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Diagnosing and Predicting Housing Bubbles: An Application to Provincial Housing Markets in Canada

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This paper proposes a methodology for diagnosing and predicting housing bubbles before they burst. The proposal is implemented in two steps. In step 1 we apply three innovative stock-bubbles tests to Canada's provincial housing markets. This allows us to classify provinces into three categories: those that have not experienced any; those that have experienced in the past; and those that are currently experiencing and may also have experienced in the past episodes of bubble-like explosive growth in the price-rent ratio. To determine whether explosive growth in the latter two categories of provinces is the result of changes in fundamentals or excessive speculation, in step 2 we use the dating chronologies for explosive growth from step 1 and probit models to evaluate the ability of many fundamentals to predict future bubble formation.

JEL Codes: C15, G12.

1. Introduction

Centuries of historical records reveal that real estate prices, like the prices of financial assets such as stocks, are susceptible to repeated speculative 'manias and crashes' (Kindleberger,1978). Furthermore, recent experience shows that the social and economic costs of major housing busts are enormous, as the U.S. housing boom-bust cycle of the last decade has clarified. Yet, progress in the development of effective empirical tools for diagnosing housing bubbles has been very slow[1]. Recent years have, however, witnessed significant progress in the development of innovative new tests that can detect and date-stamp stock market bubbles before they bust (Phillips, Shi and Yu, 2013).

This paper argues that, while the new stock market tests are not sufficient by themselves, they can be strategically combined with traditional housing-bubble detection methodologies in ways that can lead to more accurate diagnosis of housing bubbles before they burst. The rationale for combining is as follows. The traditional methodologies typically define housing bubbles as overvaluations - deviations of actual price from an unknown fundamental price. This approach employs multivariate models and methodologies to estimate the fundamental price and, therefore, calculate the size of overvaluation (bubble). But any misspecification of the fundamental determinants of price can lead to misdiagnosis of bubbles; and also it lacks the ability to determine the timing for onset and bursting of bubbles. The new tests can help overcome both of these limitations.

The new tests define bubbles, not merely as overvaluation, rather as episodes of explosive growth in an asset price. Bubble-like explosive growth in the average price of housing can, however, arise from two separate sources: excessive speculation, especially during the peak years of a

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housing boom (Blanchard, 1979; Shiller, 2000) and shift in housing demand when short-run supply of housing is inelastic and/or the housing market suffers from other inefficiencies (see Section 2 below). The univariate stock market tests are designed to detect and date-stamp all episodes of explosive growth without regard to whether the underlying cause is excessive speculation or housing market inelasticity.

One way to address this inadequacy of the new tests is to empirically evaluate, using a suitable traditional multivariate methodology such as probit models, the ability of the fundamentals to explain/predict bubble-like explosive growth paths in house prices. It, therefore, makes sense to combine the new and the old methodologies in order to take advantage of the strengths of both methodologies.

Our proposal can be implemented in two steps. In step 1, apply the stock market tests to house prices or price/rent ratio to determine if episodes of explosive growth exist in the series. If one or more episodes are located, then record the start and the end dates of each episode for use in later analysis. Conditional on the bubble chronologies saved in step 1, an evaluation is carried out in step 2, of the ability of the fundamental determinants of price or price-rent ratio to predict the likelihood of future bubbles. If, for example, only one episode of explosive growth is found, then divide the sample into two sub periods: the first characterized by stationary or at most unit root growth; the second characterized by explosive growth. The price-rent series can then be represented as a dichotomous (0, 1) variable, 0 for non-explosive growth and 1 for explosive growth, thus opening the possibility to use the probit models to evaluate the fundamentals' ability to predict future bubbles[2].

We apply the two-step procedure described above to Canada's provincial price-rent ratios over the period 1980Q1-2014Q4[3]. Step 1 of the procedure enables us to eliminate all provinces that have not experienced any explosive growth from further analysis. For provinces that have experienced at least one large episode of explosive growth, we evaluate the ability of the fundamentals to predict bubble-like growth in the piece-rent series1 to 6 quarters in advance, by using province-specific and also pooled probit models.

In the absence of any consensus among researchers about a common set of variables that should serve as fundamental drivers of house prices or price –rent ratio, we initially select a large number of theoretically-motivated variables from the housing bubble literature (Igan and Loungani, 2012; Mayer, 2011). The initial set includes national as well as province-specific variables to allow us to capture the potential segmentation of housing into provincial/metropolitan markets (Allen et al., 2009). We then assess each variable's individual ability to predict bubbles 1 to 6 quarters ahead; and include only the four-top variables with the highest average predictive abilities in our province-specific and pooled probit models (see section 5 for details).

Our paper makes a contribution to a new strand of housing bubbles literature focusing on early detection of bubbles before they burst. Some previous studies have relied solely on the stock market tests to detect housing bubbles (Phillips and Yu, 2011; Yiu and Jin, 2012); we argue here that the new tests by themselves may not be sufficient for an accurate diagnosis of housing bubbles. To our knowledge, at least one previous study (Pedersen and Schutte, 2014) has used the stock market tests in combination with probit models to assess the fundamental factors' ability to predict future housing bubbles in eighteen OECD countries. Our paper differs from these previous studies in that it provides theoretical justification and emphasizes the importance for the two-step methodology noted above for a proper diagnosis of housing bubbles (see section 2). Furthermore, our application to the provincial housing markets in Canada has produced interesting new evidence, including the finding that fundamental factors by themselves cannot adequately explain bubble-like growth in several provinces, suggesting that non-fundamentals such as investor exuberance and speculation may also have contributed to such rapid growth in house prices.

The rest of the paper is organized as follows. Section 2 explains why house prices can experience explosive dynamics due to factors other than excessive speculation. Section 3 describes the new tests and reports the results from applying them to provincial price-to-rent ratios. Section 4 describes the specification of probit models. Section 5 reports the findings from the probit analysis. Section 6 concludes the paper.

2. Sources of Exaggerated House Price Fluctuations

A proper diagnosis of asset bubbles hinges critically on our ability to accurately decompose an asset price (P_t) into a fundamental and a non-fundamental (bubble) component (Summers, 1986),

$$P_t = P_{ft} + P_{nt} \qquad (1)$$

Achieving this decomposition empirically is difficult because both the fundamental P_{ft} and the non-fundamental component P_{nt} are unobserved. Traditional methodologies for detecting housing bubbles address this problem by estimating the fundamental price P_{ft} from observable market demand and supply factors, and attributing the residuals $P_{nt} = P_t - P_{ft}$ to the non-fundamentals (or bubble) component. In contrast, the new stock market tests directly estimate periods of bubble-like explosive growth in P_t and attribute such periods to the bubble component. The two approaches may not yield the same result. In particular, the traditional methodologies will tend to misdiagnose bubbles, whenever the underlying determinants of the fundamental price are not correctly identified. Furthermore, bubbles may also be misdiagnosing bubbles arise since bubble-like fluctuations in P_t may arise, not just from excessive speculation but also from rigid supply conditions (and other housing market inefficiencies) delaying the response to demand side shocks. The bubbles literature points to several such sources of excessive price fluctuations that are unrelated to housing speculation or other non-fundamental factors.

One, property markets are typically highly segmented regionally and in terms of quality; thus, price can vary widely across regions and over time, reflecting relative supply and preference structures. In places where short-run supply of land for housing development is highly inelastic in the short run due to geography or zoning laws, shift in housing demand due to a change in credit conditions, or mortgage rates may cause substantial short-term overvaluation of price relative to the trend (fundamental) price (Igan and Loungani, 2012).

Two, houses represent what economists call “positional goods” – an asset that not only promises to pay a monetary return but also serves as symbol of social status - signaling their owners' high relative standing within society (Turner, 2013). As income grows, demand and price of housing may grow more than proportionately to income, as home buyers compete for the right to live in the nice parts of a city where exclusivity is accomplished through higher prices.

