Finance Neutral Output Gap Estimates for the Netherlands

Does it improve the real-time usability?

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Master's thesis

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Abstract. In this paper the hypotheses set by Borio, Sisyatat and Juselius (2013), extending the conventional HP-filter with financial cycle information increase the real-time robustness of output gap estimates, is tested. For the first time, real-time finance neutral output gaps are estimated for the Netherlands. A new constructed quarterly database is used for this purpose. Results confirm that finance neutral output gap estimates are more robust real-time relative to HP-filtered output gaps: Including financial cycle information does improve the real-time reliability and thereby the usefulness for policy makers. However, these improvements are small in magnitude and not robust during the recent global financial crisis. Considering the general drawbacks of the finance neutral approach and the specific results found in this specific paper, the by Borio et al. (2013) proposed approach is above all usable as a starting point for future research. It certainty should not be used as an omniscient instrument and neglecting other output gap estimation methods and supplementary indicators.

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Table of Contents

List of Graphs

List of Tables

1. Introduction

Macro-economic policy making requires information on the current state of the economy vis-à-vis its potential. One of the leading indicators macro-economic policy makers use, is the output gap. The output gap can be defined as the difference between the observed output and potential output. While observed, or actual, output can be measured with reasonable precision, “measuring” potential output is more challenging. It is important to stress that potential output cannot be observed, i.e. it cannot be measured directly, and therefore it needs to be estimated. Several concepts and methods exist to do so and economists take different approaches. This causes large inconsistencies, especially in the real-time estimates. While it are especially the real-time estimates which are vital, since effective policy making needs to be done real-time.

It is well documented that all the common output gap estimation methods overestimated potential output growth in the euro area prior to the global financial crisis and therefor showing too small output gaps (Marcellino & Musso, 2011). Table 1.1 displays the output gap obtained via the HP-filter method for the Netherlands in the fourth quarter of 2007, just before the outbreak of the global financial crisis. According to the real-time estimates of the output gap, the Dutch economy was operating quite close to its potential, only displaying an output gap of 0.54% of potential output. This could give a (false) sense of security towards policy makers. With hindsight, using all the data available in the fourth quarter of 2015, the output gap for the same period turned out to be substantially higher; 3.53% of potential output. With today’s knowledge, the Dutch economy was operating substantially above potential.

	Real-time Estimation	Ex-post Estimation	Revision
2007Q4 (max)	0,54%	3,53%	2,99%-point
Mean			0,85%-point

Estimations obtained via the conventional HP-filter (λ=1600; see section 4.1). Real-time refering to the GDP vintage that time, before data revisions. Ex-post refering to the 2015q4 GDP vintage, estimating the output gap with hindsight. Data from the Netherlands, N = 57. Mean Revsions refers to the period 2001Q4-2015Q4

Table 1.1 - Uncertainty of Real-time Estimates of the Output Gap. Source: Authors calculations

Policy actions that may seem perfectly reasonable and appropriated at the very moment might prove to be wholly inappropriate as new data becomes available. Policy-makers can greatly stabilize the fluctuations in an economy when taking the right actions. However, when using output gaps which are estimated imprecisely, actions may cause huge instability to the economy with all its (disastrous) consequences. While better indicators do not automatically translate into better policy decisions, they improve transparency and accountability in policy making.

Borio, Sisyatat and Juselius (2013) argue in their groundbreaking work, *Rethinking potential output: Embedding information about the financial cycle,* that the most common definition of potential output used in economic academia – the maximum level of output attainable without generating an increase in inflation – is too narrow. The core of Borio's et al. finding is that output may be on an unsustainable path because financial developments are out of kilter even if inflation remains low and stable. Borio et al. (2013) propose a new framework to estimate the output gap by embedding financial cycle information into their model. Additionally, they find that *finance neutral* estimates of the output gap are more accurate (ex-post) and robust in real-time relative to conventional estimation methods, and therefore does a better job in providing information for policy makers. This hypothesis is the starting point of this paper which focusses on the Netherlands.

The Dutch case is particularly interesting for three reasons. One, the Dutch housing market is characterized by highly interventionist public policies (Vandevyvere & Zenthöfer, 2012), because of direct and indirect government intervention, generous mortgage interest deductibility and low taxation of home ownership, combined with a relative rigid supply, led to a considerable increase in house prices, starting in the mid-1990s. Thus, innovations and liberalization in mortgage financing played a more important role in the Netherlands than in other European countries (Bernhofer et al. 2014). Two, the Netherlands is a relative small and open economy, which potentially implies more impact of the financial cycle on the business cycle (Drehmann et al., 2012). Three, the Dutch economy is a developed one, with a mature financial sector. Cecchietti and Kharroubi (2015) and Rioja and Valev (2014) suggest that the impact of the financial cycle in a more developed economy is relatively large.

The main research question of this study is*: To what extent do the finance neutral estimates of the Dutch output gap provide more accurate information for policy makers real-time relative to estimates obtained via a conventional method?*

In order to answer the research question several hypotheses are tested. The first hypothesis tests whether using a conventional method to estimate output gaps for the Netherlands, these are indeed misspecified in the way that the ex-post and real-time estimates are highly inconsistent. The second hypothesis tested is if financial variables do have explanatory value to potential output and the corresponding output gap estimates. The third hypothesis tested is if these finance neutral estimates of the output gap provide more reliable information real-time.

This study provides an extension of previous work in four ways. First, to my best knowledge this is the first study providing real-time finance neutral estimates for the Netherlands. Second, in contrast to previous empirical work, a new real-time dataset is used containing GDP vintages available that time[4]. Third, more and other financial variables, other than the most used in existing empirics, property prices and credit are tested, and added to the model.

