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# How Long Do Housing Cycles Last? A Duration Analysis for 19 OECD Countries

*Philippe Bracke*

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## How Long Do Housing Cycles Last? A Duration Analysis for 19 OECD Countries

**Prepared by Philippe Bracke**[1]

Authorized for distribution by Prakash Loungani

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## Abstract

This paper analyzes the duration of house price upturns and downturns in the last 40 years for 19 OECD countries. I provide two sets of results, one pertaining to the average length and the other to the length distribution. On average, upturns are longer than downturns, but the difference disappears once the last house price boom is excluded. In terms of length distribution, upturns (but not downturns) are more likely to end as their duration increases. This duration dependence is consistent with a boom-bust view of house price dynamics, where booms represent departures from fundamentals that are increasingly difficult to sustain.

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Author's E-Mail Address: p.bracke@lse.ac.uk

[1] I have greatly benefited from conversations with Deniz Igan. I thank the participants at the Research seminar at the IMF, the Macro workshop at the London School of Economics, and the European Doctoral Program Jamboree in Bonn for their helpful comments.

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# I. Introduction

National house prices went through an unprecedented and synchronized rise across OECD countries in the years preceding the Great Recession (Girouard et al., 2006). Many of those countries are now experiencing a violent decline. In Spain, the U.S., and Ireland, prices are down 20, 32, and 38 percent from their peaks, respectively.[2] While the magnitude of these changes is exceptional, the fact that house prices go through ups and downs is not. Referring to the U.S. housing market, Himmelberg et al. (2005) write that "Over the last quarter century, run-ups in house prices are common, but so are subsequent declines. The national average real house price fell by 7.2 percent from 1980 to 1982; rose by 16.2 percent from 1982 to 1989; fell by 8 percent from 1989 to 1995; and then rose by 40 percent from 1995 to 2004." Available historical records show that this recurring sequence of house price expansions and contractions has been a constant feature of industrial economies at least since the 17th century.[3]

In this paper, I analyze 40 years of housing cycles in 19 OECD countries and concentrate on one specific characteristic: duration. This focus has two motivations. First, policymakers have an interest in knowing how long a house price expansion (contraction) is expected to last. If historical regularities exist, the awareness of these regularities makes forecasting a little less difficult. Second, researchers put a lot of effort in constructing theoretical models able to generate the cyclical house prices observed in the data. A more exact characterization of these empirical patterns will contribute to our understanding of the functioning of housing markets.

I provide two sets of results, one pertaining to the average length and the other to the length distribution. On average, upturns are longer than downturns, but the difference disappears once the last house price boom is excluded. In terms of length distribution, upturns (but not downturns) are more likely to end as their duration increases. This finding is consistent with boom-bust theories of house price fluctuations. According to these models, housing markets are characterized by rigidities and frictions,[4] which cause prices to periodically overshoot. As expansions get longer, they are increasingly likely to terminate, signaling a progressively unsustainable departure from fundamental price valuations.[5]

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[2] Data as of March 2011. Spain: Tinsa index (http://www.tinsa.us/654-imie-spanish-real-estate-market-index.html); U.S.: Case and Shiller index (http://www.standardandpoors.com/indices); Ireland: TSB/ESRI index (http://www.esri.ie/irish_economy/permanent_tsbesri_house_p).

[3] Shiller (2005) documents the ups and downs of U.S. house prices since 1890; Eithrem and Erlandsen (2004) show Norway house prices since 1819; Eicholtz (1997) examines prices in Amsterdam starting from 1650.

[4] Such imperfections include credit constraint (Ortalo-Magne and Rady, 2005), search frictions (Wheaton, 1990; Novy-Marx, 2009), restricted supply (Gleaser et al., 2008), and market psychology (Shiller, 2007).

[5] The fact that expansions are more likely to end as they get longer might seem a trivial property, but traditional linear stochastic processes (such as random walks or autoregressive processes) do not share it. For instance, the likelihood that a random walk turns up or down is always the same independently of the length of the previous sequence of price increases. Appendix A1 discusses this intuition more in detail.

This feature is defined as "duration dependence" and has been studied extensively in the business cycle literature, following the seminal works of Diebold and Rudebusch (1990) and Sichel (1991). To the best of my knowledge, only a few papers have analyzed the issue of duration dependence in housing cycles. Claessens et al. (2011) describe the characteristics of cycles in credit, stock prices, and house prices ("financial cycles") in a dataset of advanced and emerging economies. Cunningham and Kolet (2011) study the presence of duration dependence in the house price indices of U.S. and Canada metropolitan areas. My analysis differs from these papers in (1) the way I identify housing cycles, and (2) the test I use to detect duration dependence. In the rest of the paper, I highlight these differences in more detail and compare my results with theirs. To be consistent with the terminology of Claessens et al. (2011), from now on I refer to house price expansions as "upturns", and to house price contractions as "downturns".

The translation of business cycle methods in the housing market context is of great interest but requires special care. Business cycle researchers use the official dates of the start and end of recessions to partition the GDP series into expansions and contractions. In the U.S., for instance, these turning points are announced by the National Bureau of Economic Research (NBER). No official dates exist for housing turning points, and researchers have to identify expansions and contractions by themselves. Following Girouard et al. (2006), I use the Harding and Pagan (2002) BBQ algorithm to divide house price series into upturns and downturns.[6]

The rest of the paper proceeds as follows. Section II describes the data and the algorithm employed to identify turning points. Section III analyzes average upturn and downturn durations. Section IV discusses the duration distribution and the duration dependence property. Section V concludes.

## II. Data and Methodology

### A. Data

I use an OECD dataset containing information on nominal and real house prices, price-income ratios, and price-rent ratios. The data cover 19 countries[7] and are based on official and commonly-used national sources (see p.52 in André, 2010, for a detailed list). The dataset has quarterly observations, spanning from the first quarter of 1970 to the first quarter of 2010. Since house prices display a high degree of within-year cyclicality (Ngai and Tenreyro, 2009), series are seasonally-adjusted.

[6] The algorithm is denominated BBQ because it is a quarterly (Q) application of the Bry and Boschan (1971) algorithm (BB) designed to detect business cycles in monthly data.

[7] The countries are Australia, Belgium, Canada, Denmark, Finland, France, Germany, Ireland, Italy, Japan, Korea, Netherlands, Norway, New Zealand, Sweden, Spain, Switzerland, United Kingdom (U.K.), and United States (U.S.).

The measurement of house prices poses several challenges. As a consumption good, houses are heterogeneous in terms of physical characteristics (e.g. number of rooms), location (e.g. proximity to amenities or jobs), and state of the building (e.g. repairs and improvements). As an asset, houses are not traded in a centralized market, but through a multitude of bilateral negotiations. In any given year, only a small fraction of the housing stock changes hand.[8] A lot of effort is dedicated to ensure that national indices are comparable across countries, but the interpretation of results should always keep these caveats into account. Reassuringly, the data exploited in this paper have been used in a number of other cross-country studies.[9]

I also collect data on other macroeconomic variables. Real GDP, interest and inflation rates, and working age population are from the OECD Economic Outlook. From the IMF International Financial *Statistics* (IFS) I gather data on credit to the private sector. Again the choice of sources is consistent with the literature (Claessens et al., 2011).

## B. Identifying House Price Cycles

I use the Harding and Pagan (2002) algorithm to detect turning points in quarterly data. This algorithm belongs to the strand of pattern-recognition methods pioneered by Burns and Mitchell (1946) in their work on business cycles for the National Bureau of Economic Research (NBER), and later formalized by Bry and Boschan (1971). The dating procedure consists in finding a series of local maxima and minima that allow segmenting the series into expansions and contractions. The algorithm requires implementing the following three steps on a quarterly series $y_t$:[10]

1. Identification of points which are higher or lower than a window of surrounding observations. Using a window of $j$ quarters on each sides, a local maximum $y_t^+$ is defined as an observation of the series such that $(y_{t-j}, \ldots, y_{t-1}) < y_t^+ > (y_{t+1}, \ldots, y_{t+j})$. Symmetrically, a local minimum $y_t^-$ satisfies $(y_{t-j}, \ldots, y_{t-1}) > y_t^- < (y_{t+1}, \ldots, y_{t+j})$.