Finally, house price surges can also be shaped by the mortgage financing system of a country (Tsatsaronis and Zhou, 2004). Several features of the mortgage finance system may promote property price cycles, including whether the system offers the possibility of mortgage equity withdrawal or securitization of mortgage assets. The upshot is that considerable care must be taken to assess whether soaring house prices are the result of excessive speculation or rigidities and inefficiencies in the housing market. This, in turn, means that any evidence of explosive house price growth obtained from the new tests (in step 1) must be supplemented with more direct evidence about the role of the fundamentals (step 2), for a proper diagnosis of whether or not a speculative bubble exists.

3. The New Tests: Description and Application

3.1 Description of New Tests

This section briefly describes the three stock bubbles tests that we apply to provincial price/rent ratios in Canada over the period 1980Q1 – 2014Q4. These tests in increasing importance are:

1. The rolling ADF (RADF) test (Huang P., 2008)
2. The Sup ADF (SADF) test (Phillips et. al. 2011)
3. Generalized SADF (GSADF) test (Phillips et. al. 2013)

The basic building block for all three tests is the right-tailed Augmented Dickey Fuller (ADF) unit root test, based on the assumption that the price-rent series y_t follows the following first-order autoregressive model

$$y_t = \mu + \delta y_{t-1} + \sum_{i=1}^{k} \phi_i \Delta y_{t-i} + \varepsilon_t \qquad (2)$$

The null hypothesis for all three tests is that y_t follows at most a unit root process and the alternative hypothesis is that y_t contains an explosive root:

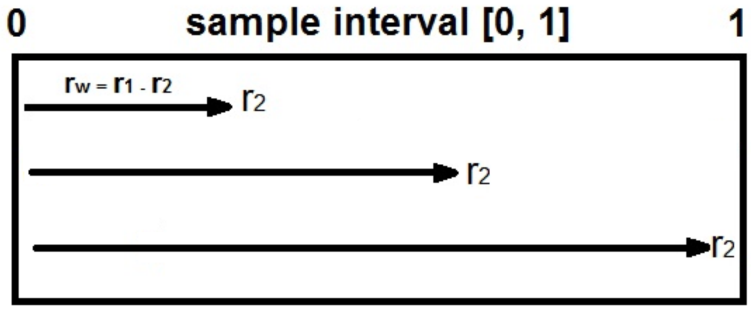
H_0: $\delta \leq 1$ (no bubbles present)
H_1: $\delta > 1$ (bubbles are present)

The right-tailed ADF statistic is the usual t-statistic (the estimate of δ divided by its standard error). However, the critical values for testing the null hypothesis are now taken from the right tail of the ADF statistic's non-normal distribution. The RADF test is a rolling version of the ADF test, where the ADF statistic is calculated repeatedly over a forward-rolling window of a fixed size. The initial size of the fixed window is chosen by the user. Then the start and end points of the window are incremented one data point at a time keeping the window size the same; and the ADF is re-estimated as the moving window rolls forward until the end of the sample. The RADF statistic is the maximal ADF statistic estimated among all possible windows.

The SADF test is based on recursive estimation of the ADF statistic over an expanding window, as shown in Figure 1 below. To implement this procedure, first the sample size T is normalized to 1, so that the full-sample interval is [0, 1], all expressed as fractions of the sample. Next, the first observation in the sample is set as the starting point of the estimation window r_1, i.e., $r_1 = 0$ and the end point of the initial estimation window r_2 such that the initial window size is $r_w = r_2 - r_1 = r_2$. Lastly, the model is estimated recursively, while incrementing the window size $r_2 \in [r_0, 1]$ one observation at a time. Each step of this estimation gives an ADF statistic denoted as $ADFr_2$. The SADF statistic is defined as the supremum value of the ADF_{r2} sequence for $r_2 \in [r_0, 1]$:

$$SADF(r_0) = \sup_{r2 \in [r_0,\, 1]} \{ADF_{r2}\} \qquad (3)$$

Figure 1: Illustration of the SADF Search procedure

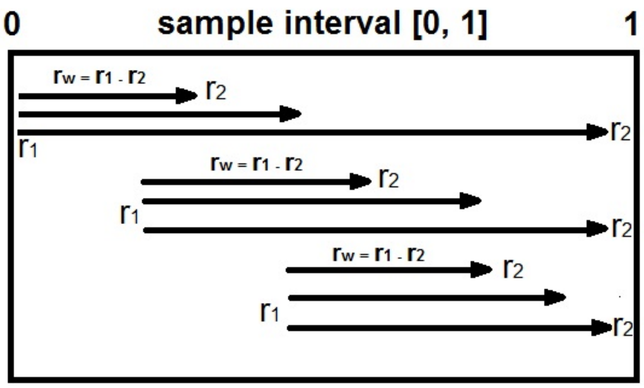


The Sup ADF test procedure suffers from a loss of power in the presence of multiple collapsing bubbles, due to its inability to fully overcome the Evans (1991) critic. The GSADF test overcomes this shortcoming by generalizing the SADF test procedure: it allows a more flexible estimation window by letting the starting point, r_1, to vary within the range $r_2 – r_0$. The additional flexibility of the GSADF over the SADF test can be seen in Figure 2 when compared to Figure 1.

Formally, the GSADF statistic is defined as

$$GSADF(r_0) = \sup_{\substack{r_2 \in [r_0,\, 1] \\ r_1 \in [0,\, r_2 - r_0]}} \{ADF_{r_1}^{r_2}\} \tag{4}$$

Figure2: Illustration of the GSADF Search procedure



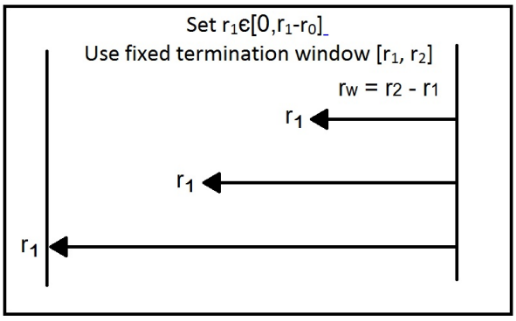
Note: Set $r_2 \in [0, r_2 – r_0]$ and $r_2 \in [r_0, 1]$. Next, use $[r_1, r_2]$ as a moving window while varying r_1 and r_2. At each step, $r_w = r_2 - r_1$ is the window width.

Date Stamping

This section explains how the Sup ADF (SADF) and the general Sup ADF (GSADF) tests are used to determine the origination and the termination dates of a bubble. The SADF test compares each of the ADF_{r2} sequence to the corresponding right-tailed critical values of the standard ADF statistic to determine if observation Tr_2 denotes the beginning of explosive behaviour in the price-rent (or price-income) series. The estimated origination date of a bubble is the first chronological observation, denoted by Tr_e, in which $ADFr_2$ crosses above the corresponding critical value, so that the ’no bubbles’ null hypothesis is rejected; and the estimated termination point of the bubble is the first chronological observation after Tr_e, denoted by Tr_f, in which ADF_{r2} crosses below the critical value, so that the null hypothesis is not rejected.

When there are multiple collapsing bubbles in the sample, the search procedures employed in the SRADF and RADF tests may fail to detect them, because past collapsing bubbles may make the data look rather stationary (Evans, 1991). The GSADF test greatly improves the identification accuracy over that of the SADF test by basing its inference on a backward SADF statistic, $BSADF_{r2}$ (Phillips et. al. 2013). The backward SADF test performs a sup ADF test on a backward expanding sample sequence where the end point of each sample is fixed at r_2 and the start point varies from 0 to $r_2 - r_0$, as shown in Figure 3 below. The backward SADF statistic is defined as the sup value of the ADF statistic sequence over this interval.

