). It is also argued that the cost of financing housing projects could go up due to increases in the equity premium caused by increased political uncertainty (Pastor and Veronesi, 2013). This can consequently affect a nation's welfare and macroeconomic conditions. Furthermore, high uncertainty tends to increase housing price volatility and hence alter the risk-return properties of property investment (André et al., forthcoming). These above set of issues point to the crucial role of the housing sector to the macro economy and the need to examine empirically its relationship with economic uncertainty. This is essentially the focus of this study.

Uncertainty is a latent variable, but, in order to quantify the impact of uncertainty on the macroeconomy, understandably, one requires ways to measure uncertainty. In this regard, there are primarily three broad approaches to quantify uncertainty, besides implied-volatility indices associated with financial market uncertainty (popularly called the VIX). They can be categorized as: news-based approaches; estimates recovered from of various types of small and large-scale structural models related to macroeconomics and finance, and measures of uncertainty based on forecaster disagreement (see for example, Pierdzioch and Gupta (2017) for a detailed discussion). However, the news-based measure of uncertainty (called the economic policy uncertainty index; EPU) of Baker et al., (2016), has gained tremendous popularity in empirical applications, primarily due to two reasons: (a) The measure does not require any complicated estimation of a large-scale model to generate it in the first place, and hence, is not model-specific, and; (2) While, the other measures of uncertainties, are also available publicly like the EPU, their coverage is primarily restricted to the US. Since our paper is a cross-country study involving 12 economies, we rely on EPU as our measure of uncertainty to ensure a degree of homogeneity across the economies. The main idea behind this approach is to perform searches of newspapers for terms related to economic and policy uncertainty, and to use the results of this search to construct measures of uncertainty across countries.

Although there are a large number of studies that have investigated the link between EPU and real economic activity (e.g. Bloom, 2009; Colombo, 2013; Jones and Olson, 2013; Mumtaz and Zanetti, 2013; Karnizova and Li, 2014; Jurado et al., 2015; Balcilar et al., 2017; Mumtaz and Theodoridis, 2017, 2017, amongst others), only a few studies have examined the impact of economic uncertainty on the housing market.

Sum and Brown (2012) examine the effect of EPU on the performance of the real estate sector proxied by Real Estate Investment Trust (REIT) returns in the United States. Results based on VAR estimated with monthly data from 1985 to 2011 show no significant causal relationship between EPU and the real estate sector.

Ajmi et al. (2014) show the existence of a two-way transmission channel between US-listed REITs conditional volatility and macroeconomic uncertainty based on data from 4th January 1999 to 28th June, 2013 and variance causality test. Antonakakis et al. (2015) investigate the relationship between housing market returns and EPU in the United States. Results based on Dynamic Conditional Correlation Generalized Autoregessive Conditional Heteroskedastic (DCC-GARCH) model show that the correlation between EPU and real housing market returns is consistently negative, but with magnitude which varies greatly over time reaching its peak during the latest financial crisis. Also Antonanakis et al. (2016) examine volatility spillovers between macroeconomic variables, EPU and the stock and housing markets. Using a VAR-based approach they find evidence of time-varying volatility spillovers from EPU to real housing returns, the stock market and the macro economy.

Su et al. (2016) examine the causal relationship between EPU and the housing returns in Germany. Using a bootstrap rolling window causality test, find no evidence in support of the EPU on housing returns and they explained this is due to the stability of the real estate market in Germany. El Montasser et al. (2016), analysed the causal relationship between EPU and real house prices in seven advanced economies namely Canada, France, Germany, Italy, Spain, UK, and US. Using a bootstrap panel VAR and quarterly data from 2001 to 2013, they find bi-directional causality for France and Spain, but only unidirectional causality for the remaining countries. André et al. (forthcoming) investigate the predictive ability of EPU for real housing returns in US using monthly data from 1953:1-2014:2 and a *k*-th order non-parametric Granger causality test. Their result shows that EPU predicts both real housing returns and its volatility.

Christou et al. (forthcoming) investigate the out-of-sample forecasting power of EPU for housing returns in ten OECD countries namely Canada, France, Germany, Italy, Japan, The Netherlands, South Korea, Spain, UK, and US. Results based on quarterly data from 2003 to 2014 and variants of panel VAR models show that EPU helps in predicting housing returns. Akinsomi et al., (2016), also indicates a similar role for EPU in forecasting US REITs. Chow et al. (forthcoming) analyse the causal relationship between EPU and housing market returns in China and India using linear and nonlinear panel and time series models. Although the nature of causality differs depending on the model used, in all cases where unidirectional causality was found, it ran from EPU to housing returns.