2. Alternation rule. A local maximum must be followed by a local minimum, and vice versa. In the case of two consecutive maxima (minima), the highest (lowest) $y_t$ is chosen.

3. Censoring rule. The distance between two turning points has to be at least $q$ quarters, where $q$ is chosen by the analyst in order to retrieve only significant series movements and avoid some of the series noise. Harding and Pagan (2002) choose $q = 2$ for U.S. GDP.

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[8] Piazzesi and Schneider (2009) write that in the U.S., in any given year, "only 6 percent of owner-occupied homes are traded. In contrast, on the New York Stock Exchange, annual volume divided by market capitalization is 120 percent."

[9] See for instance Girouard et al. (2006) and Igan et al. (2009).

[10] These tasks are usually carried out by computer programs. The Stata program used for this paper is available at http://econpapers.repec.org/software/bocbocode/s457284.htm.

The outcome is binary series where expansion quarters are tagged with "1" and contraction quarters are tagged with "0". The dating algorithm has initially been confined to the analysis of business cycles. Later its use has expanded to the analysis of asset prices: Pagan and Sossounov (2003) employ it do identify bull and bear markets in stock prices, Helbling and Terrones (2003) and Borio and McGuire (2004) use it for upturns and downturns in the housing market.

Using the dating algorithm with series different from GDP requires a decision over the dimension of the rolling window ($j$) and the minimum phase duration ($q$). Since house price cycles are known to be longer than GDP cycles (Ceron and Suarez, 2006), threshold parameters should be set at a higher level to avoid the identification of spurious phases.[11] Borio and McGuire (2004) suggest a rolling window of 13 quarters, which implies $j = 6$. Girouard et al. (2006) require a minimum phase length ($q$) of 6 quarters. In this paper I follow these indications.[12]

The method presented here examines the series in *level*, and has been referred to as the "classical cycle." In the last 20 years a major part of the academic research has been focusing more on the "growth cycle," which examines a series' *deviations from trend* (Stock and Watson, 1999). The choice of the most appropriate dating method depends on the goal of the research. Since this paper aims at uncovering a relatively new feature of the data, the dating method has to avoid restrictive parametric assumptions. By relying on the "graphical" properties of the series, the Harding and Pagan (2002) algorithm achieves this condition.[13] By contrast, most growth cycle methods rely on parametric assumptions, and results are very sensitive to the chosen de-trending method (Canova, 1998).

## III. The Average Duration of Upturns and Downturns

### A. Characteristics of Upturns and Ownturns

Table 1 shows the house price peaks and troughs for all countries and Figure 1 plots them against the house price time series. The turning points are the same as the ones identified by Girouard et al. (2006), Van den Noord (2006), and André (2010).[14]

[11] Another reason to impose wider rolling windows is that asset prices are more volatile than underlying fundamentals, potentially giving rise to a high number of spikes (Pagan and Sossounov, 2003).

[12] Additionally, one can impose a minimum cycle duration, so that the distance between two consecutive maxima (minima) is at least $k$ quarters ("Cycle rule"). Harding and Pagan (2002) choose $k = 5$, which means that one cannot have to consecutive phases with minimum duration $q = 2$. I do not impose an additional restriction on the duration of the cycle: an entire cycle already has to last longer than 12 quarters because of the censoring rule.

[13] The fact that the Harding and Pagan (2002) algorithm does not influence results is further tested in Section IV.

[14] When differences exist, turning points happen 1 or 2 quarters earlier/later. These discrepancies are due to the seasonal adjustment algorithm – the dataset changes slightly every time a new update is released. Moreover, some authors report only "major" upturns and downturns, defined as those phases where price changes exceeded 15% in absolute terms. I report all turning points.

**Table 1. Peaks and Troughs**

*Notes:* "P" denotes a peak, "T" denotes a trough. Years are followed by quarters.

| | Australia | Belgium | Canada | Denmark | Finland | France | Germany | Ireland | Italy |
|---|---|---|---|---|---|---|---|---|---|
| P | 1974:1 | | | | | | | | |
| T | 1978:4 | | | | 1972:2 | | | | |
| P | 1981:4 | | | | 1974:1 | | | | |
| T | 1987:1 | | | | 1979:1 | | | | |
| P | 1989:2 | | 1976:4 | 1973:3 | 1984:3 | | 1972:2 | 1972:2 | 1971:4 |
| T | 1991:1 | | 1985:1 | 1977:1 | 1986:2 | | 1976:3 | 1976:3 | 1973:3 |
| P | 1994:3 | | 1989:1 | 1979:2 | 1989:2 | 1980:4 | 1981:2 | 1979:2 | 1981:2 |
| T | 1996:1 | 1971:3 | 1992:1 | 1982:3 | 1993:2 | 1984:4 | 1989:2 | 1987:2 | 1986:2 |
| P | 2004:1 | 1979:3 | 1994:1 | 1986:2 | 1999:4 | 1991:2 | 1994:3 | 1990:2 | 1992:2 |
| T | 2005:3 | 1985:2 | 1998:3 | 1993:2 | 2001:4 | 1997:1 | | 1994:4 | 1997:3 |
| P | | | | 2007:1 | 2007:3 | 2007:4 | | 2006:3 | 2007:4 |

| | Japan | Korea | Nether-lands | New Zealand | Norway | Spain | Sweden | Switzer-land | United Kingdom | United States |
|---|---|---|---|---|---|---|---|---|---|---|
| P | | | | | | | | | | |
| T | | | | 1971:4 | | | | | | |
| P | | | | 1974:3 | | | | | | |
| T | | | | 1980:2 | | | | | | |
| P | | | | 1984:2 | | 1974:3 | | | 1973:3 | 1973:4 |
| T | | 1987:3 | | 1986:4 | 1972:4 | 1976:2 | 1974:2 | | 1977:3 | 1975:3 |
| P | 1973:4 | 1991:2 | | 1988:2 | 1977:1 | 1978:2 | 1979:3 | 1973:1 | 1980:3 | 1979:1 |
| T | 1977:3 | 2001:1 | | 1992:1 | 1983:4 | 1982:2 | 1985:4 | 1976:3 | 1982:1 | 1982:4 |
| P | 1991:1 | 2003:3 | 1978:2 | 1997:2 | 1987:2 | 1991:4 | 1990:1 | 1989:4 | 1989:3 | 1989:4 |
| T | | 2005:1 | 1985:1 | 2000:4 | 1993:1 | 1996:3 | 1996:1 | 2000:1 | 1996:2 | 1995:1 |
| P | | 2007:1 | | 2007:3 | 2007:3 | 2007:3 | | | 2007:4 | 2006:4 |

The two most important characteristics of cyclical phases are amplitude and duration. Amplitudes measure the cumulative increase (decrease) of house prices during an upturn (downturn). Durations are the main object of interest in this paper. For upturns, duration is defined as the distance in quarters between a trough and a peak; for downturns, it is the distance in quarters between a peak and the trough. Table 2 shows all the durations and distinguishes between ongoing and completed phases.