Figure 3: The backward sup ADF test



The origination date of a bubble is the first observation whose backward sup ADF statistic exceeds the critical value of the backward sup ADF statistic. The termination date of a bubble is the first observation after $[Tr_2]$ whose backward sup ADF statistic falls below the critical value of the backward sup ADF statistic. Note that the method provides a real-time empirical tool for detecting bubble-like growth i.e., to determine whether or not bubble-like explosive growth exists at any point in time, only current and past information is needed and there is no look-ahead bias involved.

The finite sample critical values for all test statistics are based on Monte-Carlo simulations using the following random walk process with an asymptotically vanishing drift as the null

$$y_t = d/T^{\eta} + \theta y_{t-1} + \varepsilon_t \qquad (5)$$

Where T is the sample size and ε_t is the error term, and the d, η and θ are constants set at unity (Phillips et al. 2013).

3.2 Test Results

Table 1 summarizes the results from applying the three stock market tests of explosive growth to each of the ten provincial price-rent ratios in Canada over the period 1980Q1- 2014Q4. The tests are implemented by setting the initial window size to 15% of the sample (21 observations). For each test, the parameters that define the unit root (random walk) null hypothesis are set at values suggested by Phillips et al. (2013) and the finite-sample critical values of the tests are obtained from Monte-Carlo simulations with 2000 replications.

The three tests in Table 1 do not agree about the dating chronologies or the number of episodes of explosive growth experienced by the provinces. To save space, we focus here only on the results from the most powerful of the three tests - the GSADF test (see last column, Table 1). Consider the results for British Columbia (last cell, row 1). For visual illustration, we also display the results for British Columbia in Figure 4. The top panel of Figure 4 is a table that contains the estimated GSADF t-statistic (4.759), followed by the corresponding (right-tailed) 99%, 95% and 90% critical values of 2.418, 1.885 and 1.593 respectively. Since the GSADF statistic exceeds the critical value at the 1% significance level (4.759 > 2.418), this gives clear evidence that the price-to-rent series for this province has experienced at least one episode of explosive growth.

The bottom panel of Figure 4 contains a chart that shows the number of episodes of explosive growth and the date-stamping procedure. The graph includes plot of the price-rent series, the estimated backward Sup ADF sequence, and the corresponding 95% critical values sequence for the test. It is evident from the graph that the GSADF statistic identifies three separate episodes of explosive growth: the first two that are relatively short-lived (1988Q3-1989Q2 and 1994Q4-1995Q1) and the third is long, beginning in 2003Q4 and ending at the last observation in the sample, 2014Q4, with only a short break in 2012Q3-2012Q4.

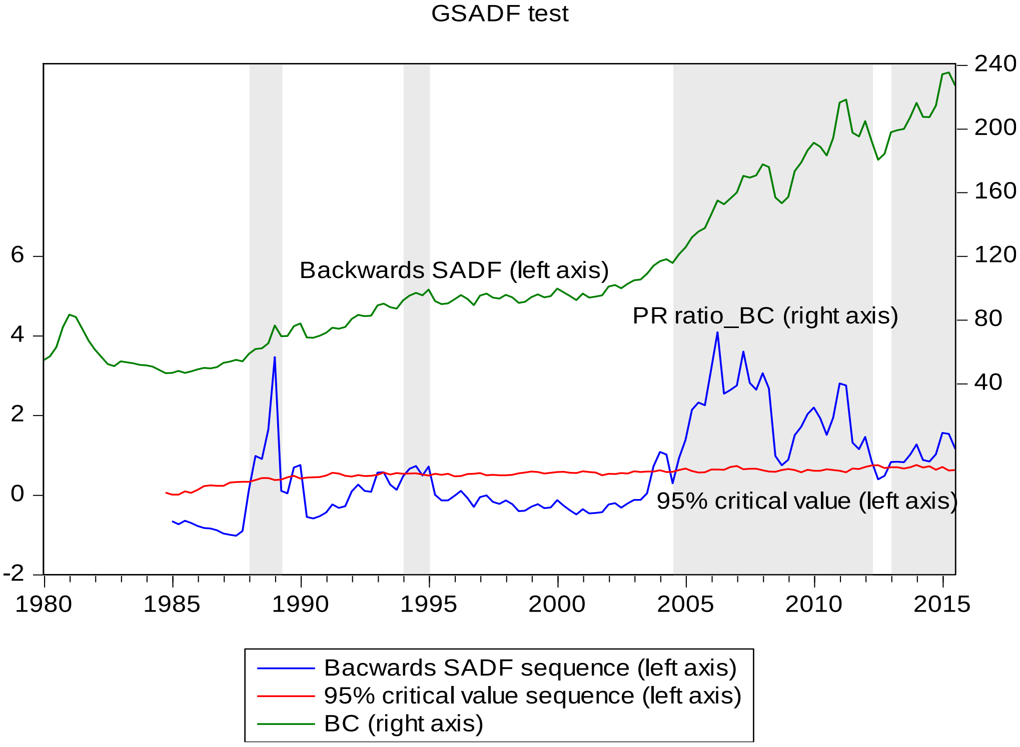
Based on the evidence in Table 1 (last column), we may classify all provinces into three groups. The first group covers provinces that are currently (at the last observation in the sample) experiencing and have experienced in the past bubble-like explosive growth (British Columbia, Quebec, Newfoundland); the bottom panel of Figure 4 depicts the general pattern of experiences for group 1 provinces. The second group includes provinces that have in the past, but are not currently experiencing explosive growth (Ontario, Alberta, Manitoba, and Saskatchewan). The third group covers provinces that have not experienced any explosive growth during the sample period (New Brunswick, Nova Scotia, Prince Edward Island). No figures are shown for group 2 and 3 provinces.

Table 1:Testing for explosive growth in provincial price-rent ratios: 1980Q1-2014Q4			
	Rolling ADF	Sup ADF	GSADF
British Columbia Critical Value Explosive Growth	Max ADF = 3.453 0.063 at 95% level 1987Q1-1988Q3 2003Q3-2007Q4	Sup ADF = 2.327 1.383 at 95% level 2005Q1 2014Q4	GSADF = 4.074 2.096 at 95% level 1988Q3-1989Q2 1994Q4-1995Q1 2003Q4-2012Q2 2013Q1 - 2014Q4
Alberta Critical Value Explosive Growth	Max ADF = 1.663 0.036 at 95% level 2006Q1-2007Q3	Sup ADF = 2.053 1.383 at 95% level 2006Q1-2011Q1 2014Q1-2014Q4	GSADF = 3.139 2.104 at 95% level 2005Q4-2008Q1
Saskatchewan Critical Value Explosive Growth	Max ADF = 2.674 0.036 at 95% level 2007Q4-2009Q1	Sup ADF = 2.501 1.383 at 95% level 2008Q2 -2014Q4	GSADF = 4.345 2.134 at 95% level 2007Q3-2014Q4
Manitoba Critical Value Explosive Growth	Max ADF = 0.559 0.036 at 95% level None	Sup ADF = 1.498 1.383 at 95% level 2009Q1-2014Q4	GSADF = 1.834 2.134 at 95% level 2004Q1-2008Q1 2009:Q4-2012Q3
Ontario Critical Value Explosive Growth	Max ADF = 2.879 0.036 at 95% level 1987Q1-1990Q1	Sup ADF = 2.627 1.383 at 95% level 1987Q1-1990Q1 2013Q3-2014Q4	GSADF = 2.878 2.134 at 95% level 1987Q1-1990Q1
Quebec Critical Value Explosive Growth	Max ADF = 1.541 0.036 at 95% level 2003Q1-2005Q2	Sup ADF = 1.246 1.383 at 95% level 2005Q1 2014Q4	GSADF = 1.794 2.134 at 95% level 2003Q3-2014Q4
New Brunswick Critical Value Explosive Growth	Max ADF = -0.409 0.023 at 95% level None	Sup ADF = -0.700 1.383 at 95% level None	GSADF = -0.192 2.134 at 95% level None
Nova Scotia Critical Value Explosive Growth	Max ADF = 2.674 0.036 at 95% level 2007Q1-2008Q3	Sup ADF = -0.509 1.383 at 95% level None	GSADF = -0171 2.134 at 95% level None
Price Edwards Island Critical Value Explosive Growth	Max ADF = -1.507 0.036 at 95% level None	Sup ADF = -2.429 1.383 at 95% level None	GSADF = -1.275 1.943 at 95% level None
Newfoundland Critical Value Explosive Growth	Max ADF = 2.136 0.036 at 95% level 2008Q3-2010Q4	Sup ADF = 1.895 1.383 at 95% level 2008Q2-2014Q4	GSADF = 2.745 2.134 at 95% level 2008Q2-2014Q4
Data Source: All data are taken from Statistics Canada's CANSIM database			