The remainder of this research is structured as follows. Section two reviews the concept of potential output and the output gap, and the different estimation methods available. Section three describes the data and variables used in this research, and discussed the descriptive statistics. Section four provides the approach and methodology of conventional output gap estimation methods, focusing on the HP-filter. Hereafter, the extension of the HP-filter as proposed by Borio et al. (2013) is introduced. In section five both the conventional- and finance neutral estimation methods are executed. The estimation results of both methods are displayed and discussed. Section six draws conclusions and deals with possible policy implications and future research recommendations in this field.

[4] Section 3.1 elaborates on the difference between real-time, quasi real-time and ex-post data.

2. The Output Gap: Concept and Estimation Methods

In this chapter, the review of potential output and the corresponding output gap is provided regarding the definition of the two concepts, estimation methods and the inconsistency and uncertainty surrounding them. Further there is dealt with the impact of the global financial crisis on the output gap. This chapter closes by focusing on the groundbreaking work of Borio et al. (2013) and following empirical work in this specific field.

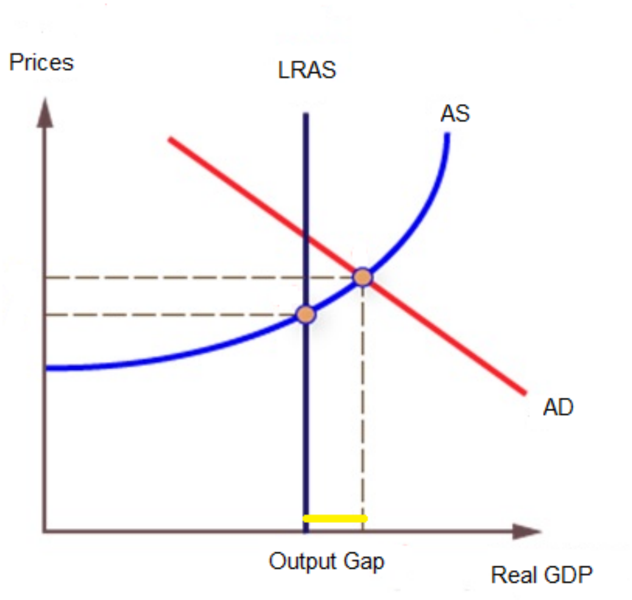
2.1 Concept

The output gap is an economic measure of the difference between the actual output of an economy and its potential output. Where the actual output, or Gross Domestic Product (GDP), can be measured with reasonable precision by adding the market value of all final products and services produced in a country in a given period of time, giving a value to the potential output is more challenging. It is important to stress that potential output cannot be observed, i.e. it cannot be measured directly, and therefore it needs to be estimated.

Historically, potential output is seen as the maximum amount of goods and services an economy can turn out when it is most efficient, running at full-capacity, using all its resources most efficiently. An output gap suggests that an economy is running at an inefficient rate, either overworking or underworking its resources. While overworking, output is more than full-capacity output, which seems to be contradictory. However, when thinking about a factory running overtime, it makes sense that this is not sustainable on the long run; i.e. machines cannot be maintained in the way they should be. This is in fact what happens when the economy is operating above potential. A factory or an economy can run above potential output for a short period, though on the long-run this is unsustainable. Vice versa, a negative output gap implies that the economy is underworking its resources; not using the available resources most efficiently. The concept of full-capacity output suggests that there is no output gap at the moment that all resources are used most efficiently. When thinking about labor as factor input this concept suggest there is no unemployment when the economy is running at its potential level. However, this contradicts with the concept of natural rate of unemployment.

Nowadays, the concept of potential output is more and more associated with equilibrium output. Accordant this concept, an output gap exists of the difference between the long-run aggregate supply (LRAS) curve and the short run equilibrium level of output. The output gap is positive, where the equilibrium output is greater than the LRAS (graph 2.1), and negative when it is less than the LRAS.

There is a clear relationship between the output gap and the behavior of prices. When output is below potential, total (long run average) supply for goods and services exceeds total (equilibrium, short run) demand in an economy and subsequently prices tend to decrease. On the other hand, when output is above potential, demand exceeds supply and prices tend to increase[5]. Thus, prices tend to react on unsustainable levels of output, being above or below potential.



Graph 2.1 – Equilibrium Output Gap

Since the sustained increase in general price level of goods and services in an economy over a period of time in economics is called inflation, the concept of inflation is in macro-economic considered as the key symptom of unsustainability. In the same line of reasoning, the most common used definition of potential output in economic academia and policy making is the maximum level of output attainable without generating an increase in inflation (Gibbs, 1995): The level of output consistent with no pressure for prices to rise or fall. This definition origin from Okun (1962) who defined potential output with reference to the full economic utilization of factor inputs and to inflation developments[6]. He linked this level of output to unemployment via what has come to be known as 'Okun's law.' In this context, the output gap is a summary indicator of the relative demand and supply components of

[5] Increase in demand includes the demand for workers, which leads to increase in employment. Bargaining power of workers hereby increase leading to an increase in the price of labor. This increase, expressed in the wage of workers, itself lead to further increase in employment and an increase of relative supply of labor through increase in participation rate or migration. Thus, also a strong theoretical association between the output gap and (un)employment exist.

[6] A more extensive assessment on the evolution of the concepts output gap is provided by Kiley (2013), Hauptmeier et al. (2009) and Congdon (2008) gives a full historical overview of the concept of potential output.

economic activity. The conceptual association between potential output and inflation is so strong that hardly anyone would question this characterization.

2.2 Estimation Methods

Since the output gap cannot be observed directly, it needs to be estimated. Several concepts and methods exist to do so and economists take different approaches. Because of the wide variety of methods used by different institutions and since estimation results are often quite sensitive to the specific method employed; estimates of potential output and output gap are inherently model-dependent. The objective of this section is not to give a full summary of all estimation methods available, although some explanation improves understanding of the problems[7].