# Figure 1. House Price Indices and Turning Points

*Note:* Prices are normalized to 100 on 2005 Q2

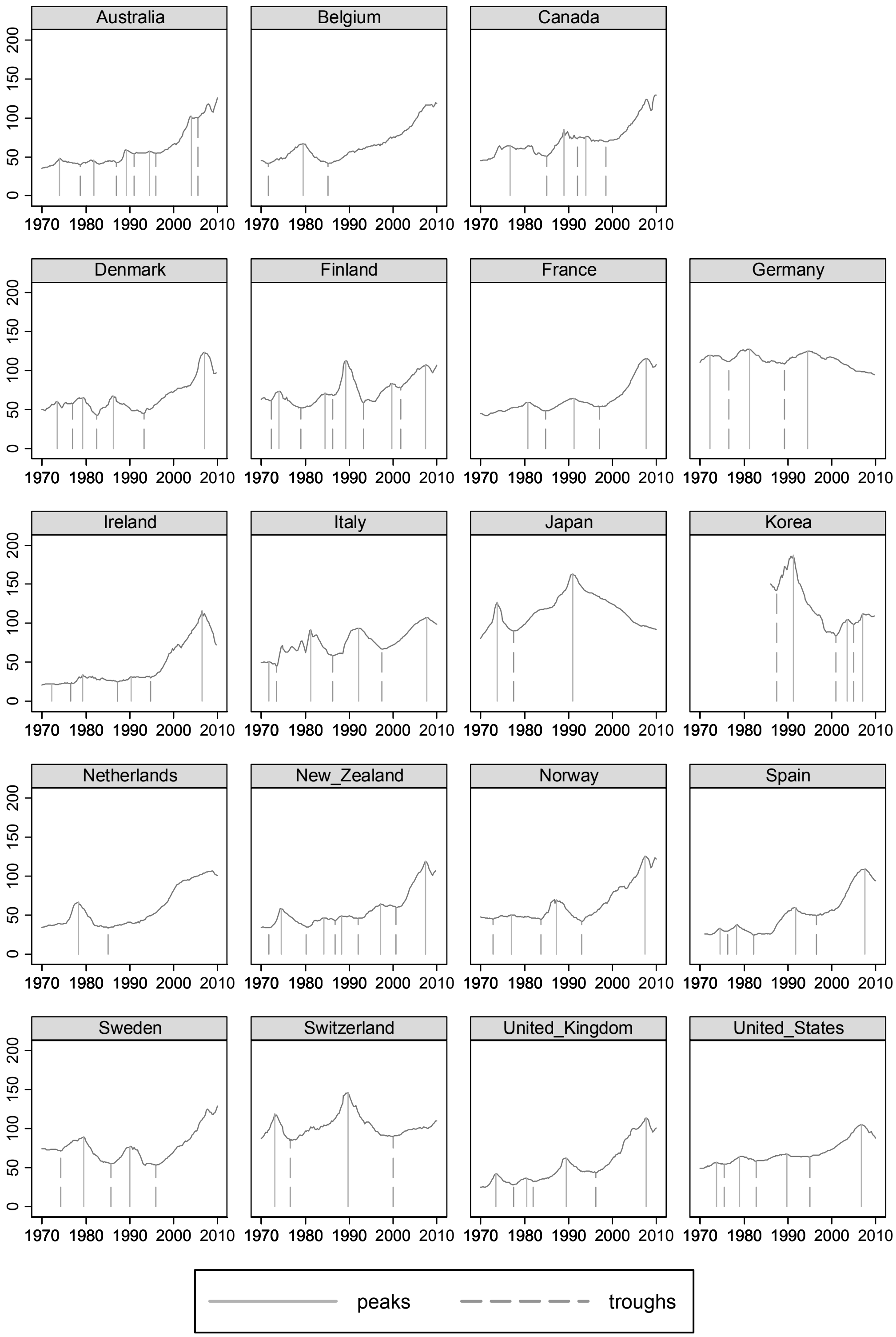


Table 3 shows the descriptive statistics (mean and standard deviations) for durations and amplitudes, distinguishing between upturns and downturns. The structure of the dataset is such that every country has an ongoing upturn or downturn at the time of the last observation (2010q1). The descriptive statistics are computed with and without those censored phases. The dataset contains 49 completed upturn, 49 complete downturns, 6 right-censored upturns, and 13 right-censored downturns. On average, upturns last more than downturns, consistently with Claessens et al. (2011). Not surprisingly, the amplitude of upturns is also larger. In terms of standard deviations, downturns display less duration variability than upturns, which hints at the "clustering" of downturn durations that is discussed in the next section.

**Table 2. Duration of Phases (Quarters)**

*Notes:* Italics denote ongoing upturns or downturns. "U" indicates upturns and "D" indicates downturns.

| | Australia | Belgium | Canada | Denmark | Finland | France | Germany | Ireland | Italy |
|---|---|---|---|---|---|---|---|---|---|
| U | 19 | | | | | | | | |
| D | 12 | | | | 7 | | | | |
| U | 21 | | | | 20 | | | | |
| D | 9 | | | | 22 | | | | |
| U | 7 | | 33 | 14 | 7 | | 17 | 17 | 7 |
| D | 14 | | 16 | 9 | 12 | | 19 | 11 | 31 |
| U | 6 | | 12 | 13 | 16 | 16 | 32 | 32 | 20 |
| D | 32 | 32 | 8 | 15 | 26 | 26 | 21 | 12 | 24 |
| U | 6 | 23 | 18 | 28 | 8 | 23 | *61* | 18 | 21 |
| U | *18* | *99* | *46* | 55 | 23 | 43 | | 47 | 41 |
| D | | | | *11* | *10* | *9* | | *13* | *9* |

| | Japan | Korea | Nether-lands | New Zealand | Norway | Spain | Sweden | Switzer-land | United Kingdom | United States |
|---|---|---|---|---|---|---|---|---|---|---|
| U | | | | | | | | | | |
| D | | | | 11 | | | | | | |
| U | | | | 23 | | | | | | |
| D | | | | 16 | | | | | | |
| U | | | | 10 | | 7 | | | 16 | 7 |
| D | | 15 | | 6 | 17 | 8 | 21 | | 12 | 14 |
| U | 15 | 39 | | 15 | 27 | 16 | 25 | 14 | 6 | 15 |
| D | 54 | 10 | | 21 | 14 | 38 | 17 | 53 | 30 | 28 |
| U | *76* | 6 | 27 | 14 | 23 | 19 | 24 | 41 | 27 | 21 |
| U | | 8 | *100* | 27 | 58 | 44 | *56* | *40* | 46 | 47 |
| D | | *11* | | *9* | *10* | *10* | | | *9* | *13* |

**Table 3. Descriptive Statistics**

*Notes:* Left-censored phases (those for which the starting date precedes 1970q1 and is unknown) are excluded. The amplitude of upturns is the difference between the peak and its preceding trough, divided by its preceding trough. The amplitude of downturns is computed as the difference between the preceding peak and the trough divided by the trough.

| | | Duration (quarters) | | Amplitude (%) | |
|---|---|---|---|---|---|
| | Sample | Mean | StDev | Mean | StDev |
| Complete upturns | 49 | 24.1 | 14.8 | 61.3 | 56.3 |
| Complete + ongoing upturns | 55 | 28.0 | 20.6 | 66.7 | 60.1 |
| Complete downturns | 49 | 18.2 | 8.7 | 30.7 | 28.4 |
| Complete + ongoing downturns | 62 | 18.4 | 12.5 | 28.8 | 27.5 |

## B. The Role of the Last Upturn

The house price boom that involved OECD countries at the end of the 20th century and the first part of this century was exceptional under many aspects, not least for its duration (Girouard et al., 2006). For each country, Table 4 shows the dates for the last upturn as detected by the BBQ algorithm.[15] Germany and Japan are excluded because they have been experiencing a house price downturn since the nineties. The table distinguishes between countries whose upturn is terminated and countries whose upturn is still on (see Igan and Loungani, 2010, for a discussion of this dichotomy). Most national indices started to rise in the middle of the 1990s; Belgium and Netherlands have been experiencing rising house prices since 1985. It is not surprising that the amplitude of these price movements has been considerable. Ireland's index nearly tripled between 1994 and 2006.