Figure 4: British Columbia (Group 1)

		t-Statistic	Prob.*
GSADF		4.074142	0.0000
Test critical values:	99% level	2.824990	
	95% level	2.133503	
	90% level	1.854161	

*Right-tailed test



The classification noted above allows us to eliminate provinces in group 3 that have not experienced explosive growth from further analysis. In sections 4 and 5 below, we expose the remaining provinces in groups 1 and 2 to further analysis in order to determine whether bubble-like growth in these provinces is the result of changes in housing market fundamentals or excessive speculation.

4. Predicting Bubbles with Probit Models

If explosive growth is triggered by speculation and, not by supply inelasticity (see section 2) then fundamental variables should not have an ability to explain/predict future bubble formation. We, therefore, devote the remainder of this paper to an evaluation of the market fundamentals' ability to predict bubble-like growth in provincial price-rent ratios using probit models. There are two key components to our bubble prediction methodology: construction of bubble chronologies and specification of probit models (described in this section) and the estimation results (described in section 5 below).

For each province which has experienced one or more episodes of bubble-like explosive growth in the price-rent series, we construct a binary (0, 1) bubble indicator variable B_t, such that,

$$B_t = \begin{cases} 1 & if \;\; there\, is\, a\, bubble\;\; at\, time\, t, according\, to\, the\;\; GSADF\, test \\ 0 & if \;\; there\, is\, no\, bubble\, at\, time\, t, according\, to\, the\;\; GSADF\, test \end{cases}$$

Conditional on the explanatory variables contained in the information set I_t, the bubble indicator B_t follows a Bernoulli distribution with a probability parameter pr_t; i.e., $(B_t \mid I_{t-1}) \sim ß_t(pr_t)$. Letting $E_{t-1}(.)$ be the conditional expectation and P_{t-1} be the conditional probability given the information set, the conditional probability that B_t takes the value of 1 satisfies,

$$E_{t-1}(B_t) = P_{t-1}(B_t = 1) = \Phi(\varpi) = pr_t$$

where $\Phi(.)$ is The Standard Normal Cumulative Distribution Function and ϖ is a linear function of the explanatory variables in the information set. In our specification of province-specific static probit model, ϖ takes the form,

$$\varpi_t = \alpha + \mathbf{x'_{t\text{-}k}}\, \boldsymbol{\beta} \qquad (6)$$

where $\mathbf{X'_{T\text{-}K}}$ is a set of explanatory variables that are deemed to contain useful information about future bubble formation and K Is the lag order (forecast horizon) of the explanatory variables. Note that the static model fails to take into account potential the autocorrelation structure of B_t, which can lead to spurious prediction. To account for this autocorrelation, we also consider a dynamic probit model which includes a lagged value of B_t in ϖ,

$$\varpi_t = \alpha + \mathbf{x'_{t\text{-}k}}\, \boldsymbol{\beta} + \lambda B_{t-1} \qquad (7)$$

The parameters θ_1 =(α, **β**) in (6) and θ_2 =(α, **β,** λ) in (7) are estimated using the maximum likelihood estimator. To evaluate model performance, we use Estrella's (1998) modified version of McFadden's Pseudo-R^2 statistic. This statistic outperforms all other competing statistics in the selection of the right model. It is calculated as,

$$Pseudo - R^2 = 1 - \left[\frac{LogL(\theta)_{UR}}{LogL(\theta)_R} \right]^{-(2/T)LogL(\theta)_R} \qquad (8)$$

Where $LogL(\theta)_{UR}$ is the maximized value of the log-likelihood function for the unrestricted (full) model and $\log L(\theta)_R$ is the maximized value of the log-likelihood function for the restricted model (i.e. model with only the intercept in it).

We initially assemble a large number of explanatory variables from the housing bubbles literature (Mayer, 2011; Igon and Loungani, 2012) and evaluate their individual ability to predict bubbles. The first variable we consider is housing affordability, measured by the provincial house price-to-disposable income ratio, denoted by PI. This variable is expected to capture slow adjustment of price-rent ratio towards a long-run equilibrium value. As disposable income grows, housing demand should also grow. Yet, depending on how sluggish housing supply response is, an income shock could push price too far in the sense that housing affordability deteriorates. Over time, housing demand would have to subside so that house prices come back in line with income. Since the PI ratio is non-stationary, we transform it into growth rate, denoted by GPI, to make it stationary, by first-differencing the logarithm of PI series.

Another variable we consider is the growth rate of provincial real GDP, denoted by GGDP. Persistent of strong growth in real GDP may induce expectation of higher long-term income growth and, consequently, an increasing willingness to take on more debt and spend larger share of income on housing and mortgage payments (Angello and Schuknecht, 2011). Thus, higher income growth may be positively associated with bubble formation.

Provincial unemployment rate, UR, is also includeded in our initial set. High unemployment may be a risk to housing markets, as joblessness can lead people to try to sell quickly or to default on payments (CMHC, 2016). In this view, average house prices tend to fall, perhaps with a time lag, when unemployment rate rises and rise when unemployment rate is falls. We also include two provincial demographic variables: growth rate of the working-age population (aged 24 -64), denoted by GPOP, and net migration into a province, NMIG. These variables are the primary determinants of new household formation in a province and, hence, may contain information about province-specific pace of growth of house prices.

The ‘financial approach’ to housing (Blanchard and Johnson, 2010) points to several forward-looking, national financial variables as key drivers of house prices. We consider three financial indicators of housing bubble formation: risk premium demanded by home investors, RP, short-term (safe) interest rate, R, and the five-year conventional mortgage interest rate, MORT. In addition, the growth rate of the narrow money supply, GM, is also included in the initial set.

Our initial set also includes several variables that may serve as proxies for inelasticity of local housing supply. These include growth of building permits issued each period, GBP, growth of housing completion, GHC, growth of housing starts, GHS, and the growth of housing uncomplete, GHU. A final variable we consider is the interest rate spread, SPRD, defined as the gap between the long term (ten-year plus) government of Canada bond interest rate and short-term 3-month t bill. Inversion of SPRD has consistently fared well as a reliable leading indicator of recessions, especially at longer forecast horizons. We include this series here to see if it can also predict future bubble formation in provincial housing markets.

5. Estimation Results and Sensitivity Analysis

Our evaluation of the predictive ability of the fundamentals (noted above) proceeds in three steps. In step 1, we assess each variable’s individual ability to predict bubble formation by estimating a single-variable probit model for the form,

$$P_{t-1}(B_t=1) = \Phi(\alpha + \beta x_{t-k}) \qquad (9)$$

Here $P_{t-1}(B_t = 1)$ is the conditional probability that the bubble indicator variable B_t will take the value 1, Φ is the standard normal cumulative distribution function and x_t is one of the fourteen fundamental variables described in section 4. For each variable, we estimate model (9) for each lag from k=1 through k=6, and assess the variable’s quantitative predictive ability at each lag based on Estrella’s pseudo R^2 statistic.

