2. CONFIDENCE VS. UNCERTAINTY: AN EXPLANATION OF HOUSING PRICES IN THE OLD EU MEMBER STATES[1]

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Abstract

This paper aims to shed some light on the soft data determinants of real housing prices in 14 developed European economies. Acknowledging heterogeneity and interdependence between the national real estate markets and their determinants, we apply a heterogeneous panel Granger causality test which allows for cross-sectional dependence. We discriminate between two groups of survey-based indicators: economic confidence and uncertainty. Results show that confidence exhibits a very strong short-run impact on house prices in the European economies. Uncertainty indicators, on the other hand, are mostly not significant.

Our findings identify the construction sector confidence indicator as the relative "winner" of this empirical analysis, suggesting that the forecasting models of real housing prices should be augmented by the stated indicator.

Keywords: housing prices, real estate market, business and consumer surveys, economic uncertainty, economic policy uncertainty index

JEL Classification: C23, E03, E32, R30

1. Introduction

The US housing market bubble and the resulting global financial crisis (Damianov and Elsayed, 2018) emphasized the importance of understanding the formation process of the real estate prices. A number of recent studies show that "hard" macroeconomic and financial variables cannot fully explain housing prices (Škrabić Perić *et al*., 2022, Zhu *et al*., 2017; Algieri, 2013). This paper accounts for that by putting soft data into the focus, and tries to elucidate the phenomenon of housing prices from a survey-based perspective. To be specific, we test for Granger causality between house prices and seven different soft indicators in 14 developed European countries (Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Portugal, Spain, Sweden, and the United

1 **Acknowledgement:** *This work has been fully supported by the Croatian Science Foundation under the projects IP-2018-01-4189 and IP-2019-04-7816.*

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Kingdom). Only few empirical studies attempted to model the psychological component of the real estate prices. These studies mostly focused on *global* uncertainty, finding a negative link between it and housing prices (Hirata *et al*., 2012; Cerutti *et al*., 2017; Banti and Phylaktis, 2017).

Empirical verifications of confidence-driven real estate prices have also been rather scarce. Bauer (2017), Lambertini *et al*. (2013) and Gupta (2020) document a significant positive effect of various expectations on the housing markets.

As Shiller (2007, p.13) points out, "*just because we cannot precisely quantify and prove such an effect does not mean we should revert back to a null hypothesis that the changing psychology has no effect on home prices*". This paper aims to fill in that particular niche, and quantify the extent to which housing prices are governed by psychology itself. Since market participants have insufficient information about prices and transactions, they may base investment decisions on their uncertainty assessments and expectations of market fundamentals (Bade, 2016). The aim of this paper is to scrutinize to what extent this is true.

We add to the existing literature in several aspects. Our first contribution is a meticulous segregation of two classes of soft drivers of housing prices. The first class comprises three different confidence indicators, while the second class consists of four economic uncertainty measures. Such analysis enables us to establish which of these two indicator classes adds the most to our understanding of real housing prices. Our second contribution is purely methodological. Recent research has devoted a lot of attention to international co-movements of housing prices. To that end, we utilize a panel Granger causality test with cross-sectional dependence. Some studies try to assess the observed cross-dependence by including global variables in the model (Adam *et al*., 2012; Banti and Phylaktis, 2017). However, this approach treats the influence of global factors equally for all countries. Contradicting that, we estimate cross-sectional dependence for each pair of the observed economies. Considering the observed heterogeneity of real estate markets (Algieri, 2013; Cesa-Bianchi *et al*., 2015), our preferred *heterogeneous* panel Granger causality test seems to be a viable route. As our third contribution, we examine the impact of macroeconomic and financial determinants of housing prices. Our results show that confidence in the construction sector is more closely tied to house prices than any of the fundamentals. Economic confidence represents a separate transmission channel to housing prices (independent of fundamental economic tendencies).