The fact that upturns are longer than downturn is largely due to the exceptional duration of the last upturn experienced by OECD countries. Imagine redrawing Figure 1 excluding the last upturn from the country charts. While the original Figure 1 gives the impression that house prices are characterized by an upward trend, the new charts would convey no such message. Regressing the real house price index on country fixed effects ($\alpha_c$), and a linear time trend ($t$) yields:

[15] The last datapoint available is 2010q1. By construction, the dating algorithm avoids choosing turning points that are in the last year and a half of data. For those points, it is not possible to construct the window of observations over which local maxima and minima are computed.

$$INDEX_{ct} = \alpha_c + \underset{(.042)^{***}}{.291} t$$

for the complete sample, and:

$$INDEX_{ct} = \alpha_c + \underset{(.048)}{.094} t$$

for the sample excluding the last boom.[16] Once the last boom is excluded, it is not possible to reject the null hypothesis of no constant time trend. This result is consistent with Eicholtz (1997) and Shiller (2006), who study historical house price data and show that in the long run the upward trend in real house prices is negligible.

**Table 4. Characteristics of the Last Upturn**

| Country | Trough-Peak | Duration (quarters) | Amplitude (%) |
|---|---|---|---|
| *Complete upturns* | | | |
| Denmark | 1993q2-2007q1 | 55 | 176.6 |
| Finland | 2001q4-2007q3 | 23 | 37.6 |
| France | 1997q1-2007q4 | 43 | 117.8 |
| Ireland | 1994q4-2006q3 | 47 | 286.4 |
| Italy | 1997q3-2007q4 | 41 | 59.3 |
| Korea | 2005q1-2007q1 | 8 | 14.0 |
| New Zealand | 2000q4-2007q3 | 27 | 98.5 |
| Norway | 1993q1-2007q3 | 58 | 200.1 |
| Spain | 1996q3-2007q3 | 44 | 121.6 |
| United Kingdom | 1996q2-2007q4 | 46 | 160.7 |
| United States | 1995q1-2006q4 | 47 | 64.3 |
| *Ongoing upturns* | | | |
| Australia | 2005q3- | 18 | 26.3 |
| Belgium | 1985q2- | 99 | 186.7 |
| Canada | 1998q3- | 46 | 86.9 |
| Netherlands | 1985q1- | 100 | 199.8 |
| Sweden | 1996q1- | 56 | 140.2 |
| Switzerland | 2000q1- | 40 | 22.5 |

[16] Eicker-White heteroskedasticity-consistent standard errors are shown. $^{***}$ denotes 0.1% significance.

# IV. Duration Dependence

## A. The Duration Distribution

Studies of economic cycles often cite just the average duration of phases without describing the whole distribution of realized upturn or downturn lengths. This neglects a lot of information. The same mean duration can stand for different distributions: in one of them the probability of ending an upturn or a downturn could be the same in every period, and in another the probability of terminating a cyclical phase could be increasing with time. In other words, the average duration is not informative about duration dependence, the property that describes if and how the likelihood of exiting an upturn or downturn changes at different durations.

Before explicitly analyzing the issue of duration dependence, I discuss the duration distribution of upturns and downturns found in the data. Table 5 shows a breakdown of this distribution by relevant percentiles. The construction of upturns and downturns is such that the minimum duration is 6 for both phases. The 10th, 25th, and 40th percentiles of the two distributions are substantially equal. Upturns are longer than downturn only above the 40th percentile. Figure 2 conveys this message graphically. The frequencies of upturn durations decay slowly, and the frequencies of downturns cluster in the 10-20 quarter range, with very few downturns lasting more than 20 quarters.

**Table 5. Distribution of Durations**

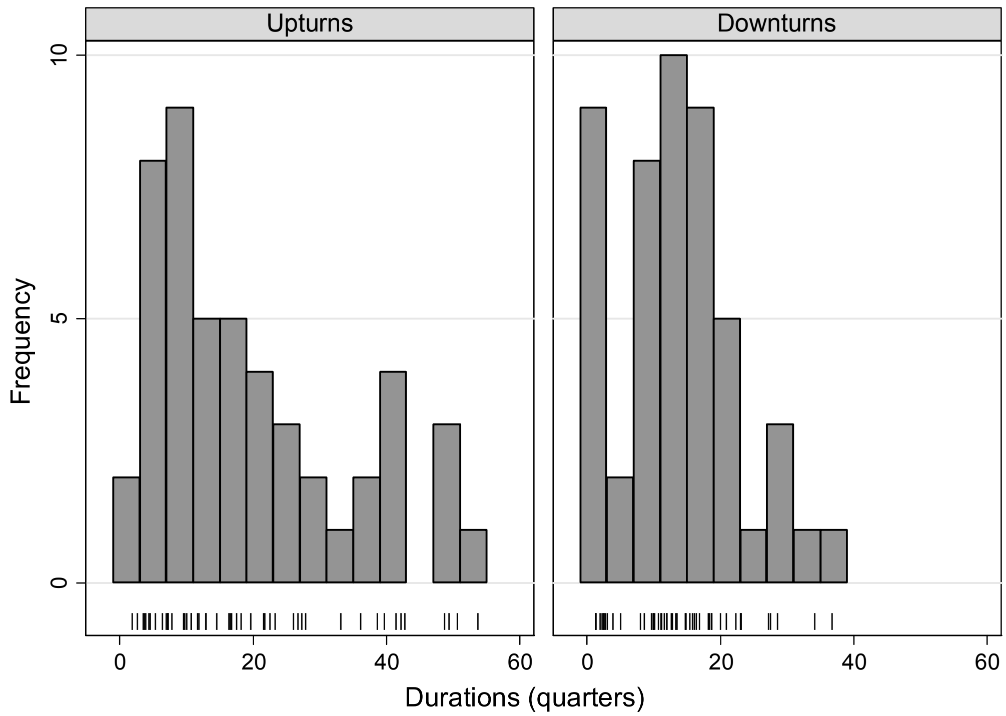
*Note:* The table shows the percentile of the duration distribution for 49 complete upturns and 49 complete downturns.

| | Min | Pct10 | Pct25 | Pct40 | Median | Pct60 | Pct75 | Pct90 | Max |
|---|---|---|---|---|---|---|---|---|---|
| Complete upturns | 6 | 8 | 12 | 16 | 21 | 24 | 32 | 47 | 58 |
| Complete downturns | 6 | 7 | 13 | 16 | 17 | 20 | 23 | 32 | 41 |

The presence of a one-to-one relation between the distribution of realized durations and the shape of duration dependence would suggests a test for duration dependence based on the distribution data in Table 5 (Diebold and Rudebusch, 1990). However, international housing cycles are at least partially synchronized (Ceron and Suarez, 2006; Igan et al., 2009; Claessens et al., 2011) and this feature would produce spurious clusters of durations around certain values. To control for synchronization, a regression-based test is more appropriate.

**Figure 2. Housing Cycles: Distribution of Durations**

*Notes:* Only completed durations are included. To adjust for left-truncation in the dating algorithm, the first 5 observations of every upturn and downturn are discarded.




### B. A Nonparametric Test of Duration Dependence

Ohn et al. (2004) suggest a very straightforward method to check if the upturns and downturns of a series $y_t$ display duration dependence. Suppose the binary variable $S_t$ takes value 1 if $y_t$ is in an upturn and 0 otherwise. For upturns, the test consists in keeping only the observations where $S_{t-1} = 1$ and running the following regression:

$$S_t = \alpha + \beta\, d_{t-1} \tag{1}$$

where $d_t$ is the ongoing duration of the upturn at time $t$. For downturns, the procedure is exactly symmetrical. A significant $\beta$ denotes duration dependence.[17]

Different country indices are pulled together in the OECD house price dataset, and, despite the efforts to make the series homogeneous, some countries could display more price volatility just because of a different methodology in constructing the index. A greater volatility would generate more cycles, resulting in lower durations and impacting on the duration dependence test. To control for this possibility, I run Equation 1 with country fixed effects ($\alpha_c$), consistently with

[17] Standard linear data generating processes, such as random walks and autoregressive processes, do not display any duration dependence – see Appendix A1.