The existing methods of estimating the output gap can be categorized in several ways. For this paper, grouping all these methods in two main categories does the job; univariate methods and multivariate methods. Univariate methods use information inherent to GDP only, whereas multivariate methods also use additional variables to explain business cycle fluctuations.

The Hodrick-Prescott filter (HP-filter) is a simple, pure statistical and widely used technical method (based on Hodrick & Prescott, 1997). The HP-filter is a method for finding the value of potential output that minimizes the difference between actual output and potential output while imposing constraint on the extent to which growth in potential output can vary. One advantage of the HP-filter is that the method is simple to use. One major disadvantage is that the level of potential output is more affected by variations in actual output at the end of the period than in the rest of the period. This is because at the end of the sample, the filter it is forced to change from two-sided filtering (using observations both backwards and forwards in time in order to estimate potential output) to one-sided filtering since at the end of the sample there are no observations forwards in time. As a result the estimated output gaps at the end of a sample, thus real-time, are strongly biased towards the GDP volume of the latest period in the sample. This end-point problem is rather large and can be a substantial factor of uncertainty in real-time estimates. The use of another univariate method, the Band-pass filter (BP), is based on the idea that fluctuations in a time series are composed of fluctuations from different sources. The filter largely removes

[7] Help with finding the preferred method for policy purposes see Cotis, Elmeskov, & Mourougane (2005).

the high- or low frequency components of the GDP series, leaving the fluctuations that can be interpreted as cyclical fluctuations. High frequencies are associated with the cycle; low frequencies are associated with the trend. This is achieved by means of a time series analysis based on an estimated moving average of GDP (Baxter and King, 1999). Like the HP-filter, the BP-filter is a two-sided filter. However, in contrast to the HP-filter, the BP-filter does not become a one-sided filter at the end of the sample. Estimating the output gap at the end of the sample therefor is impossible. When estimating the output gap real-time, which is most useful for policy making, the GDP time series needs to be extended with estimates. A result is that estimates of potential output and the derived output gap become particularly uncertain when the end of the original sample is approaching. Another example of an univariate method is the unobserved component (UC) method which is based on the premise that an observable variable is composed of two or more components that are not observable. The basic idea is that the unobservable variables can be identified by assuming that they affect the variable that can be observed. Both the unobservable variables and the observable variable are modelled and estimated as a maximum likelihood system using the Kalman filter (Kalman, 1960; Harvey, 1990). One advantage of this method in relation to other univariate methods is that both the output gap as potential output are modelled directly. In general, the most appealing reason to use univariate filter is because they are easy to use. One only needs one input variable (GDP), therefor these methods can also be used easily by countries without a well-developed bureau for statistics.

In contrast to univariate methods, multivariate approaches aim to overcome the drawback of using information only from the observed GDP series. Multivariate approaches derive the trend of the output series by also using information from another time series which are related. Multivariate filtering approaches incorporate some elements of economic theory – i.e. choice of which variable(s) to include commonly inflation and unemployment are used. Although incorporating more information is promising for ‘better’ estimates of the output gap, they also these need to be used with care. The recent global financial crisis is only one example of this. Real-time estimates did not for see the build-up of unsustainable imbalances which ex-post became visible. Because of the estimates that associate potential output with non-inflationary output a false sense of security was created.

One of the most widely used methods is the Production Function Method (PF-method) which combines detailed information about the utilization of factor inputs with a Philips curve. Well respected international organizations like the European Commission (Havik et al., 2014) and the OECD (2011) use different forms of this PF-method. This approach differs from the statistical multivariate approach described above in a way that it takes a structural view and builds a model of the supply side of the economy, based on economic theory, which can then be used to help explain the key economic forces underlying GDP. The PF-method relates output to the level of technology (TFP) and factor inputs, mostly labor and capital. The key challenge is the measurement of the factor inputs, which often also in fact is an estimate made by using a some sort of filtering techniques like the HP-filter (Havik et al., 2014; p. 70). For this reason the PF-method is criticized as being a method shifting the end-point problem to the sub-components of the PF-method; Total Factor Productivity, Capital and Labor (Anderton, et al., 2014).

Another example of a multivariate model is the Structural Vector Auto Regression (SVAR) approach. The general philosophy underlying the SVAR approach to estimate potential output rests on the theoretical idea that demand shocks are transitory (short-run), while supply shocks permanently affect output (long-run), following Blanchard and Quah (1989)[8].

2.3 Uncertainty

Different estimations methods, however, often produce different values for the output gap. This model uncertainty is one of the three sources of uncertainty surrounding output gap estimates (Murray, 2014). Also with hindsight, using ex-post data, inconsistency among output gap estimates derived by different approaches last. Although, all commonly used methods do show output gap estimates which qualitatively describe the same historical path (Bjørnland, 2005) and show a high degree of correlation between the models over a long period, different approaches' estimates do diverge both in regard of magnitude of fluctuations and dates they occur in some periods.