2. Literature Review

The main hypothesis of this paper is that soft factors add to our understanding of the housing boom and bust cycles. This section presents the theoretical foundations for such a hypothesis, along with its rare empirical verifications. Psychological drivers of the national economy are widely recognized in literature ever since Keynes and his *animal spirits* syntagm. Modern macroeconomic models recognize two classes of soft indicators in that sense. The first one relates to the average level of sentiment related to the perceptions/expectations of the current state of the economy. This class of indicators is quantified following the European Commission's Joint Harmonized European Business and Consumer Surveys (BCS), and is related to the expectation (first moment of the probability distribution). The second class of soft indicators relates to the variance as the second moment of the distribution. Therefore, it comprises the uncertainty indicators. The sole term *uncertainty* has been coined by Knight (1921) to capture the inability of economic agents to assess future events or their probability distributions. Quantitative uncertainty indicators have become highly popular after the 2008 crisis, when many authors highlighted that the intensity of the global crisis was a direct consequence of economic uncertainty (*e.g.*, Bachmann *et al*., 2013; Baker *et al*., 2016; Gu *et al*., 2018).

It would perhaps seem reasonable to assume that a high level of uncertainty implies a low level of confidence or, in other words, that an adequately low level of economic sentiment activates the exact same mechanisms as uncertainty. However, recent studies show that confidence and uncertainty form two utterly separate transmission mechanisms from economic agents to the real sector activity (Škrabić Perić and Sorić, 2018).

The notion of real estate prices driven (at least to some extent) by psychological factor is introduced by Guttentag (1986) and Herring and Wachter (1999). They use the psychological behavior of investors, creditors and regulators to explain how macroeconomic stability and real estate growth affect the reduction in risk premium and bank capital. Their theory explains how investors and creditors often underestimate the business risk due to high expectations of future housing prices. Additional psychological causes of real estate cycles can be found in the herd behavior of investors and creditors (Scharfstein and Stein, 1990; Hott, 2012). Salzman and Zwinkels (2017) underline how, insofar, homebuyers underestimate the importance of psychology in making housing decisions, although economic theories and empirical studies do recognize their significance.

In line with the described theories that explain the role of psychological factors in the formulation of real estate decisions, we assumed that excessively optimistic or overly pessimistic expectations, just as well as high uncertainty regarding future market tendencies, might shift the housing prices far from the fundamentals. However, only a small number of existing empirical studies make the effort to model the psychological components associated with real estate prices. For example, Hirata *et al.* (2012) and Banti and Phylaktis (2017) use global financial market indicators (volatility of the G7 share index and the VIX index) as proxy variables for investors' uncertainty assessments. Their results show that uncertainty might have an impact on real estate prices. Hirata *et al*. (2012) find that global uncertainty shocks seem to be an important determinant of international house prices. Cerutti *et al.* (2017) and Banti and Phylaktis (2017) find a negative and weak link between housing prices and the VIX index as a measure of global risk aversion. The above-mentioned empirical results show that global uncertainty indicators cannot fully explain the differences between national components in the housing prices. Namely, most decisions that shape the supply and demand on local real estate markets are made by the consumers and local investors who are to a large extent not fully informed about the movement of global macroeconomic and financial indicators. Therefore, the global indicators are not crucial in making their micro financial decisions. Consequently, we believe that examining national confidence and uncertainty indicators can better explain the housing prices trends in the national markets.

Regarding the empirical verifications of the confidence-driven real estate prices, one should certainly mention Bauer (2017), who uses the expectations component from the long-term interest rates (representing investors' forecasts of future policy rates) as predictor of housing prices crisis. He finds the expectations component to be a much more important predictor of housing prices than the term structure risk premium. Miles (2009) finds evidence of a negative effect of uncertainty on housing starts in the USA. However, its effect on housing completions is not detected. Lambertini *et al*. (2013) examine the role of consumers' expectations of rising housing prices in the US real estate market. They find that the highlighted link is the strongest in the growth phases of business cycles, when agents' expectations account for as much as around 50% of the one year ahead forecast-error variance of housing prices, consumption and housing investment, and about 40% of mortgage credit.

To summarize, empirical studies of the soft data determinants of housing prices are rather scarce and quite methodologically diverse in terms of defyining and quantifying price expectations and uncertainty. This paper aims to scrutinize a wide set of different soft (confidence and uncertainty) drivers of housing prices, and quantify the extent to which the changes in housing prices can be attributed to these indicators.

3. Data and Methodology

This paper differentiates between confidence and uncertainty as determinants of housing prices. Within the first class of variables, we assess three different confidence indicators, all of them being quantified from the BCS.

We first analyze the Consumer Confidence Indicator (CCI). Its intention is to quantify the psychological sentiment on the demand side of the housing market. The Construction Confidence Indicator (CrCI), on the other hand, is a measure of sentiment on the supply side of the housing market (managers in the construction sector). The European Commission also publishes an economy-wide confidence indicator, the Economic Sentiment Index (ESI).