Claessens et al. (2011). Moreover, national house prices are partially synchronized, and to control for this concordance I add year fixed effects ($\gamma_t$). The equation I estimate is therefore:

$$S_{ct} = \alpha_c + \gamma_t + \beta\ d_{c,t-1} \qquad (2)$$

Table 6 shows the estimation output. I also allow for a logarithmic and a quadratic specification of $d_{c,t-1}$. Since the last boom has had exceptional characteristics, I estimate the upturn equation with and without it. Both upturn equations indicate a significant and positive effect of duration on the probability that upturns end; the downturn equation, by contrast, displays no such effect.

This result is consistent with what Cunningham and Kolet (2011) find for U.S. and Canadian cities. It seems that house price upturns, especially in their more extreme manifestations ("booms"), involve a departure of prices from fundamentals. Such departures are increasingly difficult to sustain, leading to the duration dependence we see in the data. Speculation and overbuilding are two real-world mechanisms that make the probability of a house price reversal higher and higher as a boom gets longer.[18]

Equation 2 is basically a linear probability model (LPM). Another way to test for duration dependence would be to restrict the function $\alpha_c + \gamma_t + \beta\ d_{c,t-1}$ between 0 and 1 through a link function $g$ such as probit or logit: $S_{ct} = g^{-1}(\alpha_c + \gamma_t + \beta\ d_{c,t-1})$. Many authors (e.g. Castro, 2010; Claessens et al., 2011) use link functions common in survival/duration analysis, such as Weibull (in a continuous-time setting) or log-logistic (in a discrete-time setting). I choose to stick to a LPM as my main specification. The objective of Equation 2 is diagnostic (Ohn at al., 2004): is there significant evidence in the data in favor of duration dependence? A simple OLS approach is preferable when the goal is to keep the analysis as nonparametric and transparent as possible, instead of precisely quantifying marginal effects that depend on functional assumptions.[19]

### C. Inspecting the Mechanism: The Role of Fundamentals

If the reason for positive duration dependence in upturns lies in the non-fundamental component of house price expansions, then the inclusion of macroeconomic variables in Equation 2 should not alter the main result.

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[18] Claessens et al. (2011) limit their duration dependence analysis to downturns, and find a significant positive effect. The different BBQ algorithm they employ (with minimum upturn and downturn duration of just 2 quarters) and the absence of year dummies are sufficient to explain the discrepancy between their results and the ones presented here.

[19] Appendix A2 shows that, once duration models are translated into a discrete-time setting, they are equivalent to binary limited dependent-variable (LDV) models where duration is included as an independent variable. The choice is therefore not between LPM's and duration models, but between LPM's and LDV's. Table A1 shows that the results from a logit regression are the same as those from the LPM.

The user-cost formula proposed by Poterba (1984), $RENT = PRICE(i + tax + \delta - \pi)$ is a natural starting point to think about house price fundamentals.[20] The formula suggests to include a measure of $RENT$ and interest rate ($i$) in Equation 2, although this is clearly not sufficient to cover all the possible macroeconomic determinants of house prices. The recent crisis has shown that there are various channels influencing the availability of credit, among which the interest rate is just one (Dell'Ariccia et al., 2008). To control for that, similarly to Claessens et al. (2011), I include a measure of credit to the private sector ($CREDIT_{ct}$) in the equation. All variables are expressed in real term, consistently with a model of rational economic decision makers. Recent analyses, however, suggest that inflation plays a role in aggregate house prices (Brunnermeier and Julliard, 2008), so I include a measure of inflation in the equation ($INFL_{ct}$). Finally, the user-cost formula assumes rental and owner-occupied properties to be perfect substitutes, a very strong assumption if compared to the real world. It might therefore be useful to consider other demand factors that impact on house prices (André, 2010). I also include a measure of national income ($GDP_{ct}$) and a measure of working age population ($WAP_{ct}$) in the equation.

[20] The formula describes a non-arbitrage condition between renting and buying. An individual is indifferent between paying the rent or the "user-cost" of housing. The user-cost is defined as the price of the house times the after-tax mortgage interest rate ($i$) plus property taxes ($tax$), and depreciation ($\delta$), minus expected appreciation ($\pi$).

## Table 6. Duration Dependence Test

*Note:* Results from estimating $S_t = \alpha_c + \gamma_t + \beta x$, where $x$ is one of the variables listed in the first column. For upturns, a negative coefficient indicates a positive effect of duration on the likelihood of terminating the phase. For downturn, the same effect is indicated by a positive coefficient – this is because $S_t = 1$ for upturns and $S_t = 0$ for downturns. The first 5 observations of each upturn and downturn are excluded because the algorithm does not allow any phase to last less than 6 quarters. ***,**, and * denote 0.1%, 1% and 5%, significance respectively, computed using Eicker-White standard errors.

| | *Upturns* | | | *Upturns without last boom* | | | *Downturns* | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| $\log(d_{c,t-1})$ | -0.0450*** | | | -0.0822*** | | | 0.0201 | | |
| | (0.0079) | | | (0.0146) | | | (0.0141) | | |
| $d_{c,t-1}$ | | -0.0025*** | -0.0050*** | | -0.0083*** | -0.0138** | | 0.0020 | 0.0052 |
| | | (0.0006) | (0.0012) | | (0.0020) | (0.0044) | | (0.0013) | (0.0028) |
| $d^2_{c,t-1}$ | | | 0.0000* | | | 0.0001 | | | -0.0001 |
| | | | (0.0000) | | | (0.0001) | | | (0.0000) |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 1,273 | 1,273 | 1,273 | 566 | 566 | 566 | 825 | 825 | 825 |
| R-squared | 0.1676 | 0.1601 | 0.1656 | 0.2143 | 0.2090 | 0.2133 | 0.1414 | 0.1418 | 0.1439 |

Table 7 shows the output of estimating:

$$S_{ct} = \alpha_c + \gamma_t + \beta\, d_{c,t-1} + \rho\, X_{c,t-1},$$

where $X_{c,t-1}$ are the macroeconomic fundamentals.[21] The evidence of duration dependence in upturns is still strong, despite the use of quite a few variables on a dataset that covers just 19 countries with 161 observations each. Downturns, again, do not show signs of duration dependence. The effect of duration on the likelihood of terminating an upturn is measuring something that is independent of macroeconomic fundamentals.[22]

In terms of the coefficients on $X_{c,t-1}$, positive changes in interest rates and inflation are both associated with an increase in the probability that an upturn ends. Perhaps more puzzlingly, above-trend rents and domestic product have the same effect on upturns, and an above-trend domestic product reduces the likelihood of exiting a downturn. It is worthwhile to note, however, that these coefficients measure an association between macroeconomic variables and house price peaks and troughs, not a causal relation between fundamentals and house prices. Above-trend GDP might signal an overheated economy, and this is likely to be correlated with house price peaks.

Other papers have estimated the effect of macroeconomic variables on the likelihood of terminating a house price upturn or downturn (Borio and McGuire, 2004; Van den Noord, 2006; Agnello and Schuknecht, 2009), but they have disregarded the duration term. By doing so, they might have missed an important element of the analysis, which is not captured by measures of macroeconomic fundamentals. Moreover, Harding and Pagan (2011) show that turning points algorithms produce serial correlation in the sequence of upturns and downturns. Simple probit/logit models do not control for this serial correlation, whereas the inclusion of a duration term takes time dependencies into account (Beck et al., 1996).

[21] The notes to Table 7 explain more in detail how the variables are computed and de-trended.
[22] Table A2 replicates the results with a logit model.