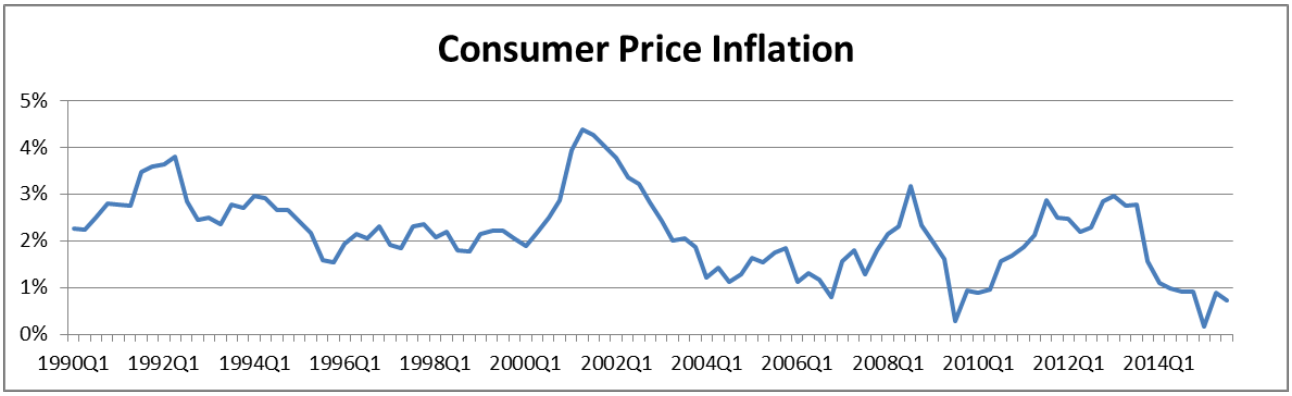
Two other dimensions of uncertainty which are more present in real-time estimates are data uncertainty and end-point uncertainty. Data uncertainty arises because the

[8] More extensive explanation of SVAR method can be found in Mitchell, Mazzi, & Moauro (2008)

information available at the time is not the final vintage of that data. It is likely to become more accurate with time passes as more information from that time period becomes available and measurement methods improve. Some methods are more sensitive to this than others. Especially GDP is often subject to substantial revisions (CBS, 2016). Although, uncertainty arising from data revisions is found to make a relative small contribution to inconsistency among ex-post and real-time estimates of the output gap (Murray, 2014).

The end-point uncertainty, which generally causes the largest bias from real-time to ex-post estimates (e.g. Orphanides & van Norden (2002) and Camba-Mendez & Rodriguez-Palenzuela (2001)), arise because the future path of output is unknown and may contain information about the cyclical position of the economy now. Especially when using univariate filters, the end-point problem is substantial. But also the estimates obtained by the widely used PF-method are indirectly affected by the end-point problem (Anderton et al., 2014). According to Gerlach (2011), Koske & Pain (2008) and earlier by Orphanis & Van Norden (2002) output gap estimates' revisions tend to be markedly larger around turning points. Turner et al. (2016) confirms this by making a comparison of OECD published output gap estimates for the G7 economies covering the prior- and post crisis period. Output gap revisions tend to be positive especially for the immediate pre-crisis years, consistent with a tendency to revise potential output downwards during the post crisis period. So, especially around cyclical turning points the inconsistency of real-time and ex-post estimates are substantial: output gap estimates perform badly in real-time.

The most pronounced turning point in the last decades is the global financial crisis. Based on output gap estimates available that time obtained via various estimation methods, there was no reason to fear that the economy was operating above its potential (among others; Bernhofer et al., 2014; De Manuel Aramendia & Raciborski, 2015). With hindsight, it is well documented that all the major estimation approaches overestimated potential output in the euro area prior to the global financial crisis (i.e. Turner et al., 2016; ECB, 2011; Marcellino & Musso, 2011). In example, Bernhofer et al. (2014) found that the consensus estimate of the euro area output gap for 2007 was negative 0.5% of potential output. So the euro area economy seemed to be operating slightly below potential. At the time of their paper, about 6 years later, the ex-post output gap for the same year is estimated to be positive 2.5% of potential output; implying that the economy was operating far above potential, which cannot be sustained for a long period of time. Despite that the economy was operating above its potential in the run up to the crisis, inflationary pressure increased only the last months prior to the bust (graph 2.2). Estimates of potential output that rely on the Philips curve relationship can be very misleading for policy purposes (Borio et al., 2003).



Graph 2.2 – Consumer Price Inflation. Source: OECD (2016)

The consensus in macroeconomics about the concept of potential output as non-inflationary output was severely challenged by the global financial crisis. The behavior of inflation that should signal whether output is above or below potential did not do its job in the run up to the crisis. Huge imbalances were building up without generating an increase in general price levels.

2.4 An Extension

In their groundbreaking work Borio et al. (2013) argue that the conventional concept of potential output – the maximum level of output attainable without generating an increase in inflation – is too narrow. The core of Borio's et al. finding is that output may be on an unsustainable path because financial developments are out of kilter even if inflation remains low and stable. The recent financial crisis is just the latest reminder of the possibility. The authors (p. 6) describe four reasons why it can be the case;

(1) Unusually strong financial booms are likely to coincide with positive supply side shocks. These shocks put downward pressure on prices (decrease inflation) while at the same time providing fertile ground for asset price booms that weaken

financing constraints. Asset prices are not directly included in the consumer basket to obtain CPI measures in the Netherlands[9] [10].

(2) Economic expansion may themselves weaken supply constraints. Prolonged and robust expansion can induce temporarily increases in the labor supply, either through higher participation rates as immigration (increase relative supply, decrease in inflation). By adding new capacity, the capital accumulation associated with economic expansion itself may also weaken supply constraints.

(3) Financial booms are often associated with a tendency for the currency to appreciate, as domestic assets become more attractive as capital flows surge. The appreciation puts downward pressure on inflation.

(4) Unsustainability may have to do more with sectoral misallocation of resources than with overall capacity constraints. In fact, the Bank of International Settlements (2012) provide cross-country evidence that a higher concentration of job losses in a specific sector explains the increase in unemployment even better than the total magnitude of output drop related to Okun's law.

The bottom line is that the financial cycle amplifies the business cycle, unnoticed by inflation and estimates of potential output based inflation as the key symptom of (un)sustainability. Altogether, the impact of the financial cycle on the real economy is too substantial to neglect in potential output estimates. By ignoring financial factors when estimating output gaps leaves out valuable information. Borio et al. (2013) stress that it is important to take into account the extent to which financial conditions facilitate or constrain economic activity when formulating judgements about the sustainable level of economic activity. Not doing so can lead to policy astray[11].