As can be seen from the above analysis, the focus has primarily been on predicting movements (returns and volatility) in housing market based on the role of uncertainty as captured by the EPU. We intend to contribute to this line of research by investigating the effect of EPU on the housing market cycle. We consider the effect of uncertainty during normal, boom and bust periods using a hazard model for the first time in the literature involving the housing market and EPU for multiple (12) Organisation for Economic Co-Operation and Development (OECD) countries.

The rest of the paper is organized as follows: section two presents the empirical model used. Section three discusses the data. Results are presented and discussed in section four, with section five concluding the paper.

2. Empirical model

The methodology will follow the standard characterization of the hazard model in discrete-time form similar to Agnello et al. (2017).[1] The authors construct a discrete-time duration model with a Weibull specification for the baseline hazard function. We will only summarize Agnello et al. (2017) in what follows but a thorough discussion of the setup of the model can be found in their paper.

The proportional hazards model is defined as:

$$h(t,x) = h_0(t)\exp(\beta'\mathbf{X}) \tag{1}$$

[1] Agnello et al. (2017) also estimate a continuous-time duration model. We are, however, not able to estimate the continuous-time model precisely due to the loss of observations when we focus only on countries with uncertainty data.

where $h_0(t)$ is the baseline hazard function and captures the duration dependence while $\mathbf{X}$ is a vector of time-invariant determinants (discussed below). The baseline hazard has common population units so $h(t,x)$ depends proportionately on $\exp(\beta'\mathbf{X})$ (c.f, Wooldridge (2010)). The baseline hazard function is parameterized using the Weibull distribution and the hazard function of the baseline becomes

$$h_0(t) = \gamma p t^{p-1} \tag{2}$$

where the variables γ is constant and positive, and $p > 0$. Agnello et al. (2017) note that p will represent the duration dependence and $p > 1$ indicates positive dependence while $p < 1$ represents negative dependence.[2]

Agnello et al. (2017) notes that housing booms, busts, and normal times are continuous processes but data is typically discrete which leads them to consider the discrete-time duration model of Prentice and Gloeckler (1978). Extending the continuous-time model to the discrete-time model allow for the inclusion of covariates that vary with time. The proportional hazard model for the discrete-time case is:

$$P_{it} = Pr[T_i = t | T_i > t, x_{it}] = 1 - exp[-exp(\theta_t + \beta' X_{it})] \tag{3}$$

where T_i an indicator for the end of the event an x_{it} are the time-varying explanatory variables. The variable θ_t is logarithm of the baseline hazard hazard function like equation (2) but in the discrete-time case. Agnello et al. (2007) notes that this discrete-time hazard proportional function is equivalent to the complementary log-log and the authors choose the Weibull to represent the baseline hazard function.

The log-likelihood function for the discrete-time duration model is

$$\ln L(t_i | x_i) = \sum_{i=1}^{n} \sum_{j=1}^{t_i} y_{it} \ln\left(\frac{P_{ij}}{1 - P_{ij}}\right) + \sum_{i=1}^{n} \sum_{j=1}^{t_i} \ln(1 - P_{ij}) \tag{4}$$

where y_{it} is an indicator variable equal to 1 for a boom, bust, or normal time in the housing market at t and P_{it} is the discrete-time proportional hazard function. Following Agnello et al. (2007), we alternatively smooth the baseline hazard function using piecewise-dummies where

[2] If $p < 1$, then the conditional probability for a particular individual (or country) that an event will end decreases with the length of time or monotonically decreasing.

the hazard rate for each piecewise time grouping is the same within but different across groups.[3] We add the means of the covariates at the year to the estimation to control for unobserved year heterogeneity (Chamberlain-Mundlak Device).