We also assess four separate uncertainty indicators. The first one is the average share of "*don't know*" responses to question 14 (propensity of buying or building a home in the next 12 months) and question 15 (likelihood of spending on home improvements or renovations over the next 12 months) in Consumer Survey. This indicator (DN hereinafter) reflects the agents' impossibility of estimating probability distributions of future outcomes (uncertainty in the Knight (1921) sense).

The second assessed indicator (EXT) approximates uncertainty as the share of extreme responses to the same BCS questions.[1]

Our third attempt of quantifying uncertainty is based on forecasters' disagreement (Bachmann *et al*., 2013). We concentrate on the fraction of positive responses ($frac_t^+$) and the fraction of negative responses ($frac_t^-$) to questions 14 and 15 in the Consumer Survey:

$$DIS\_IND_t = \sqrt{frac_t^+ + frac_t^- - (frac_t^+ - frac_t^-)^2} \quad (1)$$

The disagreement indicator is calculated for questions 14 and 15 separately. In the following step, both indicators are standardized, averaged and scaled to have a mean of 100 and a standard deviation equal to 10. That way an aggregate disagreement measure (*DIS*) is obtained.

The fourth attempt of capturing uncertainty stems from Baker *et al.* (2016), who search the newspapers' archives by specific combinations of keywords (*e.g.*, *economy*/*economic + uncertainty/uncertain + congress/deficit/legislation*, etc.) to quantify their Economic Policy Uncertainty Index. The index has insofar been introduced in more than 20 countries (source: http://www.policyuncertainty.com). Eight of them are analyzed in this paper (France,

[1] *Proposed answers to question 14 are: a) yes, definitely, b) possibly, c) probably not, d) no, and e) don't know. Possible answers to question 15 are: a) very likely, b) fairly likely, c) not likely, d) not at all likely, and e) don't know. The extreme responses are given through categories a) and e): yes, definitely and no (question 14), and very likely and not at all likely (question 15).*

Germany, Ireland, Italy, Netherlands, Spain, Sweden and the UK), so we also consider this indicator (EPU hereinafter).

Besides the seven soft indicators, additional 13 hard macroeconomic and financial variables are considered. From the Organization for Economic Co-operation and Development we gathered the data on real house prices (RHP), rent from housing markets (RENT), real interest rates (RIR), capital account balance (CAP), unemployment rate (UN), real exchange rate (RER), real share prices (RSP), and the consumer prices index (CPI). Real gross domestic product (RGDP) data is obtained from Eurostat, while global liquidity (GLB), the ratio of private sector credit to GDP (CGDP), and the ratio of household credit to GDP (HCGDP) are collected from the Bank for International Settlements (BIS). The VIX index is obtained from the Chicago Board Options Exchange, while the S&P Global REIT Index (REIT) is obtained from Reuters. The 13 stated control variables are meant to question the robustness of Granger causality test results between real housing prices and the assessed soft indicators.

The observed dataset is unbalanced. The full examined period is 1990: Q1 – 2016: Q4 (for Belgium). However, the period of analysis for other countries depends on data availability, ranging from 1990: Q1 – 2016: Q3 for the Danish data to 2000: Q1 – 2015: Q2 for Austrian house prices data. All variables are seasonally adjusted using the ARIMA X12 method.

To assess the Granger causality between real housing prices and a battery of soft indicators, an adequate panel data estimator is needed. Housing markets unequivocally exhibit heterogeneity and/or cross-sectional dependence (Algieri, 2013; Beltratti and Morana, 2010; Cesa-Bianchi *et al*., 2015). This means that housing prices may react differently to soft indicators (or to other examined variables) across individual economies. Additionally, the literature reveals that the correlation (synchronization) may vary among the housing prices of different countries. For instance, Algieri (2013) indicate that the UK housing market is more correlated with the US than with other European markets. Therefore, the goal of our research is to assess the influence of soft data on the housing price of each developed economy by controlling cross-sectional dependence between countries.

Previous studies of housing price determinants use several different panel data techniques. For example, Dröes and Francke (2017) investigate the relationship between housing prices and turnover for 16 European countries through a VAR panel by using the Generalized Method of Moments (GMM). On the other hand, Cesa-Bianchi *et al*. (2015) investigate the relationship among global liquidity, housing prices and the macroeconomy using the mean group (MG) estimator.