Borio et al. (2013) introduce the concept of finance neutral potential output as a substitute of the conventional concept of inflation-neutral potential output. As a starting point they use a simple HP-filter which is extended by embedding information representing the financial cycle. The authors find that including financial

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[9] CBS (2013) use the method of *imputes rents* when computing the housing costs in the CPI, which are not based on the value of the asset (property).

[10] Some argue a new CPI-measurement is needed to account for asset price bubbles and financial imbalances in general (Borio & Lowe, 2002; Goodhart, 2001).

[11] Borio et al. (2013) were not the first ones who suggested adding financial variables to output gap estimates. Goodhard & Hofmann (2000) did it much earlier. For me it is unclear why this research was a popular read for macroeconomist that time (prior the crisis around 60 citations, nowadays around 160). Potential reason is the timing of the publication. During the 2000s everything seems to be going well in the economy.

cycle information in the form of *property prices* and *credit* ensures estimates perform better relative to commonly used HP-filters and PF-method. Finance neutral estimates can yield measures of potential output and output gaps that are not only estimated more precisely (in the sense of lower standard errors), but also much more robust in real-time. An extended and a more technical assessment of Borio et al. (2013) novel finance neutral estimation method can be found in section 4.2, followed by estimates using Dutch data from section 5 onwards.

Following the work of Borio et al. (2013) the past few years several studies were conducted following the similar approach. All findings – except one[12] – have in common that they do confirm the hypothesis that incorporating information about the financial cycle when estimating potential output does improve its accuracy and real-time usability for economic policy makers[13].

2.5 Hypothesis Tested and Expected Findings

Based on existing literature and the country characteristics of the Netherlands, three hypotheses are particularly interested to be tested. The first hypothesis is whether using conventional methods to estimate output gaps for the Netherlands resulting in misspecified output gap estimates in the way that the ex-post and real-time estimates are highly inconsistent. Complementary can be tested which one of the three uncertainty sources causes the largest bias. The second hypothesis tested is if, and which, financial variables do have explanatory value to potential output and the corresponding output gap estimates. The third hypothesis tested is if these finance neutral estimates of the output gap provide more reliable information in real-time.

[12] Felipe et al. (2015) cannot confirm that finance neutral output gaps perform better for middle-income Asian economies, which is in line with previous work on the nonlinear effect of finance on growth (Cecchietti and Kharroubi, 2015). In the same paper they do confirm the Borio et al. hypothesis for the G5 countries and high-income Asian economies.

[13] Grintzalis, Lodge & Manu (2016) tests the Borio approach on a sample of emerging market economies. They find that financial cycle information does explain a significant part of the cyclical movements in output. De Manuel Aramedía & Rociborski (2015) applies the approach of Borio et al. on the Irish economy. By incorporating the financial variables interest rate, credit and property (housing) prices the authors obtain estimates of the finance neutral output gap that would have supported a more cautious assessment of economic conditions and in turn of the underlying fiscal position in Ireland in the years leading to the global financial crisis. Their results hold both using historical (adjusted) data as real-time data available that time. Noteworthy is that results does not hold in the period for the late 1980s and early 1990s, where conventional estimates of the output gap seems to be more plausible. The results of Amador-Torres et al. (2015) show that finance neutral output gaps in Colombia, Chile and Mexico are higher before crisis and lower after them relative to the conventional (HP-filter) estimates, although with low β coefficients (p. 14). Kemp (2014) confirms Borio's hypothesis for the South African economy. Bernhofer et al. (2014) applies the finance neutral method to four advanced economy, including the Netherlands, and four CESEE economies. Their results confirm the findings of Borio et al. (2013) and the importance of incorporating financial information in the estimate of potential output and its corresponding output gaps. Additionally they argue that finance neutral potential output growth is more stable than shown by conventional approaches.

Based on previous empirical work done and the country characteristics of the Netherlands as an small open economy with a developed financial sector, expected outcome is that including information about the financial cycle to the conventional HP-filter to estimate the potential output and corresponding output gap will improve the real-time usability. Further, I foresee a relative big impact of credit (provided as mortgage) in the Netherlands, which fueled the housing price upsweep more than in other countries.

3. Data and Descriptive Statistics

This chapter describes the data necessary for het construction and analysis of output gap estimates in this study. The focus of this chapter lies on the construction of the dataset including real-time data. Descriptive statistics and an overview of the behavior of the variables in the sample period are provided in appendix 3. Besides, a first exploration of the hypothesis is carried out.

The dataset contains quarterly data for the period 1990Q1-2015Q4 for the Netherlands, whereby real-time GDP vintages are available for the period 2001Q4-2015Q4, covering GDP from 1990Q1 up until the period of the vintage[14]. In line with Borio et al. (2013) all data is mean adjusted by Cesàro averages. This is done because most of the variables display a high degree of cyclicality. Cesàro-means produces faster convergence and reduces pro-cyclicality in the mean-adjustment. All data is added to the model(s) in natural logarithm.

3.1 Real-time GDP Vintages

As output indicator, Gross Domestic Product in constant prices (hereafter real GDP) with base year 2010 is used[15]. This is in line with all the empirical research done in this field. Series in constant prices account for the effects of price inflation and thereby measures the true growth of series, in this case GDP. All GDP data is obtained via CPB from Statistics Netherlands (CBS, 2016) database.