In step 2, we calculate each variable’s average predictive ability by taking the simple average of Estrella’s pseudo R^2 across all 6 lags and include only the variables with the four highest average predictive abilities over all six lags in our specification of the province-specific probit model. The static version of this model takes the form,

$$P_{t-1}(B_t=1) = \Phi(\alpha + \beta_1 x_{1\ t-k} + \beta_2 x_{2\ t-k} + \beta_3 x_{3\ t-k} + \beta_4 x_{4\ t-k}) \qquad (10)$$

while the dynamic version also includes a lagged dependent variable and takes the form,

$$P_{t-1}(B_t=1) = \Phi(\alpha + \beta_1 x_{1\ t-k} + \beta_2 x_{2\ t-k} + \beta_3 x_{3\ t-k} + \beta_4 x_{4\ t-k} + \lambda B_{t-1}) \quad (11)$$

We estimate equations (10) and (11) to assess the abilities of the fundamentals to predict province-specific bubble formation, again 1 to 6 quarters in advance. Models (10) and (11) allow the explanatory variables to differ across provinces, thus helping us to account for the heterogeneity of provincial housing markets in Canada. But these models also have a limitation: the binary dependent variable B_t has only limited variability, because the provincial housing have experienced only one or at most two large episodes explosive growth. In step 3 we, therefore, consider a pooled specification that allows greater variation in the dependent variable. The pooled model examines the predictive ability of a common set of fundamentals - those represented by the four-best variables that have the highest average pseudo R^2 over all six flags and across all provinces. The static and dynamic versions of the pooled model take the following forms,

$$P_{t-1}(B_t=1) = \Phi(\alpha + \beta_1 x_{1\ t-k} + \beta_2 x_{2\ t-k} + \beta_3 x_{3\ t-k} + \beta_4 x_{4\ t-k} + \sum_{i=1}^{4} D_i) \quad (12)$$

$$P_{t-1}(B_t=1) = \Phi(\alpha + \beta_1 x_{1\ t-k} + \beta_2 x_{2\ t-k} + \beta_3 x_{3\ t-k} + \beta_4 x_{4\ t-k} + \lambda B_{t-1} + \sum_{i=1}^{4} D_i) \quad (13)$$

where D_i is a dummy variable intended to capture provincial fixed effects.

It is important note here that there is a likely endogeneity problem in models (10), (11), (12) and (13) with GPI (growth of provincial house price to disposable income) as a predictor of growth in provincial house price to rent ratio or the bubble indicator BBL[4]. To address this problem we have used the growth of Canadian (national) house price to disposable income ratio, GPIC, as a proxy for the provincial GPI for any province where GPI appears as an explanatory variable. We have run Granger causality tests to confirm that causation runs on-way from the national to the provincial GPI (The results of Granger causality tests will be made available upon request).

Estimation results for models (10), (11), (12) and (13) are reported below in Table 2, Table 3 and Table 5. Table 2 reports the results for the province-specific static model 10. Before examining the details, it is instructive to first highlight some general patterns that emerge from Table 2 results. First, it is evident from Table 2 that the best-four potential predictors chosen based on the average pseudo R^2 (see section 4 above) and their statistical significance vary considerably across provinces. For example, only two of the four national variables in our initial data set (mortgage rate, MORT and the interest-rate spread, SPRD) appear in two of the provincial models (Alberta and Ontario). In addition, only four of the ten province-specific variables appear in a few of the provincial models; and their statistical significances also vary considerably across provinces. These patterns suggest that housing in Canada is not a single (national) market; rather it is segmented into many provincial markets. This finding is consistent with the evidence from previous studies that show that the housing market in Canada is segmented into many metropolitan city markets (Allen et al., 2009).

Second, Table 2 reveals that the multivariable model (10) fits the data better than the single variable model (9), as is indicate by the higher average value of the pseudo R^2 (last column Table2) for all five provinces and over all forecast horizons (0.278) compared to the average (0.135) for the single-variable model (not shown). But, in spite of this improvement in relative performance, the results also show that model 10 is not a good predictor of future bubble formation, as is suggested by the low average value of the pseudo R^2 statistic (0.278); the highest average pseudo R^2 is (0.552) for Ontario and the lowest is (0.173) for Quebec. This finding implies that even the best four provincial fundamentals, as a group, do not perform very well as predictors of future bubble formation in the provinces.

Turning to the performance of individual variables, it can be seen from Table 2 that the provincial unemployment rate performs particularly well as a predictor of future provincial housing bubble formation. For example, it has the expected negative sign and contains statistically significant information (at the 1 percent level) about the likelihood that the growth in price-rent ratio (and the bubble indicator BBL) will moderate with an increase in the unemployment rate will at all forecast horizons (k =1 through k = 6) in the provinces of Alberta, Manitoba, Ontario and Quebec. The growth rate of the provincial price-to-income ratio, using GPIC as a proxy, also has a strong ability to anticipate bubble-like growth in British Columbia and Quebec, but it plays little role in the other provinces. This finding suggests that the housing affordability and the bubble indicator variable BBL have much stronger persistence in British Columbia and Quebec than they do in the other provinces. Table 2 also shows that two additional variables have some ability to predict future bubble formation. For example, net in-migration (NMIG) has an ability to anticipate future bubble formation in the province of Manitoba at forecast horizons k = 1 through to k= 5, while growth in building permits issued (GBP) contains significant leading information only at horizon k = 6 in Alberta and horizons k =2, 3, and 6 in Manitoba.

Table 2: Static-model fit and estimation results:: Best provincial bubble indicators