In fact, both mentioned estimators are not adequate for our dataset. GMM is suitable for datasets with a large N and small T, while our dataset comprises a small number of economies and a large number of periods. In such case, GMM estimates become severely biased. Additionally, GMM requires homogenous cross-section units. Yet, the MG estimator assumes cross-sectional heterogeneity, but also cross-sectional independence. To account for one source of cross-sectional dependence, Cesa-Bianchi *et al.* (2015) augment their model by including global variables to control for the common effect of all examined countries. Being aware that global variables can control only for one common (global) source of cross-sectional dependence and considering the possibility that cross-sectional dependence between a particular pair of countries is larger than between some other pairs, this estimator is not adequate for the model analyzed here.

Acknowledging the cross-sectional dependence among world economies, panel data estimators that control for cross-sectional dependence have been developed. One group of estimators, the Common Correlated Effect Mean group Model (CCEMG) (Pesaran, 2006), and extended by Chudik and Pesaran[1] (2015) and Augmented Mean Group model (AMG, proposed by Eberhardt, 2012), allows for both cross-sectional dependence and heterogeneity of slopes. More precisely, they deal with the common factor as the source of cross-sectional dependence. These estimators are focused on the estimation and inference of the mean coefficients. Additionally, both of these estimators are suitable for datasets with moderately large N and T. In our case, N is rather small (14), and T is equal to 108. Therefore, CCEMG and AMG are not adequate for Granger causality testing in the context of this study.

Finally, Seemingly Unrelated Regressions (SUR)[2] (Zellner, 1962) are proposed for datasets with a small number of cross-section units and a large number of periods. At the same time, SUR assumes heterogeneity among countries and cross-sectional dependence. The main attraction of SUR lies in the fact that it allows for the contemporaneous error covariances between countries to be freely estimated[3], in line with our assumption that the cross-sectional dependence can vary between each pair of the hereby-analyzed countries. Across individual economies, housing prices may react differently to soft indicators. To account for both heterogeneity and cross-section dependence, while at the same time acknowledging that our dataset has a small number of cross-section units and a large number of time periods, we opt for the Seemingly Unrelated Regressions (SUR) panel model to investigate whether soft indicators cause housing prices in the Granger sense. Some versions of this estimator are used very often to investigate Granger causality for heterogeneous and cross-sectionally dependent panel datasets (see Kónya (2006) for empirical utilizations).

Additionally, this approach is suitable for calculating the short-term effects of the examined variables. Since soft factors have a strictly short-run effect on housing prices *(Burnside et al*., 2016), this makes the SUR procedure appropriate for the model analyzed here. SUR is a two-step procedure. In the first step, it estimates OLS regressions by countries and calculates cross-sectional dependence between each pair of cross-section units. In the second step, it simultaneously estimates the coefficients for each country, conditional on the observed cross-dependence. This estimator is at least asymptotically more efficient than single-equation OLS estimators. The equation of Granger causality test in the form of SUR estimator can be written as:

$$y_{it} = \alpha_{1i} + \sum_{k=1}^{K} \gamma_{1ik} y_{i,t-k} + \sum_{k=1}^{K} \beta_{1ik} x_{i,t-k} + \varepsilon_{1it}, i = 1,\dots, N,\ t = 1,\dots, T, \quad (2)$$

where: y_{it} is dependent variable (real housing prices) for i-th individual in the period t , $K \in N$ denotes the optimal lag number, $x_{i,t-k}$ is the lagged value of independent variable (one of the seven analyzed psychological indicators), γ_{1ik} is the coefficient of lagged dependent variable, β_{1ik} is the coefficient of lagged independent variable, α_{1i} is the individual-specific effect for each *i*-th individual, while ε_{1it} is the error term. The model assumes cross-sectional dependence ($Cov(\varepsilon_{1it}, \varepsilon_{1jt}) \neq 0$). In a Granger sense, variable X does not cause variable Y for i-th individual if $\beta_{1ik} = 0, \forall k$. X causes Y if $\exists k, \beta_{1ik} \neq 0$.