Real GDP data used can be divided in to three subcomponents; ex-post-, quasi real-time and real-time GDP data. The ex-post data is the data available at the end of the sample period, using the full 2015Q4 vintage up until the end of the sample period. When estimating the output gap for 2005q1 for example, data available till 2015Q4 can be used. In other words, ex-post estimates are based on full sample data. Quasi real-time data can be defined as real-time estimates using ex-post data. That is, when estimating the output gap for a particular period, researchers pretend that only data up to and including that period is available, ignoring the data after this period. By doing this, the problem of data-uncertainty is neglected. Data revisions are not taken into account. By using quasi real-time data for output gap estimates, only the

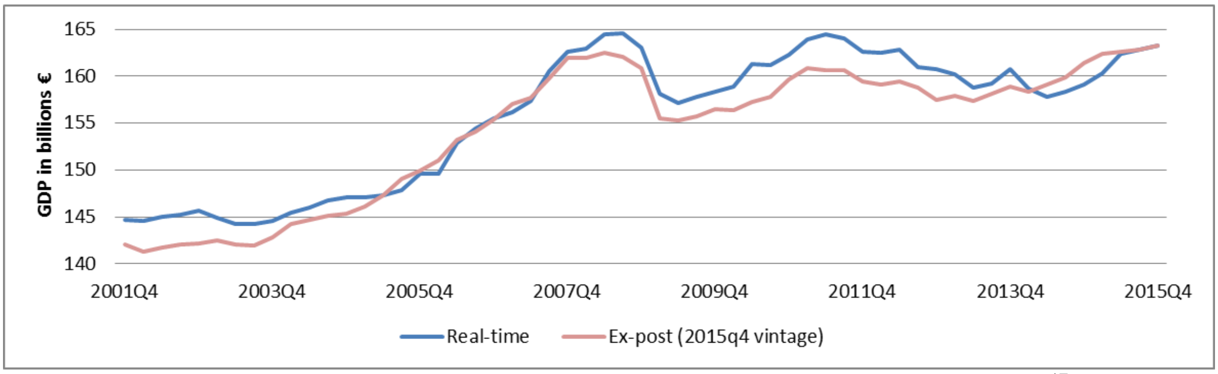
[14] Some GDP vintages start in 1996q1 (2005q1-2007q1 and 2014q1-2015q4).
[15] Technically real GDP and GDP in constant prices do differ (The World Bank, 2016). Base year 2010 applies to the 2015Q4 vintage (ex-post).

end-point uncertainty is exposed. Since policy making needs output gap estimates at the moment itself, real-time estimates are very important. Real-time data covers the data available at that time, before revisions of any kind. Estimates based on real-time data suffer, besides from the model-uncertainty, both from end-point uncertainty as from data-uncertainty.

GDP data is often subject to revisions. In general two kinds of revisions can be specified. First, (international) definitions that are used are changed because of new economic insights and changes in the underlying economy itself. These revisions occur once in several years. Second, underlying data sources change over the years. These revisions occur continuously. This second type of revision for the Netherlands is quantified by Elbourne et al. (2015). They find that between 2004 and 2014 a typical revision to GDP is about 0.2%-points between the first and second published estimates. Typical revisions from the first and the third revision are about 0.28%-points and between the first and fourth is about 0.37%-points. The final GDP data published is typically 0.35%-point higher than the first (see table 3.1)[16]. In total, GDP revisions can be substantial (graph 3.1).

		Publication lag	*Average revision in %-point vis-à-vis first publication*
First	Flash	45 days after end of quarter	
Seconds	Regular	90 days after end of quarter	0.20
Third	Provisional	6 months after end of quarter	0.28
Fourth	Revised provisional	18 months after end of quarter	0.37
Fifth	Final	36 months after end of quarter	0.35

Table 3.1 – Average GDP Revision in The Netherlands. Source: (Elbourne et al., 2015).



Graph 3.1 – Revisions of Real GDP in The Netherlands. Source: CBS (2016)[17]

[16] Concerns the average root mean square revisions.
[17] Changes in base year are filtered out by applying the mean growth rate of the period before and after the change in base year on the concerning period.

3.2 Explanatory Variables

Additional variables included in the model(s) only represent ex-post data because of data availability reasons and time constraints of this study. In general, revisions of these variables are much smaller in magnitude than GDP data. Therefore these ex-post data series are usable for the purpose of this study. In line with Borio et al. (2013) property prices and credit is used. Other variables are based on future research recommendations and economic reasoning by the author[18]. All explanatory variables are added as differences in the model[19].

Interest rate

Interest rate data is constructed, in line with Borio et al. (2013), by extracting the long-term interest rate by the consumer price inflation (CPI). Long-term interest rates refer to government bonds maturing in ten years. These interest rates are implied by the prices at which the government bonds are traded on financial markets, not the interest rates at which the loans were issued. Data is obtained from the OECD (2016). CPI data, as well obtained from the OECD (2016), measure the average changes in the prices of consumer goods and services purchased by households.

Property Prices

Property price data is included as a price index of the stock of dwellings which are owned by a private person and intended for permanent resident by a private person. The data is obtained from CBS/Land Registry Office (2016). The House Price Index of existing own homes is based on a complete registration of sales of dwellings by the Dutch Land Registry Office (Kadaster, 2016) and the value of all dwellings in the Netherlands[20]. The calculation method used is known as the Selling Price Appraisal Ratio (SPAR) method[21].

Private credit

For credit, data is obtained from the Bank of International Settlement (2016), specifically using total credit to the non-financial private sector provided by all sectors[22], valuated at market value.

[18] Borio et al. (2013) recommend including unemployment rate. Investment and manufacturing capacity are recommended by Turner et al. (2016). Goodhart & Hofmann (2000) empirically show the influence of share prices on the output gap.
[19] In line with Borio et al. (2013), interest rate is also added to the model in absolute terms.
[20] In 2014 a small revision was carried out whereby the price information for 2008 onwards has been revised because of an improvement in the weighting scheme. The weighting scheme is based on the stock of existing own homes instead of the stock of all existing homes. The effect of the revision is very small (CBS, 2016).
[21] Detailed description of the SPAR method is provided by CBS (2008).
[22] All lending sectors are covered, i.e., with the SNA classification numbering: Non-financial corporations (S11), Financial corporations (S12), General government (S13), Households (S14) and Non-profit institutions serving households (S15) and Rest of the world (S2). Source: BIS (2016).