ALBERTA	α	PROB.	$GPIC_{T-K}$	PROB.	UR_{T-K}	PROB.	$SPRD_{T-K}$	PROB.	GBP_{T-K}	PROB.	PSEUDO-R^2
K = 1	1.391	0.107	5.271	0.365	-0.435	0.006***	-0.423	0.001***	0.183	0.903	0.397
K = 2	1.474	0.086*	4.250	0.464	-0.442	0.005***	-0409	0.002***	0.656	0.674	0.383
K = 3	1.010	0.153	7.725	0.141	-0.060	0.005***	-0.295	0.010***	1.541	0.176	0.312
K = 4	0.576	0.256	3.001	0.624	- 0.259	0.002***	-0.238	0.013***	-1.277	0.625	0.192
K = 5	0.252	0.573	4.867	0.367	-0.240	0.005***	-0.183	0.063*	-1.753	0. 148	0.131
K = 6	-0 .061	0.886	3.851	0.475	-0.164	0.016**	-0.004	0.295	-2.501	0.046**	0.093
BC	**α**	**PROB.**	**$GPIC_{T-K}$**	**PROB.**	**UR_{T-K}**	**PROB.**	**GBP_{T-K}**	**PROB.**	**$GPOP_{T-K}$**	**PROB.**	**PSEUDO-R^2**
K = 1	2.374	0.000***	8.134	0.033**	-0.303	0.000***	-0.291	0.782	352.26	0.122	0.218
K = 2	2.138	0.000***	9.153	0.016**	-0.272	0.000***	-0.927	0.346	274.15	0.211	0.192
K = 3	1.906	0.000***	7.676	0.036**	-0.242	0.000***	- 1.011	0.304	301.72	0.168	0.164
K = 4	1.827	0.000***	7.231	0.056*	-0.231	0.000***	-0.371	0.711	423.06	0.082*	0.170
K = 5	1.735	0.000***	10.897	0.006***	-0.205	0.000***	0.261	0.778	393.00	0.100*	0.180
K = 6	1 .536	0.000***	7.812	0.029**	-0.193	0.000***	-0.767	0.431	102.56	0.583	0.117
MANITOBA	**α**	**PROB.**	**$NMIG_{T-K}$**	**PROB.**	**GBP_{T-K}**	**PROB.**	**$MORT_{T-K}$**	**PROB.**	**$GPOP_{T-K}$**	**PROB.**	**PSEUDO-R^2**
K = 1	3.122	0.021**	0.000	0.041**	0.237	0.077*	-0.614	0.001***	105.421	0.001***	0.520
K = 2	4.168	0.017**	0.001	0.071**	-2.540	0.003***	- 0.752	0.003***	376.063	0.471	0.529
K = 3	4.693	0.013***	0.001	0.007***	-4.036	0.005***	-0.862	0.002***	114.853	0.183	0.608
K = 4	2.477	0.103*	0.002	0.000***	1.375	0.101	-0.551	0.006***	430.432	0.343	0.611
K = 5	3.528	0.013***	0.001	0.007***	1.018	0.146	-0.653	0.002***	144.253	0.309	0.532
K = 6	4.381	0.007***	0.002	0.113	-1.839	0.037**	-0.747	0.001***	133.869	0.814	0.504
ONTARIO	**α**	**PROB.**	**GHC_{T-K}**	**PROB**	**UR_{T-K}**	**PROB.**	**GHS_{T-K}**	**PROB.**	**$SPRD_{T-K}$**	**PROB.**	**PSEUDO-R^2**
K = 1	2660	0.000***	0.676	0.336	-1.061	0.000***	0.024	0.947	0.158	0.121	0.346
K = 2	4.884	0.000***	0.105	0.901	-0.878	0.001***	0.107	0.047	0.150	0.155	0.281
K = 3	4.424	0.000***	0.245	0.765	-0.812	0.001***	0.177	0.573	0.199	0.064*	0.252
K = 4	3.952	0.000***	0.455	0.627	-0.741	0.000***	-0.037	0.916	0.231	0.032**	0.224
K = 5	3.241	0.000***	0.528	0.54	-0.639	0.000***	0.256	0.448	0.231	0.027**	0.191
K = 6	2.230	0.005***	0.350	0.689	-0.484	0.000**	-0.231	0.458	0.208	0.024**	0.137
QUEBEC	**α**	**PROB.**	**$GPIC_{T-K}$**	**PROB**	**UR_{T-K}**	**PROB.**	**GBP_{T-K}**	**PROB.**	**$GPOP_{T-K}$**	**PROB.**	**PSEUDO-R^2**
K = 1	2.37	0.000***	8.134	0.033**	-1.333	0.032**	-1.291	0.781	352.26	0.122	0.217
K = 2	2.13	0.000***	9.153	0.016**	-0.272	0.000***	-0.927	0.348	274.31	0.211	0.191
K = 3	1.90	0.000***	7.677	0.035**	- 0.242	0.000***	1.011	0.340	301.77	0.168	0.164
K = 4	1.82	0.000***	7.231	0.056*	-0.231	0.000***	0.371	0.771	423.06	0.082*	0.170
K = 5	1.74	0.000***	10.997	0.007***	-0.221	0.000***	-0.281	0.778	393.00	0.100*	0.182
K = 6	1.53	0.000***	7.812	0.029**	-0.193	0.000***	-0.995	0.431	102.806	0.563	0.117

Notes: The results for New Brunswick, Prince Edward Island, Newfoundland and Nova Scotia are missing since these provinces have not experience bubble-like explosive growth in house prices. Estimation for Saskatchewan and Nova Scotia was not possible due to insufficient variation in their bubble indicator variable, BBL. The stars denote statistical significance at a 10% (*), 5% (**) and 1% (***) level.

We now turn to the estimation results from the dynamic model (11) reported in Table 3 below. Since model (11) differs from model (10) only in the fact that it contains the lagged dependent variable, BBL_{t-1} as an additional explanatory variable, two issues are relevant in evaluating these results: the performance of $BBLt_{-1}$ itself and the sensitivity of the coefficients of the fundamentals due to the presence of BBL_{t-1}.

Even a cursory look at Table 3 makes clear that dynamics play a dominant role in our ability to predict provincial housing bubble formation. This is evident both from the strong statistical significance of BBL_{t-1} (see second last column of Table 3) and also from the marked increase in the estimated values of the pseudo R^2 statistic (see last column of Table 3) compared to estimates in Table 2. Notably, BBL_{t-1} has an ability to predict future bubble formation at the 1 percent significance level in all provinces and at all six forecast horizons, except for Manitoba where it is significant only at forecast horizons k = 2, 4 and 6. These results clearly suggest that bubble-like explosive growth in price-rent ratio has a strong momentum across all five provincial housing markets.

Table 3 results also show that the presence of the variable BBL_{t-1} generally weakens the predictive ability of the fundamental variables in all provinces. In particular, changes in provincial unemployment rate (UR) now has significant predictive ability only in Ontario, while its predictive ability is much diminished in Alberta and British Columbia and Quebec. The same pattern is also observed for the growth of the national price-income ratio (GPIC), net in-migration (NMIG) and growth of building permits (GBP), which retain limited predictive ability only at specific forecast horizons in some of the provinces. Overall, Table 3 results suggest that it is dynamics (persistence of explosive growth) and not the fundamental factors that are largely responsible for the superior performance of the dynamic model 11 relative to the performance of the static model 10.

Table 3: Model fit and estimation results: Dynamic model: Best provincial bubble indicators

Alberta	α	prob.	$GPIC_{t-k}$	prob.	UR_{t-k}	prob.	$SPRD_{t-k}$	prob.	GBP_{t-k}	prob.	BBL_{t-1}	prob	Pseudo -R^2
K = 1	-1.14	0.154	11.261	0.093*	-0.145	0.229	-0.233	0.055*	-2.366	0.141	3.035	0.000***	0.721
K = 2	- 1.31	0.067*	7.790	0.153	-0.189	0.135	-0.054	0.713	-5.519	0.000***	3.646	0.000***	0.733
K = 3	-2.11	0.002***	1.019	0.755	-0.048	0.626	0.123	0.276	1.900	0.083*	3.592	0.000***	0.691
K = 4	-2.21	0.018	25.451	0.000***	- 0.150	0.308	0.097	0.295	4.176	0.088*	4.562	0.000***	0.813
K = 5	-2.89	0.000***	6.111	0.487	-0.019	0.801	0.396	0.016**	-0.436	0.563	4.247	0.000**	0.714
K = 6	-3.24	0.000***	5.054	0.432	-0.036	0.756	0.522	0.067*	-2.979	0.016**	4.513	0.000***	0.730

BC	α	prob.	$GPIC_{t-k}$	prob.	UR_{t-k}	prob.	GBP_{t-k}	prob.	$GPOP_{t-k}$	prob.	BBLt-1	prob.	Pseudo-R^2
K = 1	-0.26	0.675	7.359	0.139	-0.124	0.102*	-1.071	0.285	224.84	0.100*	2.610	0.000***	0.620
K = 2	-0.48	0.396	6.742	0.203	-0.102	0.095*	-1.691	0.202	12.38	0.965	2.647	0.000***	0.611
K = 3	-0.62	0.255	1.676	0.679	-0.083	0.148	-0.848	0.116	233.27	0.116	2.634	0.000***	0.601
K = 4	-0.59	0.374	3.601	0.344	-0.101	0.179	2.699	0.045**	561.28	0.057*	2.850	0.000***	0.642
K = 5	-0.46	0.412	13.729	0.005***	-0.109	0.078*	0.239	0.836	195.18	0.309	2.696	0.000***	0.627
K = 6	-1.10	0.027**	0.437	0.928	-0.042	0.421	-2.570	0.104*	339.07	0.111	3.038	0.000***	0.618