[1] *Chudik and Pesaran (2015) extend CCEMG to heterogeneous panel data model with lagged dependent variables and or weakly exogenous regressors.*

[2] *A precondition for utilizing the SUR model is that T has to be significantly larger than N, as in our case. Otherwise, it becomes impractical and very often it is not possible to estimate the model.*

[3] *However, this attraction makes it unsuitable for dataset with large N.*

To ensure robust results of Granger causality tests between real housing prices and soft indicators, we augment this bivariate setting by the already established macro determinants of housing prices (as found in Cesa-Bianchi *et al*., 2015; Hirata *et al*., 2012; Bauer, 2017). Previous studies also corroborate that these determinants of housing prices are mutually correlated (Favilukis *et al*., 2012). To avoid problems of multicollinearity and over-parametrization, we follow Favilukis *et al.* (2012) and extend the bivariate case by only one fundamental variable in each iteration of the causality test.

4. Empirical Results

To avoid spurious regression issues, all variables are tested for stationarity[1]. Acknowledging the correlations among national markets, augmented Dickey–Fuller test (Pesaran, 2007) which assumes heterogeneity and cross-sectional dependence is applied to all variables except the global ones. For them, the Augmented Dickey-Fuller test is performed. To ensure stationarity, all I(1) variables are econometrically modelled in first differences: DRHP, DRGDP, DCAP, DCGDP, DUN, DCPI, DHCGDP, DEXT, DDIS, DGLB and DREIT.

Table 1. Unit Root Test Results

Variable	Statistics	p value	Variable	Statistics	p value
RHP	2.79	0.9970	Survey-based indicators		
DRHP	-7.18	0.0000			
RGDP	0.91	0.8190	CCI	-3.25	0.0010
DRGDP	-9.62	0.0000	CrCI	-2.14	0.0160
RIR	-4.07	0.0000	ESI	-4.91	0.0000
CAP	0.62	0.7320	DN	-5.17	0.0000
DCAP	-11.71	0.0000	EXT	0.52	0.6980
CGDP	-1.01	0.1560	DEXT	-17.08	0.0000
DCGDP	-6.95	0.0000	DIS	-1.40	0.0810
UN	0.39	0.6510	DDIS	-16.77	0.0000
DUN	-6.48	0.0000	EPU	-2.25	0.0120
RER	-3.12	0.0010	Global variables		
RSP	-13.39	0.0000	VIX	-3.34	0.0164
CPI	0.79	0.7850	GLB	-1.66	0.4495
DCPI	-8.14	0.0000	DGLB	-3.34	0.0164
RENT	-5.632	0.0000	REIT	-1.726	0.416
HCGDP	-1.284	0.981	DREIT	-6.01	0.00
DHCGDP	-3.417	0.000			

Note: Shaded areas denote variables in first differences.

The next step was to detect the optimal lag order. According to the Schwarz Bayesian Information Criterion for panel data, for each combination of DRHP and sentiment or uncertainty indicator, the optimal lag order is 1. Therefore, we opt for using one lag in the assessed models. Additionally, similar studies that deal with quarterly housing price data (Beltratti and Morana, 2010; Lambertini *et al*., 2013; Cesa-Bianchi *et al*., 2015; Dröes and Francke, 2017) also use one lag.

[1] *We do not use bootstrapped standard errors as Konoya (2006); therefore, we have to ensure stationarity of all variables in our equations.*

For each specification, two diagnostic tests are conducted. We test for cross-sectional dependence with an LM-type test and we formally test for slope homogeneity. Table 2 comprises the results of Granger causality test based on SUR estimaton of equation (2), comprising an individual soft indicator and RHP. The estimated models largely indicate significant cross-sectional dependence and slope heterogeneity, giving support to our utilization of SUR estimator.

Table 2. Granger Causality Test Results (ΔRHP Is the Dependent Variable)