Share Price Index

Share Price data is obtained from OECD (2016) and is calculated from the prices of common shares of companies traded on national stock exchanges, using the closing daily values for the monthly data; and index is constructed. The Share Price Index measures changes in the market capitalization of the basket of shares in the index.

Market Value on Euronext

Market Value on Euronext concerns the exchange value of all outstanding common shares of all Dutch companies and funds listed on Euronext Amsterdam at the end of every month. The value of the total market is the sum of the official and the new market values. The market value is calculated by multiplying the number of outstanding shares of a company by the share price. Data is obtained from Statistics Netherlands (CBS, 2016). The statistics only deals with stocks that provide an equal right in the control of the company. Other kinds of stocks, such as preferred stocks, are not included.

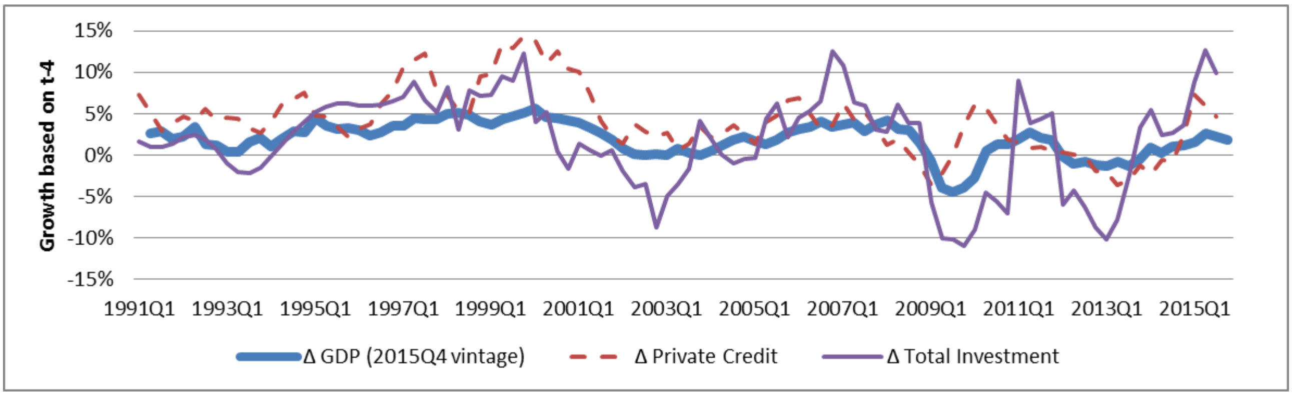
3.3 A First Exploration of the Hypotheses

As displayed in table 3.2, most explanatory variables included in the model are highly correlated with GDP (2015Q4 vintage). One of the hypotheses set is if, and which, financial variables do have explanatory value to potential output and the corresponding output gap estimates. Although, this table displays the correlation between financial variables and the observed (actual) GDP volumes, and not the estimated potential GDP, a strong relationship is suggested between some (especially Private Credit, and to a lesser degree Total Investment) of the financial variables and potential GDP. This is because potential output estimated, and ex-post observed output is theoretically highly correlated. In graph 3.2 the variables which are most highly correlated with GDP are displayed.

	GDP (2015Q4)						
	1990-1995	1995-2000	2000-2005	2005-2010	2010-2015	Excluding GFC	Total Sample Period
Interest rate	0,46	-0,04	-0,27	-0,22	-0,53	-0,30	-0,24
Property Prices	-0,39	0,69	0,87	0,96	0,78	0,76	0,71
Private Credit	0,57	0,75	0,92	0,75	0,53	0,82	0,76
Share Prices	0,00	0,28	0,71	0,70	0,21	0,49	0,57
Market Value on Euronext	0,04	0,28	0,71	0,58	0,16	0,48	0,53
Private Investment	0,68	0,56	0,56	0,89	0,58	0,65	0,73
Total Investment	0,59	0,50	0,60	0,89	0,60	0,71	0,75

Correlation based the growth rate (t-4). Source: Authors calculations.

Table 3.2 – Correlation Matrix GDP. Source: Authors Calculations.



Graph 3.2 – Growth Rate Explanatory Variables. Source: Authors Calculations.

4. Methodology

In this section the empirical approach of this study is described. It starts with one of the most common used methods to estimate the output gap, the Hodrick-Prescott (HP) filter, which is used as a baseline result and represent the conventional method of estimating an output gap[23]. Hereafter, the extension proposed by Borio et al. (2013) is discussed and evaluated extensively. Final, the methodological approach to compare both methods with one another is discussed.

4.1 Conventional Output Gap Estimation Method

The idea behind the HP-filter is to decompose a time series into a trend component, g_t, and cyclical component c_t, and utilizes a long run, symmetric, moving average technique to achieve the decomposition.

$$y_t = g_t + c_t$$

In order to obtain the cyclical component, $\mathrm{g_t}$ is chosen to minimize:

$$\{g_t\}_{t=0}^{T+1} = argmin \sum_{t=1}^{T} \{(y_t - g_t)^2 + \lambda[(g_{t+1} - g_t) - (g_t - g_{t-1})]^2\}$$

In the equation above, λ is the smoothing parameter and determines how smooth the trend will be by penalizing variation in its growth rate. Hodrick and Prescott (1997) recommended a value of $\lambda = 1600$ for quarterly data. In line with Borio et al. (2013) this recommendation is adopted[24].