Man	α	prob.	$NMIG_{t-k}$	prob.	GBP_{t-k}	prob.	$MORT_{t-k}$	prob.	$GPOP_{t-k}$	prob.	BBLt-1	prob.	Pseudo-R^2
K = 1	2.63	0.066*	0.001	0.215	-0.964	0.143	-0.554	0.004***	690.79	0.131	0.629	0.156	0.534
K = 2	2.87	0.110	0.001	0.249-	-3.789	0.000***	-0.626	0.015**	817.41	0.150	1.322	0.006***	0.591
K = 3	3.87	0.070*	0.002	0.019**	-3.810	0.011***	-0.758	0.011***	191.41	0.172	0.485	0.297	0.618
K = 4	1.08	0.359	0.001	0.003***	2.741	0.005***	-0.424	0.009***	459.19	0.308	1.166	0.024**	0.648
K = 5	3.11	0.052**	0.002	0.084*	-0.852	0.219	-0.602	0.005***	369.22	0.389	0.452	0.366	0.539
K = 6	3.00	0.064*	0.001	0.424	-2.705	0.015***	-0.601	0.008***	53.98	0.931	1.157	0.011***	0.554

Ontario	α	prob.	GHC_{t-k}	prob	UR_{t-k}	prob.	GHS_{t-k}	prob.	$SPRD_{t-k}$	prob.	BBLt-1	prob.	Pseudo-R^2
K = 1	2.21	0.048**	1.609	0.058*	-1.600	0.000***	0.102	0.827	0.152	0.334	2.293	0.000***	0.594
K = 2	1.09	0.334	-0.838	0.296	-0.418	0.012***	0.161	0.539	0.124	0.415	2.334	0.001***	0.565
K = 3	1.26	0.211	0.419	0.586	-0.462	0.002***	0.191	0.532	0.215	0.158	2.387	0.001***	0.572
K = 4	0.93	0.412	0.413	0.753	-0.411	0.008***	-0.292	0.545	0.217	0.159	2.433	0.000***	0.568
K = 5	0.14	0.897	0.384	0.589	-0.301	0.051**	0.407	0.325	0.159	0.296	2.488	0.000***	0.562
K = 6	-0.81	0.403	0.094	0.923	0.153	0.235	0.088	0.667	0.132	0.249	2.539	0.000***	0.536

Quebec	α	prob.	$GPIC_{t-k}$	prob	UR_{t-k}	prob.	GBP_{t-k}	prob.	$GPOP_{t-k}$	prob.	BBLt-1	prob.	Pseudo-R^2
K = 1	0.28	0.674	7.359	0.139	-0.123	0.102*	-1.071	0.285	224.85	0.100*	2.611	0.000***	0.620
K = 2	-0.487	0.396	6.723	0.202	-0.102	0.095*	-0.691	0.202	12.38	0.968	2.647	0.000***	0.611
K = 3	-0.62	0.256	1.676	0.679	- 0.848	0.147*	-0.848	0.407	233.26	0.116	2.634	0.000***	0.601
K = 4	-0.59	0.375	3.601	0.344	-0.101	0.179	2.699	0.046**	451.28	0.057*	2.850	0.000***	0.642
K = 5	-0.46	0.412	13.729	0.005***	-0.109	0.078*	-0.239	0.836	195.19	0.309	2.698	0.000***	0.627
K = 6	-1.10	0.026**	0.437	0.928	-0.042	0,421	-2.570	0.104*	339.07	0.111	3.038	0.000***	0.618

Notes: The results for New Brunswick, Prince Edward Island, Newfoundland and Nova Scotia are missing since these provinces have not experience bubble-like explosive growth in house prices. Estimation for Saskatchewan and Nova Scotia was not possible due to insufficient variation in their bubble indicator variable, BBL. The stars denote statistical significance at a 10% (*), 5% (**) and 1% (***) level.

The province-specific models (10) and (11) results discussed above suffer from a problem: their dependent variable BBL has only limited variability, since a province has experienced at most one or two large episodes of explosive growth during the sample period. The pooled models (12) and (13) help to relax this constraint somewhat, but only at the cost of imposing a common set of explanatory variables on all provinces. Table 4 (panel A and panel B) report results for the static and dynamic pooled models respectively. The explanatory variables in these models (those with the highest average values of the individual pseudo R^2 across all lags and all provinces) are the growth of Canada-wide price-income ratio, GPIC, the provincial unemployment rate, UR, growth of building permits GBP, and the growth of working-age population (aged 24-65), GPOP.

Table 4 (panel A) results provide evidence of a consistently highly significant predictive ability for three of the four fundamental explanatory variables at all forecast horizons k =1 through to k = 6.

Table 4: Model fit and estimation results, Pooled model specifications

Panel A: Static models	C	$GPIC_{T-K}$	UR_{T-K}	GBP_{T-K}	$GPOP_{T-K}$	**Provincial Fixed Effect**	**Pseudo- R^2**
k=1	1.059	6.134	-0.294	-0.153	72.101	yes	0.103
	(0.000***	(0.001)***	(0.000)***	(0.633)	(0.005***)		
k=2	0.991	9.945	-0.192	-0.382	74.009	yes	0.093
	(0.003)***	(0.001)***	(0.000)*	0.233	(0.004***)		
k=3	3.949	6.538	-0.183	-0.464	79.040	yes	0.091
	(0.00)***	(0.000)***	(0.000)***	(0.144)	(0.002)***		
k=4	- 0.965	7.340	-0.180	0.940	92.483	yes	0.101
	(0.000)***	(0.000)***	(0.000)***	(0.000)**	(0.000)***		
k=5	0.968	6.992	-0.175	-0.285	102.491	yes	0.096
	(0.000)***	(0.001)***	(0.000)***	(0.372	(0.000***)		
k=6	0.912	4.749	- 0.161	-0.195	107.219	yes	0.077
	(0.000)***	(0.005)***	(0.000)**	(0.539)	(0.000***)		

Panel B: Dynamic models	C	$GPIC_{T-K}$	UR_{T-K}	GBP_{T-K}	$GPOP_{T-K}$	BBL_{T-1}	**Provincial Fixed Effect**	**Pseudo-R^2**
k=1	-1.051	6.063	-0.074	-0.487	38.898	2.837	yes	0.619
	(0.009***)	(0.019)**	(0.065)*	(0.251)	(0.260)	(0.000)***		
k=2	-1.049	2.668	-0.072	-0.314	40.980	2.871	yes	0.617
	(0.007***)	(0.262)	(0.061)*	(0.056)**	(0.233)	(0.000)***		
k=3	-0.984	4.388	-0.073	-0.073	52.695	2.291	yes	0.613
	(0.013)***	(0.061)*	(0.055)**	(0.251)	(0.149)	(0.000)***		
k=4	-1.031	4.151	-0.076	-2.024	68.923	2.967	yes	0.639
	(0.010)**	(0.110)	(0.033)**	(0.000)***	(0.079)*	(0.000)***		
k=5	-0.918	2.619	-0.071	-0.178	72.878	2.789	yes	0.610
	(0.019)**	(0.251)	(0.048)**	(0.660)	(0.042)**	(0.000)***		
k=6	-1.101	2.029	-0.052	-1.072	65.892	2.928	yes	0.613
	(0.001)***	(0.353)	(0.154)	(0.049)**	(0.006)***	(0.000)***		

Notes: Provincial dummy variables: Since all models include an intercept, one provincial dummy was dropped to avoid the dummy variable trap. Standard errors are reported underneath the coefficient estimates. The stars denote statistical significance at a 10 %(*), 5 %(**) and 1 %(***) level.

These variables include the growth of the price-income ratio ($GPIC_{t-k}$), the provincial unemployment rate UR_{t-k} and the growth of working-age provincial population (aged 24-65), GPOP. But, in spite of their high statistical significance, the overall joint ability of the fundamentals in model (12) to predict future provincial bubble formation is clearly low, as is indicated by low estimated values of the pseudo R^2 statistics at all forecast horizons (see last column, Table 4, panel A).