3. Data

The paper used quarterly data spanning from 1985:1 to 2012:2, with the start and end dates being driven purely by data availability on the various variables used. It pertains to twelve (12) OECD countries including Australia, Canada, Chile, France, Germany, Ireland, Italy, Japan, The Netherlands, Spain, Sweden, United Kingdom and United States. The main variables of interest are the real housing price and the log of EPU (*luncertainty*). The other control variables included, following the literature on housing (Agnello and Schuknecht, 2011; Taylor, 2007; Agnello et al., 2017; Agnello et al., forthcoming) are: *dl_rgdp.q*: which is the growth rate real GDP capturing the income transmission channel; *dl_credit.q*: growth rate of domestic credit to the private sector capturing the credit channel; *lend_rate*: log of lending rate; *oil_pr*: the oil price for each individual country capturing the oil transmission channel; *eur*: dummy variable for countries in Europe included to test whether there are significant differences in the duration of housing booms/busts in European countries relative to non-European countries. All data were obtained from the same source as Agnello et al. (2017), with exception of the economic policy uncertainty which were obtained from www.policyuncertainty.com. Baker et al., (2016) perform month-by-month searches of leading newspapers in each country, for terms in all three categories pertaining to uncertainty, the economy and policy. Since the uncertainty data is monthly, while our remaining variables are quarterly, EPU is converted into its quarterly frequency by taking averages over three-months comprising a quarter. Following Agnello et al. (2017), the real housing price indices and the data for the individual-country oil prices are provided by the OECD. Further, as in Agnello et al. (2017), the time series of the real GDP growth rate, the lending interest rate, and the growth rate of domestic credit to the private sector are obtained from the International Financial Statistics (IFS) of the International Monetary Fund (IMF).

The data used in the duration analysis are organized in spells, which represents the duration of a boom, a bust or a normal period. This is captured as *ln d*, that is the natural log of time, *t*. The episodes of booms and busts in the housing markets are identified using a simple

[3] The piecewise results, which are available upon request from the authors, are qualitatively the same to those reported in Table 1.

statistical approach as in Agnello et al., (2017). Given the quarterly frequency of our data, we start by smoothing the logarithm of the real housing price series, Y_t, to avoid capturing undesirable high frequency movements by computing their centered-moving average ($\overline{Y}_t = \sum_{j=-n}^{n} Y_{t+j} / (2n)$). Then an 'upturn' ('downturn') defined as an interval of time during which the change in the centered-moving average ($\Delta\overline{Y}_t$) is positive (negative) for all t. A peak or trough is the last period within an upturn and a downturn, respectively. The price change in a run-up (downturn) is required to exceed (fall below) a minimum (maximum) bound before it can be labeled as a boom (bust). Formally, a housing boom (bust) is defined as an (a) upturn (downturn) such that $\overline{Y}_T - \overline{Y}_{T-L} > z\,(\overline{Y}_T - \overline{Y}_{T-L} < z)$, where T indicates the peak of the boom or the trough of the bust and L is the duration of the upturn or the downturn. The identification of booms and busts is based on the assumption that $n = 5$ and $z = 0.15$. Given that the housing booms and the housing busts reflect house price misalignments, then we can interpret the normal times as periods during which house prices are in line with their equilibrium values.

4. Result

The scatter diagrams of the (non-negative) housing market cycles and economic policy uncertainty for each individual country is shown in the upper panel of Figure 1. The results suggest that the association between the length of the housing booms and economic policy uncertainty is negative. In contrast, the duration of housing busts and normal times seems to be positively correlated with economic policy uncertainty. The middle and lower panel of Figure 1 plots the non-parametric estimates of the survival functions and hazard rates respectively for the each of the housing type spell. These are basically replications from Agnello et al. (2017), and hence similar results are obtained. Specifically, the hazard rates show that, as each phase of the housing market cycle becomes older, the likelihood that it will end at time t increases and consequently, the survival functions fall gradually for all housing spell types.

[INSERT FIGURE 1 HERE]

Given that it is somewhat difficult to categorically attribute the patterns to economic policy uncertainty, we now statistically examine the relationship using the parametric hazard model. In Table 1, we present the estimates of the discrete-time Weibull (Cloglog) duration model with time-varying controls and economic policy uncertainty (luncertainty) for all housing

event types.[4] The table is broken down into 3 segments: 1) columns (1)-(3) for booms, 2) columns (4)-(6) for busts, and 3) columns (7)-(9) for normal times. For housing event types, the variable *ln d* is the log duration of the event and *P* indicates positive duration dependence which is increasing over time.

For real GDP growth, all coefficients are significant except for housing booms. Higher GDP growth increases the probability of exit from a housing bust and decreases the likelihood of exit during housing booms and normal times. In the case of normal times that reach time *t*, an increase in GDP growth by 1% increases the probability of exit by 63% to 89%. The lending rate is significant for both housing booms and busts, with a higher lending rate increasing the likelihood of exit from each housing event. Credit growth is found to be insignificant across booms, busts and normal times.

We also find a longer duration of the housing booms in the group of the European countries than non-European countries. The converse is the case for housing busts and normal times. In other words, the probability of exiting the housing busts and normal times increases in European countries than non-European countries, hence the duration of these events are shorter in the former. Higher oil prices do not seem to significantly affect the duration of the housing booms, but it significantly decreases the probability of housing busts coming to an end. In general, our results are in line with those of Agnello et al. (2017), who used however, 20 industrialized countries, and did not incorporate the role of uncertainty in their analysis.