## Table 7. Duration Dependence and Fundamentals

*Notes:* Results from estimating $S_t = \alpha_c + \gamma_t + \beta X$, where $X$ is the vector of variables listed in the first column. ***, **, and * denote 0.1%, 1% and 5% significance respectively. I retrieve an index of real rents by combining the real house price dataset with the rent-price ratio dataset, both from the OECD. As a proxy of the real mortgage interest rate ($i_{ct}$), I use three-month money-market rates deflated by national Consumer Price Indices (CPIs). $RENT_{ct-1}$, $GDP_{ct-1}$, and $CREDIT_{ct-1}$ are expressed as deviations from the trend (computed with a Hodrick-Prescott filter). $i_{ct-1}$ and $INFL_{ct-1}$ enter as annualized changes, whereas $WAP_{ct-1}$ is expressed as annualized growth.

| | *Upturns* | | | *Upturns without last boom* | | | *Downturns* | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| $\log(d_{c,t-1})$ | -0.0334*** | | | -0.0649** | | | 0.0150 | | |
| | (0.0072) | | | (0.0167) | | | (0.0117) | | |
| $d_{c,t-1}$ | | -0.0020** | -0.0041*** | | -0.0070** | -0.0069 | | 0.0016 | 0.0045 |
| | | (0.0006) | (0.0010) | | (0.0020) | (0.0051) | | (0.0012) | (0.0021) |
| $d^2_{c,t-1}$ | | | 0.0000* | | | -0.0000 | | | -0.0001* |
| | | | (0.0000) | | | (0.0001) | | | (0.0000) |
| $RENT_{c,t-1}$ | -0.4549* | -0.5016* | -0.4710* | -0.7304 | -0.6040 | -0.6040 | -0.1539 | -0.1442 | -0.1350 |
| | (0.1622) | (0.1866) | (0.1698) | (0.7731) | (0.8170) | (0.8185) | (0.2934) | (0.3026) | (0.2961) |
| $i_{c,t-1}$ | -0.7415** | -0.7394** | -0.7424** | -0.7562* | -0.7556* | -0.7555* | 0.0350 | 0.0347 | 0.0355 |
| | (0.2545) | (0.2495) | (0.2522) | (0.3014) | (0.3000) | (0.3005) | (0.1292) | (0.1291) | (0.1291) |
| $INFL_{c,t-1}$ | -1.0049* | -0.9933* | -1.0029* | -1.1175* | -1.1089* | -1.1087* | 0.0801 | 0.0768 | 0.0784 |
| | (0.3530) | (0.3493) | (0.3530) | (0.4765) | (0.4819) | (0.4852) | (0.2247) | (0.2237) | (0.2247) |
| $CREDIT_{c,t-1}$ | -0.1471 | -0.1466 | -0.1479 | -1.1855* | -1.1784* | -1.1784* | -0.4356 | -0.4440 | -0.4243 |
| | (0.1035) | (0.1082) | (0.1087) | (0.4455) | (0.4770) | (0.4776) | (0.2292) | (0.2293) | (0.2222) |
| $GDP_{c,t-1}$ | -2.2733* | -2.2841* | -2.3370* | -2.1464 | -2.4671 | -2.4701 | -1.5534* | -1.5500* | -1.5568* |
| | (0.9001) | (0.9109) | (0.9072) | (1.2983) | (1.3769) | (1.3359) | (0.6516) | (0.6512) | (0.6454) |
| $WAP_{c,t-1}$ | -0.0190 | 0.0059 | -0.0341 | 2.8257 | 2.7888 | 2.7855 | -11.6136 | -11.7701 | -11.5827 |
| | (0.3836) | (0.3802) | (0.3785) | (3.1628) | (3.2276) | (3.1704) | (7.9127) | (7.8913) | (7.8651) |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 1,132 | 1,132 | 1,132 | 444 | 444 | 444 | 723 | 723 | 723 |
| R-squared | 0.2130 | 0.2101 | 0.2149 | 0.2944 | 0.2996 | 0.2997 | 0.1268 | 0.1277 | 0.1293 |

## V. CONCLUSION

In this paper, I study 40 years of housing cycles in 19 OECD countries and concentrate on one specific characteristic: duration. The descriptive analysis shows that upturns have been longer than downturns on average, but this difference is largely due to the last house price boom, which was particularly long. When I focus on the entire distribution of durations and I test for duration dependence, I show that house price upturns are more likely to end as they get longer, whereas house price downturns are not. This result holds independently of whether the last boom is included or not in the sample.

The result on duration dependence brings forward two insights. First, since duration dependence is not a feature displayed by standard linear stochastic processes, aggregate house price indices behave in a nonlinear way. These nonlinearities can be accounted for using Markov regime-switching models (Ceron and Suarez, 2006) or models with conditional heteroskedasticity (Miles, 2008). Without the need to engage with more complex models, the notion of duration dependence provides an intuitive way to think about these nonstandard features.

The second insight relates to our theoretical understanding of house price cycles. “Hot” housing phases produce fast appreciation, high transaction volumes, and overbuilding; “cold” housing market phases, by contrast, are characterized by low transaction volumes and slow nominal price adjustment (Leamer, 2007). It seems natural to frame cyclical upturns as hot periods in which housing valuations depart from fundamentals, and downturns as periods in which corrections need to take place. In such a framework, the probability of a house price reversal increases as the imbalances of the upturn grow larger, and this generates the statistical regularity of duration-dependent upturns.

From a practical perspective, this paper contributes to the current policy debate on how to deal with real estate booms (Allen and Carletti, 2010; Crowe et al., 2011). In all the countries analyzed here, house prices are cyclical: no nation has ever lived through a perennial house price expansion or contraction. The question is where and when house price reversals are more likely to happen. Despite the usual caveats associated with econometric estimates, it seems fairly safe to conclude that an “overheated” economy, be it because of an unusually long house price upturn or because of above-trend GDP growth, is more likely to initiate a house price downturn.

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**Appendix A1 – The Distribution of Phase Durations for an ARIMA(1,1,0) Process**

*Simulation.* This Appendix first clarifies what an "ordinary" distribution of durations would look like. To address this issue, I simulate a process that contains the properties that are usually associated with house price indices. First, the series must contain a unit root – Igan et al. (2009), using the same house price data as the present paper, show that every national series except Italy's is at least integrated of order 1.[23] Second, I insert a drift in the growth rate of the series to generate an upward trend. Third, since the seminal paper of Case and Shiller (1989), a large literature has shown that house price *growth* is in part predictable, i.e. price changes are autocorrelated. Glaeser et al. (2010) show that in the U.S. a 1 dollar increase in real constant quality house prices in one year is associated with a 60-80 cent increase the next year. To match this feature, I impose a first-order autocorrelation of 0.8 on house price growths.

I randomly generate 100,000 observations from the ARIMA(1,1,0) process $y_t = 0.1 + y_{t-1} + 0.8\,\Delta y_{t-1} + \epsilon_t$. On it, I apply the same dating algorithm used for the national house prices. I count 2248 upturns and 2248 downturns, and plot the distribution of their durations in Figure A1. Durations are corrected for left-truncation by removing the first 5 observations. The frequencies of both upturn and downturn durations show a decaying pattern typical of a geometric distribution. To confirm this intuition, I draw a quantile-quantile (Q-Q) plot next to the histograms to compare the simulated distribution with the theoretical geometric distribution: the two are almost identical.

In general, a geometric distribution $f(x) = (1-\lambda)^{x-1}\lambda$ represents the probability of getting $x-1$ successes before encountering a failure in a sequence of Bernoulli (binary) trials. The crucial feature of such distribution is that probability $\lambda$ is constant. In the context of macroeconomic cycles, this means that the probability of an upturn (downturn) ending is the same no matter how long the upturn (downturn) has lasted. This is equivalent to the absence of duration dependence.

To confirm the result of no duration dependence, I run the regression described by Equation 1 on the simulated upturns and downturns. For upturns I get:

$$S_t = \underset{(.00133)^{***}}{.96159} - \underset{(.00003)}{.00001}\, d_{t-1}, \tag{A1}$$

and for downturns I get

$$S_t = \underset{(.00322)^{***}}{.08223} - \underset{(.00016)}{.00003}\, d_{t-1}. \tag{A2}$$

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[23] Igan et al. (2009) show that many house prices series can actually be characterized as I(2). It would be interesting, as a direction for future research, to check if there is a link between this feature and duration dependence.