A comparison of the results from the dynamic pooled model (13) (see Table 4 panel B) to those from the static pooled model (12) (see Table 4 panel A) reveals the same general pattern of changes we compared the results from province-specific static and dynamic model (see Table 2 and 3). As in the case of the province-specific static and dynamic models (Table 2 and 3), we again observe large improvements in model fit as we go from the static to the dynamic version of the pooled model. This improvement in model performance is evident both from the systematic pattern of high statistical significance of the lagged dependent variable BBL_{t-1} and also from the large improvements in the estimated values of the pseudo R^2 statistic at all forecast horizons. Furthermore, we also observe that the introduction of dynamics results is a deterioration of the performances of the fundamentals, but not to the same extent as was case for the province-specific static and dynamic models (Tables 2 and 3). In particular, all four fundamentals – the provincial unemployment rate UR_{t-k}, changes in building permits issued GBP_{t-k} growth of working-age population $GPOP_{t-k}$ and growth of price-income ratio, $GPIC_{t-k}$ – continue to retain some limited ability to anticipate future bubble formation at specific forecast horizons.

6. Conclusions

This paper combines innovative new stock bubbles tests with traditional multivariate probit models for predicting housing bubbles in provincial housing markets in Canada. The evidence shows that five of the ten provinces have not experienced any episodes of bubble-like growth in price-rent ratio during the sample period. For the remaining five provinces which have experienced at most two large episode of bubble-like growth, the paper employs multivariate province-specific and pooled probit models to evaluate the ability of the fundamentals to predict future bubble formation one to six quarters ahead. The evidence from this analysis reveals several key findings.

First, among the many fundamental factors we have evaluated, only three turn out to have some limited ability to predict bubble formation in provincial housing markets. Interestingly, we also find that bubble-like growth is primarily driven by local factors (growth in provincial price-to-income ratio (purged of the effect of price-rent ratio), unemployment rate and changes in building permits issued). None of the forward-looking (national) financial variables (interest rate, risk premium, mortgage rate, growth in money supply) exhibit an ability to predict provincial bubbles. This evidence is consistent with the view that housing in Canada is not a national market, rather is segmented into provincial markets.

Second, the results show that proper accounting of dynamics is crucial to our ability to predict housing bubbles. This finding is confirmed by the fact that dynamic versions of both province-specific and pooled models perform markedly better that the static models. It reveals that housing bubbles are characterized by strong momentum; that is, the presence of a bubble in the current quarter increases the probability of a bubble in the next quarter as well.

Third, overall the findings of this paper suggest that fundamental factors alone cannot fully account for the large episodes of bubble-like (explosive) growth observed in British Columbia, Alberta, Manitoba, Ontario and Quebec; this, in turn, implies that investor exuberance (housing speculation) may also have contributed to such rapid growth in price-rent ratio in these provinces. Finally, it should be noted that the findings of this paper are subject to an important limitation. Due to the lack of long enough bubble chronology, we have only examined in-sample forecasts in this paper. But in-sample fit may not always translate into out-of-sample predictive ability. Even though our pooled models somewhat increases the bubble chronology, it comes at the cost of imposing a common set of explanatory variables on the provinces. Ideally, what is needed is a sample period that covers house prices over a much longer period, covering multiple episodes of explosive growth in house prices.

Endnotes

[1]The use of inept bubble metrics combined with an inability of the traditional methods to deal with large nonlinearities in house price dynamics are two factors that may have contributed to this slow progress (Gurkaynak, 2005; Evans, 1991)
[2] This procedure is similar to the use of probit models in the 'indicator approach' to predicting recessions (Estrella and Mishkin, 1998).
[3] The average price-rent ratio in Canada has grown rapidly after the early 1990s, leading to large deviations of the price-rent ratio from its historical (trend) growth path. The OECD (2014) and the IMF (2016) have interpreted these large deviations as indicators of house price overvaluation, while others (Peterson and Zheng, winter 2011-2012) have argued that these deviations can be largely explained by changes in the fundamentals.
[4] We are grateful to an anonymous referee for pointing out the endogeneity problem to us.

References

Allen, J, Amano, R, Byrne, DP, & Gregory, AW 2009, 'Canadian city housing prices and urban market segmentation', *Canadian Journal of Economics* vol. 42, no 3, pp.1132-1149.
Angello, L & Schuknecht, L 2011, 'Booms and busts in housing markets', *European Central Bank Working Paper No 1071*. July, available at http://www.ecb.euriopa.eu
Blanchard, O 1979, 'Speculative bubbles, crashes and rational expectations', *Economic Letters*, vol. 3, pp. 387-389.
Blanchard, O & Johnson, D 2010, *Macroeconomics*, Pearson, Toronto.
Canada Mortgage and Housing Corporation, 2016, 'Speaking notes for Evan Siddall', Panel session at the Global Risk Institute Annual Conference, http://www.cmhc-hchl.gc.ca/en/corp/nero/sp/2015-11-10-1500.cfm
Case, KE & Shiller, RJ 1990, 'Forecasting Prices and Excess Returns in the Housing Market', *NBER Working Paper No. 3368,* Issued in May, 1990
Estrella, A, & Mishkin, FS 1998, 'Predicting U.S. recessions: Financial variables as leading indicators', *The Review of Economics and Statistics*, vol. 80, no1, pp. 45–61.
Evans, GW 1991, 'Pitfalls in testing for explosive bubbles in asset prices', *American Economic Review* 81, pp. 922-930.
Gurkaynak, RS 2005, 'Econometric tests of Asset Price Bubbles: Taking Stock', *Federal Reserve Board Finance and Economics Discussion Series*, 2005-04.
Himmelberg, C, Mayer, C, & Sinai, T 2005, 'Assessing high house prices: bubbles, fundamentals, and misperceptions', *Journal of Economic Perspectives, vol* 19, no 4, pp. 67–92
Huang, P 2008, 'Rolling ADF tests: Detecting rational bubbles in greater China stock market', *Dissertations and Theses Collections*, available at: http://ink.library.smu.edu.sg/etd_coll/36.
Igan, D. & Loungani, P 2012, 'Global Housing Cycles', *International Monetary Fund Working Paper*, WP/12/217, 1-55.
International Monetary Fund, 2016, 'The Global Housing Watch', IMF, April. http://www.imf.org/external/research/housing/
Kindleberger, C *1978, Manias, panics and crashes: A history of financial crises*, New York, Basic Books.
Mayer, C 2011**, '**Housing Bubbles: A Survey**',** *Annual Review of Economics**,** Vol.* 3, pp. 559-577
Perdersen, BP & Schutte, ECM 2014, 'Detecting and predicting housing bubbles: An application of the generalized sup ADF test and dynamic probit models', MSc thesis, Department of economics and finance, Arahus University, Denmark.
Organization for Economic Co-operation and Development 2014, OECD Economic Surveys: Canada 2014, Paris: OECD publishing.

Peterson, B and Y. Zheng, 2011-2012, Medium-term fluctuations in Canadian house prices', *Bank of Canada Review*, winter, pp. 30-42.

Phillips, P. C. B. and J. Yu, 2011, 'Dating the timeline of financial bubbles during the subprime crisis', *Quantitative Economics* 2, 3, 455-491.

Phillips, PCB, Shi, S & Yu, J 2013, 'Testing for bubbles 1: Historical episodes of exuberance and collapse in the S&P 500', *SMU Economics and Statistics Working Paper Series*. Paper No. 04-2013.

Shiller, R 2000, 'Measuring bubble expectations and investor confidence', *Journal of Psychology and Financial Markets* 1, 49-60.

Summers, LH 1986, Does the stock market reflect fundamental values', The *Journal of Finance*, vol 41, no 3, pp. 591-601.

Tsatsaronis, K. & Zhou, H 2004, 'What drives house price dynamics: Cross-country evidence', *BIS Quarterly Review, Bank of International Settlement*, March, pp. 65-78.

Turner, A 2013, 'The Consequences of Money-Manager Capitalism', *Speech given to the Institute for New Economic Thinking*, October 25.

Yiu, MS & Jin, L 2012, 'Detecting bubbles in the Honk Kong Residential property market: An explosive-pattern approach' *Honk Kong Institute of Monetary Research, Working paper no 01/2012.*