	Confidence indicators			Uncertainty indicators				
Independent variable	CCI	CrCI	ESI	DN	DEXT	DDIS	EPU	VIX
Slope homogeneity test								
χ^2	185.15	107.94	210.89	192.15	200.18	191.07	54.66	181.23
p value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Austria	-0.067**	0.045*	-0.046*	-0.379	0.647	0.004		-0.014
Belgium	0.007	0.023***	0.014*	-0.005	-1.423	-0.004		-0.016
Denmark	-0.003	0.002	-0.010	-0.025	0.773	0.012		-0.01
Finland	-0.01	0.002	0.0004	0.692***	1.959	0.013		0.017
France	0.009	0.002	0.004	-0.253	3.936	-0.013	-0.0003	0.001
Germany	0.013*	0.041***	-0.0001	-0.065*	3.229	0.012	0.007***	-0.004
Greece	0.044***	0.02***	0.075***	-0.239	0.675	0.004		-0.040*
Ireland							0.002	
Italy	0.026***	0.051***	0.029***	-0.041	-4.108**	0.015	-0.003*	0.015
Netherlands	0.032***	0.023***	0.028***	-0.279	3.3	0.016	-0.016***	-0.016
Portugal	0.031***	0.017**	0.024**	0.074	4.774	-0.021		0.017
Spain	0.015	0.017***	0.027**	0.082	-7.086*	0.013	-0.003	-0.008
Sweden	0.018	0.008***	0.018*	-0.171	-0.373	0.001	-0.008	0.018
UK	0.002	0.004	-0.014	-0.009	-22.60***	0.095***	-0.002*	0.021
Cross-sectional dependence test								
χ^2	159.31	133.40	128.92	165.86	171.94	174.64	62.72	123.24
p value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001
Lag order selection	1	1	1	1	1	1	1	1

*Notes: Table entries are the coefficients values. *, **, *** indicate significance at 10%, 5% and 1%. Irish BCS data is not publicly available. Shaded columns correspond to first differenced variables.*

Table 2 indicates that three examined confidence indicators significantly feed into RHP. CrCI Granger-causes housing prices in nine out of 13 analyzed economies (Austria, Belgium, Germany, Greece, Italy, Netherlands, Portugal, Spain, and Sweden).

It is followed by ESI (eight significant relationships), while CCI Granger-causes housing prices in six countries. It should also be noticed that the obtained confidence coefficients are mostly of the (expected) positive sign.

Uncertainty indicators should theoretically be negative in sign, implying that agents postpone irreversible decision (such as buying real estate) when faced with uncertainty. This leads to a reduction in aggregate demand, ultimately lowering housing prices. However, our uncertainty indicators do not reveal strong relationships with housing prices at all. This can be explained by the fact that real estate investments have a long-term character and high transaction costs. It follows that agents' *short-term* uncertainty assessments are not significant for *long-term* real estate investors. One should also have in mind that both confidence and uncertainty are latent variables, so it is impossible to identify the correct measure of these two concepts. In that sense, our results are possibly driven by some kind of bias arising from *e.g*., sample selection, respondents' selective memory, or any type of cognitive bias exhibited by respondents.

The only assessed global uncertainty measure (VIX) has by far the worst predictive characteristics. This corroborates our presumption that national-level psychological indicators should be more important for housing prices than the global ones.

The bad leading characteristics of uncertainty indicators are in line with the results of Škrabić Perić and Sorić (2018). They find that economic confidence adds surprisingly more to GDP predictions than a battery of uncertainty indicators.

Since CrCI is found to have a significant impact on housing prices in the largest number of analyzed economies, we continue by investigating the robustness of its dominance through 13 additional models. Each of them includes one already established RHP determinant, along with CrCI. The observed variables are: DRGDP, RIR, DCPI, DUN, DCGDP, RSP, RER, DCAP, DGLB, VIX, RENT, DREIT, and DHCGDP.

Table 3 shows that CrCI affects housing prices in more countries than the macroeconomic fundamentals do. Our results show that the unemployment rate is a significant predictor of housing prices in the highest number of countries (6 countries), followed by the real exchange rate and global liquidity (5 countries), etc. Evidently, different macro variables govern the housing price in different countries. This supports our decision to apply a *heterogeneous* Granger causality test.

The results obtained for both credit variables are quite unexpected, revealing a significant influence in only two and four countries. This result might stem from the fact that credit markets of the advanced economies are functioning well and shocks in these markets are often relatively small (Hirata, 2012).

A significant influence of capital account deficit is obtained for only four countries. Recent studies highlight the capital account as one of the most important determinants of housing prices growth, so our results seem unexpected. However, Cesa-Bianchi *et al*. (2015) find that capital flows are more important for housing prices dynamics in the emerging economies than in the advanced economies. Favilukis *et al.* (2012) provide evidence that current account deficit has small explanatory power when credit standards are included in the model. It can, however, be postulated that the lowering of credit standards reflects banks' assessment of positive market tendencies. In that sense, it is no wonder that economic confidence outperforms the effect of capital account deficit in our models.