The variable log uncertainty and its lags are only significant in the case of housing busts. For columns (4)-(6), luncertainty and its lags increase the probability of exit. The second lag of luncertainty, in the case of housing busts, indicates that higher uncertainty increases the likelihood of leaving the housing bust at time *t*. The hazard rate (odds) of ending the housing busts is much larger than that of ending the housing boom when uncertainty is high. Specifically, an increase in uncertainty by 1% increases the probability of exit by 0.98% in the initial period and 1.3% in (*t+1*). The fact that higher uncertainty enhances the probability of leaving the bust phase might seem a bit counterintuitive. However, we consider this result to be highlighting that fact that housing might be serving as a hedge against uncertainty

[4] We also smooth the baseline hazard function using piecewise-dummies and the results are very similar. The results are available upon request.

during its downward phases. Specifically, when uncertainty increases, and the housing market is in a bust phase, i.e., house prices are relatively lower, investors might want to allocate their portfolios towards housing than any other financial assets, which are, in general, more riskier and affected negatively by higher uncertainty (for a detailed review dealing with the impact of uncertainty on financial markets, see Chuliá et al. (forthcoming) and references cited therein). The higher investment in housing could be due to the fact that it is viewed as a more stable investment, and forward-looking investors expect prices to rise in the future, given that it is already in a bust phase, and hence making their investment profitable. Also, as outlined in the literature on uncertainty and the macroeconomy at the beginning of the paper, higher uncertainty tends to result in expansionary monetary policy, thus reducing credit constraints and making the housing market suitable for buying, especially when prices are already low. Whether it is due to the hedging characteristic of housing against uncertainty or because of lower interest rates, our results tend to imply that higher uncertainty during bust phases increases housing demand and hence, the probability of exiting such phases. The line of reasoning that housing serves as a hedge against uncertainty is also somewhat vindicated economically (though not statistically) by our results that, higher uncertainty during the normal periods and booms, reduces the probability of exiting these phases, as agents in the housing market still continue to believe in the stability of such an investment in the wake of an uncertain environment.

[INSERT TABLE 1 HERE]

5. Conclusion

This paper investigates the spill over effect of economic policy uncertainty on housing market cycles using quarterly data of 12 OECD countries. Using discrete-time duration model, we find that the probability of ending housing market busts significantly increases with higher economic policy uncertainty. This means that the duration of a housing bust is shorter with increasing uncertainty, suggesting that housing seems to serve as a hedge against economic uncertainty. This results in higher housing demand conditional on the fact that housing prices are already low, and in turn, results in higher probability of exiting bust phases in the wake of higher economic uncertainty.

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Figure 1: Scatter diagrams, survival functions and hazard rates of the duration of housing cycles