*BBQ algorithm and duration dependence.* This simulation shows that the BBQ algorithm does not create duration dependence endogenously. A clear distortion created by the algorithm is the fact that no phase ends before 6 quarters. This left-truncation problem is addressed by ignoring observations with duration less than 6, and rescaling durations so that the 6th quarter of a phase corresponds to $D = 1$ (Jenkins, 2005). However, there might be concerns that the dating algorithm generates duration dependence in another, more subtle way, which does not disappear with the suppression of earlier durations. The way in which turning points are constructed is highly nonlinear, mainly because of the rolling window of observations over which local maxima and minima are computed. Harding and Pagan (2011) show that many cycles constructed in this way display the properties of higher-order Markov processes. Since duration independence implies a first-order Markov process,[24] one needs to check that the algorithm is not creating duration dependence artificially. Equations A1 and A2 show that this is not the case.

[24] Imagine a binary variable $S_t$ that indicates the state of $y_t$: it is equal to 1 if $y_t$ is in an upturn and 0 otherwise. Suppose one wants to forecast $S_{t+1}$ with the information available at $t$: the object of interest is Pr $(S_{t+1}|S_t)$. If $S_t$ is the *only* information needed to forecast $S_{t+1}$, then $\Pr(S_{t+1} \mid S_t, S_{t-1}, \ldots, S_{t-k}) = \Pr(S_{t+1} \mid S_t)$, and $S_t$ is said to be a first-order Markov process. Duration dependence is a violation of the Markov property. When $S_t$ is duration dependent, $\Pr(S_{t+1} \mid S_t, d_t) \neq \Pr(S_{t+1}|S_t)$, and $d_t$ represents the number of periods spent in the current state ("ongoing duration").

## Appendix A2 –
## Discrete-Time Hazard Models and Binary-Dependent Variable Regressions

In the first part of this Appendix I introduce parametric hazard models according to their original continuous-time formulation. I then switch to a discrete-time setting and show that the estimation of these models is equivalent to the estimation of a classic probit/logit model where duration is included as explanatory variable. Most of the material presented here comes from Jenkins (2005).

*Continuous-time hazard models.* The distribution of durations of a process brings about its "survivor function" $G(x)$, the probability that an upturn or downturn reaches *at least* duration $x$. The hazard rate $\lambda(x)$ is defined as the probability that the process fails at duration $x$ conditional on having reached $x$: $\lambda(x) = f(x)/G(x)$. There is a one-to-one relation between the hazard rate and the survivor function – specifying a functional form for the hazard rate is equivalent to specifying a functional form for the survivor function.

In empirical analyses one has a set of durations $D$ from which the parameters of the function $\lambda(x)$ have to be retrieved. It is not necessary that all the analyzed phases be complete, because for incomplete phases the survivor function $G(x)$ suffices. Parameters are estimated through maximum likelihood and the likelihood contribution of a right-censored phase with ongoing duration $d$ is $G(d)$. The likelihood contribution of a complete phase is $f(D) = \lambda(D)G(D)$, and the loglikelihood of the entire sample is:

$$\text{logL} = \sum_{n=1}^{N} \{c_n[\log \lambda(D_n) + \log G(D_n)] + (1 - c_n) \log G(d_n)\} \qquad (1)$$

where $c_n$ is a dummy variable with value 1 if $n$ is a complete phase and 0 if $n$ is right-censored.

Sichel (1991) is the first to suggest a parametric model to analyze duration dependence in macroeconomic cycles. In his model the hazard rate is parameterized as

$$\lambda(D) = \mu\alpha D^{\alpha-1}$$

where $\mu$ and $\alpha$ are two constants. This hazard yields a Weibull distribution of durations with parameter $\alpha$. When $\alpha$ is greater than unity the series displays positive duration dependence, when $\alpha < 1$ there is negative duration dependence, and with $\alpha = 1$ the duration term disappears (duration independence). Claessens et al. (2011) use this model on credit, stock, and housing cycles.

*Hazard models in discrete-time.* Duration models, including the Weibull model, have been initially conceived for a continuous-time setting. Some authors (Ohn et al., 2004; Castro, 2010) claim that a discrete-time setting is more appropriate when the minimum duration of phases is a small multiple of the reference time unit (a quarter) – as is the case here. In a discrete-time setting, the survivor function at ongoing duration $d$ can be represented as $\prod_{q=1}^{d}(1 - \lambda(q))$, the product of the survival probabilities for each period $q$ at risk. One can use this insight to rewrite equation (1) for the discrete-time case as:

$$\text{logL} = \sum_{n=1}^{N}\sum_{q=1}^{Q}\left[y_{nq}\log\lambda(d_{nq}) + (1-y_{nq})\log[1-\lambda(d_{nq})]\right] \qquad (2)$$

where every quarter $q$ of phase $n$ enters the loglikelihood; $y_{nq}$ is equal to 1 if the observation is the last one of the upturn/downturn, and 0 otherwise.
Equation (2) is the log-likelihood of a standard binary model where $y_{nq}$ is the dependent variable. For the present paper I assume the probability $\lambda(d_{nq})$ takes a logit form:

$$\lambda(D_{nq}) = \frac{\exp\left(h(d_{nq})\right)}{1+\exp\left(h(d_{nq})\right)}$$

where $h(d_{nq})$ is some function of $d_{nq}$. To estimate this model it is sufficient to run a logit regression on the quarter-country dataset, where the dependent variable $y_{nq}$ takes value 1 on the last quarter of expansions or contractions, and a variable $d_{nq}$ is created that keeps track of ongoing durations. As with the descriptive analysis, it is important to (1) run the model separately on upturns and downturns, and (2) discard the observations that are not at risk (those where $d_{nq}$ is less than the minimum allowed number of quarters, 6) and rescale the duration variable accordingly. Discrete-time models allow a lot of flexibility in the way $d_{nq}$ enters the equation. In what follows, I experiment with three specifications. The first specification is one where $h(d_{nq}) = \gamma_0 \log d_{nq}$; the second is a simple linear term $\gamma_1 d_{nq}$; the third is a quadratic polynomial, $\gamma_1 d_{nq} + \gamma_2 d_{nq}^2$.

The most common way to add explanatory variables to the specification is to estimate a mixed proportional hazard model:

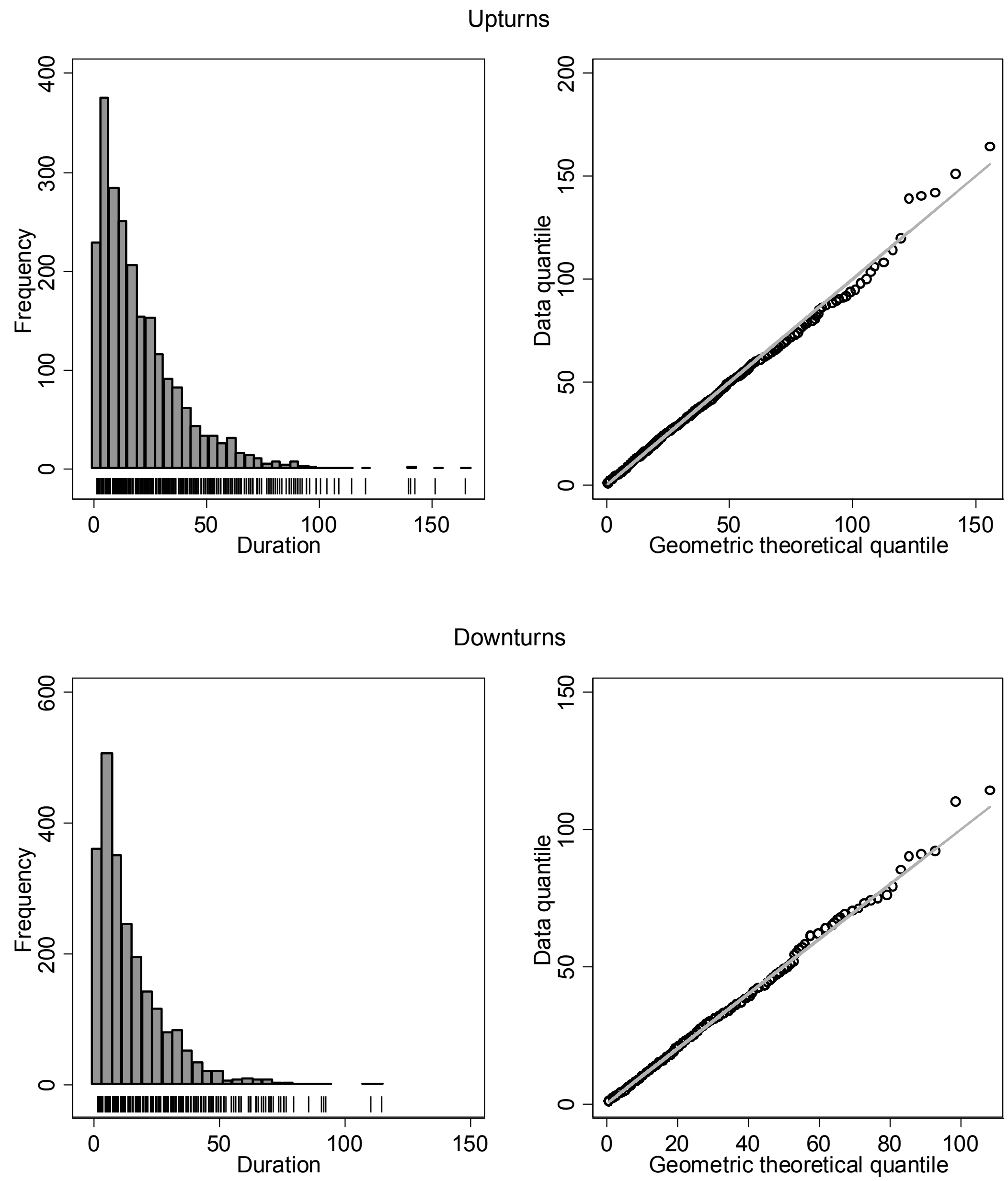
$$\lambda(D, X) = h(D)e^{\beta' X}$$

where $h(D)$ is the baseline hazard rate and regulates the relationship between the hazard rate and duration; $X$ is a set of explanatory variables. The baseline hazard is a function of $D$ that takes one of the shapes discussed above: for instance, Weibull or logarithmic. This class of models is called "proportional" because the explanatory variables do not alter the shape of the baseline hazard; they shift it up or down. When the explanatory variables are all equal to zero the hazard rate is simply equal to the baseline hazard. The $\beta$ coefficient can be interpreted as the proportional effect on the hazard of a one unit change in the explanatory variable (semi-elasticity): $\beta_k = \frac{\partial \log\lambda(D,X)}{\partial X_k}$. In the context of a logit duration model the hazard rate is:

$$\lambda(d_{nq}, X_{nq}) = \frac{\exp\left(h(d_{nq}) + \beta' X_{nq}\right)}{1+\exp\left(h(d_{nq}) + \beta' X_{nq}\right)} \qquad (3)$$

## Figure A1. Simulated Phase Durations of an ARIMA (1,1,0) Process

*Notes:* 100,000 observations from the ARIMA (1,1,0) process $y_t = 0.1 + y_{t-1} + 0.8\,\Delta y_{t-1} + \epsilon_t$ were generated. On these observations, the same BBQ dating algorithm used for the national house prices was applied. Durations are adjusted for left-truncation – i.e., the first 5 observations of each upturn and downturn are discarded. The parameter $\lambda$ of the theoretical geometric distribution corresponds to the unconditional probability of an upturn (downturn) ending. It is computed as the ratio between the number of complete upturns (downturns) and the total amount of quarters spent in upturns (downturns).



## Table A1. Logit Duration Dependence Test

*Notes:* The table displays the results of logit regressions. ***, **, and * denote 0.1%, 1% and 5%, significance respectively.

| | *Upturns* | | | *Upturns without last boom* | | | *Downturns* | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| $\log(d_{c,t-1})$ | -1.727*** | | | -2.099** | | | 0.569 | | |
| | (0.447) | | | (0.709) | | | (0.337) | | |
| $d_{c,t-1}$ | | -0.077*** | -0.242** | | -0.139** | -0.301** | | 0.067 | 0.268* |
| | | (0.019) | (0.080) | | (0.044) | (0.108) | | (0.038) | (0.126) |
| $d_{c,t-1}^2$ | | | 0.003* | | | 0.004 | | | -0.006 |
| | | | (0.001) | | | (0.002) | | | (0.003) |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 834 | 834 | 834 | 441 | 441 | 441 | 595 | 595 | 595 |
| Loglikelihood | -152.9 | -163.2 | -155.6 | -105.7 | -112.4 | -109.5 | -148.0 | -147.7 | -144.1 |

## Table A2. Logit Duration Dependence and Fundamentals

*Notes:* The table displays the results of logit regressions. ***, **, and * denote 0.1%, 1% and 5%, significance respectively. $RENT_{ct-1}$, $GDP_{ct-1}$, and $CREDIT_{ct-1}$are expressed as deviations from the trend (computed with a Hodrick-Prescott filter). $i_{ct-1}$ and $INFL_{ct-1}$ enter as annualized changes, whereas $WAP_{ct-1}$ is expressed as annualized growth.

| | *Upturns* | | | *Upturns without last boom* | | | *Downturns* | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| $\log(d_{ct-1})$ | -2.457*** | | | -4.134*** | | | 0.563 | | |
| | (0.717) | | | (0.848) | | | (0.504) | | |
| $d_{ct}$ | | -0.103** | -0.303*** | | -0.358*** | -0.532*** | | 0.071 | 0.314 |
| | | (0.038) | (0.084) | | (0.080) | (0.142) | | (0.070) | (0.165) |
| $d_{ct-1}^2$ | | | 0.003** | | | 0.004 | | | -0.007 |
| | | | (0.001) | | | (0.003) | | | (0.005) |
| $RENT_{ct-1}$ | -14.120 | -13.383 | -8.447 | -17.216 | -20.037 | -17.822 | -10.372 | -10.794 | -13.497 |
| | (10.230) | (9.273) | (9.513) | (11.840) | (11.752) | (12.172) | (11.794) | (11.739) | (12.838) |
| $i_{ct-1}$ | -13.489** | -10.987** | -13.385** | -25.774* | -23.750* | -24.931* | -0.503 | -0.547 | -0.179 |
| | (4.765) | (4.198) | (4.625) | (10.941) | (9.220) | (10.585) | (2.547) | (2.558) | (2.713) |
| $INFL_{ct-1}$ | -22.903** | -19.284* | -23.602** | -34.071** | -34.065** | -35.217** | -0.627 | -0.813 | -0.301 |
| | (8.032) | (9.229) | (8.716) | (12.906) | (12.193) | (12.731) | (5.912) | (5.865) | (6.950) |
| $CREDIT_{ct-1}$ | -7.714 | -8.255 | -8.564 | -52.741* | -40.712* | -43.082* | -11.545* | -11.955* | -11.584* |
| | (4.646) | (4.285) | (4.656) | (21.910) | (15.901) | (20.072) | (5.326) | (5.738) | (5.078) |
| $GDP_{ct-1}$ | -72.122** | -62.569** | -86.650*** | -98.697*** | -127.515*** | -130.883*** | -43.812* | -43.344* | -44.362** |
| | (21.957) | (22.412) | (22.239) | (29.748) | (35.282) | (34.187) | (17.234) | (17.284) | (17.111) |
| $WAP_{ct-1}$ | 20.416 | 13.061 | 31.131 | 429.209 | 387.202 | 450.917 | -550.759** | -548.992** | -537.965** |
| | (68.183) | (49.757) | (71.261) | (294.755) | (250.365) | (298.960) | (171.639) | (170.379) | (173.121) |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 592 | 592 | 592 | 261 | 261 | 261 | 497 | 497 | 497 |
| Loglikelihood | -96.44 | -104.0 | -95.18 | -48.19 | -50.74 | -49.55 | -109.5 | -109.0 | -106.0 |