Table 3. Granger Causality Test Results (DRHP Is the Dependent Variable and Independent Variables are CRCI and One of Other Potential Determinants of House Prices)

MODEL		Austria	Belgium	Denmark	Finland	France	Germany	Greece	Italy	Netherlands	Portugal	Spain	Sweden	UK
1	CrCI	0.045*	0.023***	0.002	0.002	0.002	0.041***	0.020***	0.051***	0.023***	0.017**	0.017***	0.008***	0.004
2	CrCI	0.048**	0.027***	-0.002	0.001	0.001	0.041***	0.020***	0.015**	0.023***	0.010	0.012**	0.005*	0.003
	DR GDP	-0.344	0.042	0.295***	0.187***	0.010	-0.060	-0.017	0.034	0.350***	0.132	0.391**	0.119	0.113
3	CrCI	0.017	0.022***	-0.001	-0.003*	0.004*	0.043***	0.015*	0.050***	0.024***	0.016**	0.016***	0.002	0.003
	RIR	-0.475***	-0.027	-0.051	-0.146***	-0.056***	-0.087***	0.043	-0.025	0.007	-0.003	-0.017	-0.158***	-0.050
4	CrCI	0.039*	0.020**	0.004	0.007*	0.001	0.042***	0.019***	0.053***	0.023***	0.020***	0.020***	0.009***	-0.003
	DCPI	-0.086	0.172	-0.628	-1.042***	0.079	-0.106	0.085	-0.487**	-0.326	-0.449**	-0.458	-0.457***	-0.876***
5	CrCI	0.044*	0.025***	0.004	-0.002	0.001	0.042***	0.016**	0.049***	0.020**	0.014**	0.015***	0.006**	0.011*
	DUN	0.989	0.241	-0.233	-0.447	-0.200	0.094	-0.614**	-0.757**	-0.436	-0.517*	-0.331*	-0.580**	1.059**
6	CrCI	0.042*	0.024***	0.000	0.001	0.000	0.042***	0.020***	0.054***	0.024***	0.024***	0.021***	0.006**	0.004
	DC GDP	-0.042	0.053	0.064	0.106	0.159**	0.055	0.113	0.141	0.030	-0.111*	-0.071	0.079	0.046
7	CrCI	0.046**	0.030***	0.003	0.002	0.003	0.042***	0.022***	0.053***	0.030***	0.015***	0.018***	0.013***	0.005
	RSP	0.006	0.030***	0.028	0.012	0.016**	0.000	0.013	0.014	0.041***	-0.018*	0.009	0.042***	0.024
8	CrCI	-0.006	0.019**	0.001	0.002	0.002	0.040***	0.000	0.051***	0.020***	0.017**	0.014**	0.007**	0.006
	RER	-3.212**	0.465	0.080	0.365	0.377	-0.265	3.097***	0.642*	1.367***	0.080	0.812	0.009	1.527*
9	CrCI	0.043**	0.044***	0.001	-0.009**	-0.002	0.041***	0.011*	0.011*	0.024***	0.013*	0.019***	0.004	0.005
	DCAP	-0.158	-0.041	0.619***	0.050	0.012	-0.060	-0.164**	-0.235***	-0.135*	-0.087	0.214	-0.024	0.053
10	CrCI	0.047*	0.027***	0.001	0.002	0.002	0.042***	0.028***	0.051***	0.029***	0.016**	0.020***	0.008***	0.003
	VIX	0.004	-0.023**	-0.015	0.014	-0.000	0.006	-0.064***	0.011	-0.028**	0.009	-0.020	0.014	0.020
11	CrCI	0.044**	0.022**	0.005	-0.015***	0.001	0.050***	0.020***	0.014**	0.021***	0.014**	0.012**	0.004	0.006
	DGLB	-1.2e-6**	.49e-7**	-1.3e-7	3.5e-7	3.0e-7*	-2.5e-7*	1.6e-7	3.5e-8	1.5e-7	-6.9e-7***	3.1e-7	-2.9e-8	-3.6e-7
12	CrCI	-0.012	0.019**	0.002	0.003	0.003	0.044***	0.011	0.052***	0.025***	0.017**	0.015**	0.005	0.003
	RENT	0.084***	-0.004	-0.002	0.001	0.0001	0.014***	-0.524***	-0.004	-0.012**	0.001	-0.002	0.021**	-0.0003
13	CrCI	0.025	0.046***	-0.008	-0.079	-0.003	0.053***	0.008	0.029***	0.027***	0.017	0.017**	0.003	-0.003
	DREIT	-0.030	0.0175**	0.016	0.0117	0.017***	0.0018	0.0188	0.003	0.02	0.001	0.007	0.005	0.004
14	CrCI	0.042*	0.0217***	0.002	0.001	0.001	0.045***	0.019***	0.047***	0.0244***	0.023***	0.0187***	0.006**	-0.001