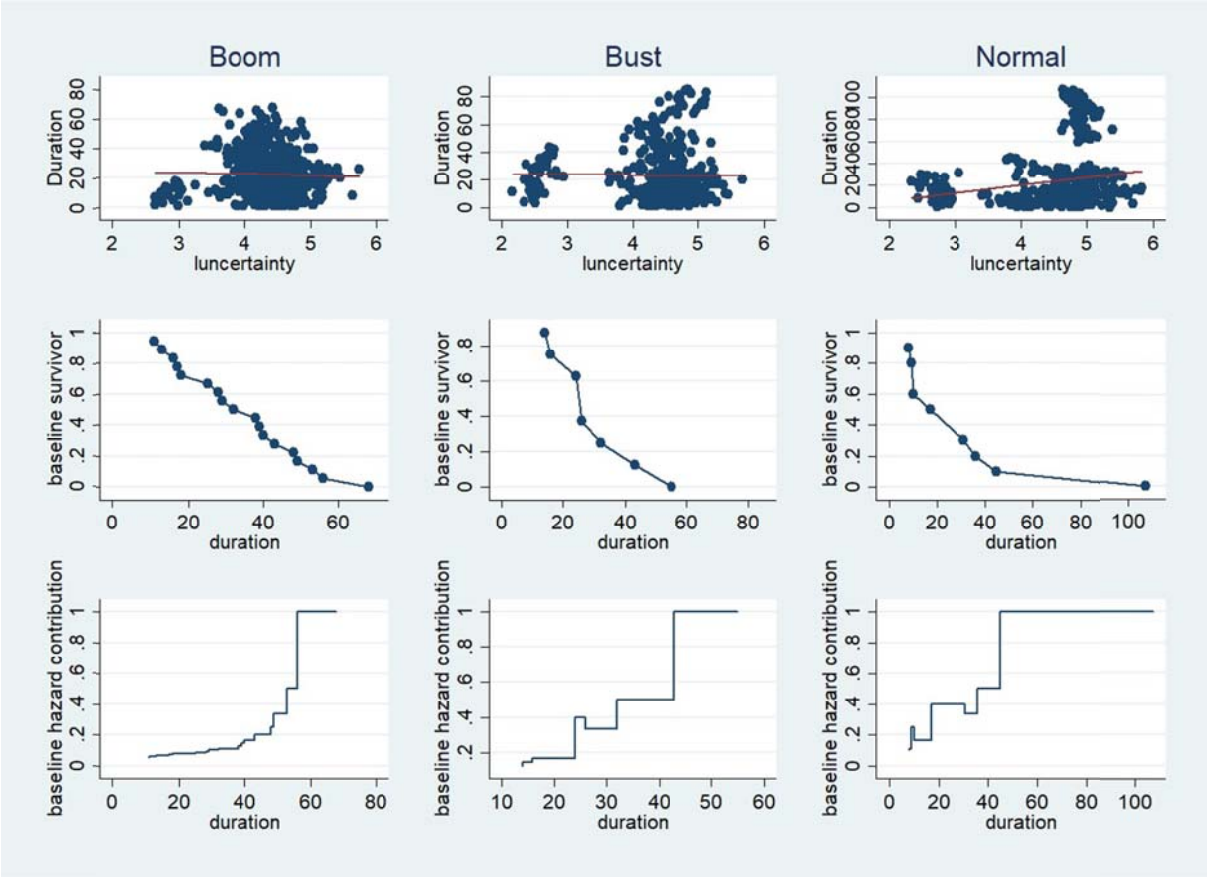

Table 1: Discrete-time Cloglog Results

	Boom			Bust			Normal		
ln d	3.337*	3.596**	3.415*	9.403***	9.747***	10.263***	2.271***	2.012***	1.799***
	(1.919)	(1.810)	(1.868)	(2.505)	(2.826)	(2.168)	(0.681)	(0.491)	(0.541)
L.dl rgdp q	-0.320	-0.320	-0.336	2.111***	2.085**	2.124***	0.494*	0.610*	0.635*
	(0.213)	(0.195)	(0.226)	(0.724)	(0.848)	(0.732)	(0.284)	(0.332)	(0.339)
L.dl cred q	0.066	0.067	0.066	-0.101	-0.147	-0.132	-0.063	-0.081	-0.130
	(0.042)	(0.042)	(0.042)	(0.157)	(0.168)	(0.155)	(0.263)	(0.284)	(0.295)
L.lend rate	0.915**	0.968***	0.955**	0.306**	0.248*	0.272	0.304	0.393	0.541
	(0.383)	(0.360)	(0.388)	(0.144)	(0.134)	(0.175)	(0.355)	(0.348)	(0.468)
eur	-2.023**	-2.054**	-2.002**	4.066**	4.079**	4.157**	5.450***	4.414***	3.213***
	(0.909)	(0.907)	(0.914)	(1.731)	(1.740)	(1.654)	(1.964)	(1.351)	(1.175)
oil pr	0.195	0.140	0.147	-2.396***	-2.449***	-2.449***	-0.041	-0.193	-0.310
	(0.174)	(0.234)	(0.173)	(0.482)	(0.562)	(0.465)	(0.317)	(0.382)	(0.316)
luncertainty	-0.018			0.981*			2.308		
	(1.348)			(0.561)			(1.544)		
L.luncertainty		-0.740			1.309*			1.027	
		(1.428)			(0.771)			(1.129)	
L2.luncertainty			-0.590			1.540***			-0.145
			(1.757)			(0.457)			(1.161)
P	4.34	4.60	4.42	10.40	10.75	11.26	3.27	3.01	2.80
Year Means	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Log Lik	-32.246	-31.981	-31.765	-18.446	-18.125	-17.274	-25.564	-27.091	-27.619
AIC	88.492	87.963	87.529	52.892	52.249	50.547	69.128	72.183	73.238
BIC	137.615	137.085	136.488	83.476	82.834	81.060	103.238	106.292	107.292
Obs	443	443	437	338	338	335	327	327	325

Note: Clustered standard errors in parentheses; $^{*}p < .10$, $^{**}p < .05$, $^{***}p < .01$.