MODEL		Austria	Belgium	Denmark	Finland	France	Germany	Greece	Italy	Netherlands	Portugal	Spain	Sweden	UK
	DHC GDP	-0.154	0.068	0.091	0.025	0.015	0.158*	0.448**	-0.47***	0.145	-0.181	-0.107	0.216	0.365**

Slope homogeneity and Cross-sectional dependence tests for models 1-14														
Model	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Slope homogeneity test χ^2	237.57	274.41	291.27	276.17	274.41	255.58	282.39	274.51	299.72	185.96	157.9	306.51	220.57	274.10
p value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Cross-sectional dependence test χ^2	133.4	177.1	128.2	110.2	134.4	133.6	137.8	128.5	148.7	135.4	169.2	128.56	184.2	133.6
p value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

*Notes: Table entries are the coefficients values. *, **, *** indicate significance at 10%, 5% and 1%, respectively.*

When the same set of 13 augmented models are estimated for the other two confidence indices, the results change immensely. CCI and ESI stay significant in a negligible number of economies. Housing prices seem to be mostly influenced by the judgments of the construction sector.

With respect to confidence in the construction sector, our results are extremely robust to including different variables in the model. Taking into account the results from models 2 to 14 from Table 3, in literally all of the estimated models, confidence in the construction sector does not lose statistical significance by adding different macroeconomic and financial fundamental variables. CrCI performs comparatively the worst when it is combined with two real estate market variables (RENT and REIT), but even then, it is significant in a larger number of countries than these two control variables. We interpret this as a sign that CrCI obviously possesses more information than the pure economic fundamentals.

5. Conclusion

This paper provides an attempt at elucidating survey-based determinants of real housing prices. Acknowledging the synchronization of national housing cycles and heterogeneity among the relevant determinants of national housing markets, we apply the heterogeneous panel Granger causality test to inspect for causal links between seven different soft indicators and real housing prices in 14 developed European economies. A particularly relevant contribution of the paper is provided through a meticulous differentiation between two classes of soft indicators: confidence and uncertainty. The latter (with the exception of the Economic Policy Uncertainty Index) seems to possess only minor added value in predicting real housing prices. Confidence indicators, on the other hand, are confirmed as significant leading indicators of housing prices. The strongest influence in that sense is found for the Construction Confidence Indicator, corroborating the dominance of the judgments of the building sector managers (in comparison to consumers) in explaining housing prices. The stated conclusion is fairly robust to adding a variety of macroeconomic and financial fundamental variables to the model. A limitation of this study is that the utilized methodology is unable to capture all observed macroeconomic and financial control variables in a single (catch-all) model. To counteract that, we estimate a battery of bivariate and trivariate models to discern the robustness of our results.

It is obvious that expectations about future housing market parameters feed into real housing prices. This conclusion is quite robust to the inclusion of various macro-fundamental variables in the model. In that sense, it is clear that economic confidence in the construction sector represents a separate transmission channel from the economic agents to housing prices (apart from the financial conditions, macroeconomic stability or any other fundamental factor). These results provide valuable impulses for investors, creditors and especially for the policy makers. All agents from real estate markets should improve their efforts in making information about the prevailing confidence levels more available to the interested parties in order to make better investment decisions.

Another important conclusion provided by this study is that causality is found also from the housing prices to the Construction Confidence Indicator. For instance, rising housing prices are boosting confidence, which later causes an increase in housing prices. In this way, the housing bubble is feeding itself and creating a potential problem to the financial stability.

In line with this result, further research may focus on the behavior of confidence on housing prices in different stages of the real estate cycles. Our results raise a doubt that expectations about future housing prices can create and deflate housing bubbles. Taking into account the strong consequences of housing bubbles on the real economy, researchers should focus more of their attention to this channel of transmission.

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