Nevertheless, the reliability of filtering methods like the HP-filter to decompose a series into its trend and gap components, especially in real-time, has been questioned and empirical results have pointed out the existence of a great uncertainty about these estimates especially at sample end-points (Orphanides and van Norden, 2002; Watson, 2007). Other disadvantages of a HP-filter include the difficulty in identifying the appropriated de-trending parameter λ, the possibility of

[23] For illustrative reasons also output gap estimates from the European Commission production function approach is displayed, although these contain annual data and therefore not suitable for a quantitative comparison (Appendix 1).
[24] The higher the value assigned to lambda is, the greater the end point problem becomes (Bernhardsen, Eitrheim, Jore, & Røisland, 2004).

inducing spurious cyclicality when applying the filter to near-integrated series and excessive smoothing of structural breaks (Harvey & Jaeger, 1993; among others).
Our main interest is in the inaccuracy of the HP-filter estimates of the output gap at the endpoints of a finite sample of observations. Especially when estimating potential output real-time, we are dealing with a finite sample. Estimates can only be made using data available up to that point, and hence only using one-sided HP-filters. Ex-post estimates, in the context of this paper are referring to estimates based on the full sample, hence can two-sided HP-filters are used.

To compare the performance of the HP-filter with finance neutral estimation techniques in a later stage of this paper suggested by Borio et al. (2013), both ex-post, quasi real-time and real-time estimates are generated. Comparison between real-time and ex-post displays both the end-point uncertainty and the data-uncertainty. Comparison between quasi real-time estimates of the output gap and the ex-post ones, isolate the end-point uncertainty.

4.2 An Extension

In line with the approach of Borio et al. (2013) and the subsequent work of the authors cited, the finance neutral output gap for the Netherlands will be estimated by extending the HP-filter to include financial cycle information. Technically this is done by adding financial variables to the HP-filter equation and use the Kalman filter to derive new estimates of potential output. The data is allowed to determine whether financial variables are informative about the cyclical component of output fluctuations themselves. This in contrast to popular methods who impose on the estimates of potential output a Phillips curve relationship, i.e. a relationship that forces the behavior of inflation to be driven by the output gap.

Empirical specification

The HP-filter can be cast in state-space form by specifying the state and measurement equations as

$$\Delta y_t^* = \Delta y_{t-1}^* + \varepsilon_{0,t} \qquad (1)$$

$$y_t = y_t^* + \varepsilon_{1,t} \qquad (2)$$

Where $y_t = Ln(Y_t)$, y_t is real GDP and y_t^* is potential GDP. $\varepsilon_{i,t}$ is assumed to be normally and independently distributed error with mean zero and variance σ_i^2. The parameter λ_1 , $\lambda_1 = \sigma_1^2/\sigma_0^2$, is set so that the duration of the estimated output gap is at most eight years and implies a value of 1600 in a quarterly sample. When λ_1 becomes very large, potential output approximately follows a linear trend. Vice versa, when λ_1 approaches zero, potential output follows actual output.

In line with Borio et al. (2013) financial information is embedded in the output gap estimation equation by augmenting equation (2) that

$$y_t - y_t^* = \gamma' \, x_t + \varepsilon_{2,t} \qquad (3)$$[25]

where x_t is a vector of economic variables, possibly containing lags of the output gap itself. In order to preserve the same duration of the business cycle as implied by the standard HP-filter when moving from (2) to (3), Borio et al. use as state equation in the form (1) and set the signal-to-noise ratio $\lambda_2 = \sigma_2^2/\sigma_0^2$ such that

$$\frac{var(y_t - y^*_{(2),t})}{var\left(\Delta^2 y^*_{(2),t}\right)} = \frac{var(y_t - y^*_{(3),t})}{var\left(\Delta^2 y^*_{(3),t}\right)} \qquad (4)$$

where $y^*_{(2),t}$ and $y^*_{(3),t}$ are the potential output estimates obtained from (2) and (3). Setting λ_2 such that condition (4) holds implies a relative volatility of potential output that is comparable to that obtained from the standard HP-filter. Since results are very sensitive to the value of λ_2 it is important that (4) holds. Besides, from a theoretical point of view (4) needs to hold to preserve the same duration of the business cycle; around 8 years[26] [27]. The approach based on (1) and (3) represents a compromise between theoretical and pure statistical approach of estimating potential output. The advantage of this novel approach lies in the fact that standard estimators of the parameters γ' in (3) will assign a zero weight to any information in x_t that does not help in explaining business cycle fluctuations.

Several specifications of (3) will be considered. A basket of financial and economic variables will be evaluated and added to the model (5). In line with Borio et al. (2013)

[25] both γ' as x_t are vectors
[26] In line with empirical assessment on typical business cycle durations (i.e. Filardo, 1998).
[27] Take into account that financial cycles typically are considerably longer (16 to 20 years). However, the choice to assume cycle of 8 years (like business cycles) allows comparing estimates with those in the literature more easily.

interest rate, real credit and property prices will be included[28]. Following, other financial and macroeconomic variables will be added to the equation. Variables which will be evaluated are total- and private investment share in GDP (in line with Turner, et al (2016)) and share prices (Goodhart & Hofmann, 2000)[29].

$$y_t - y_t^* = \beta(y_{t-1} - y_{t-1}^*) + \gamma_n \Delta x_{t-k_x} + \varepsilon_{n,t} \qquad (5)$$

All the variables are allowed to enter only once with a lag between 0 and 4, chosen to maximize statistical fit. The procedure to determine which variables to include into the model is based on the proportion of the variation of the estimated output gap that the model explains [30], in combination with their economic- and statistical significance[31]. First, model (5) will be determined without any additional variables except from the output gap estimate of the previous period, resulting in estimates named the *dynamic output gap*. Second, all variables are included into (3) one by one (table 5.1). Third, the optimal model is determined, based on economic and statistical significance (table 5.2) of a model with multiple variables included. The optimal model is than used to obtain finance neutral output gap estimates.

To estimate (5) a conventional Bayesian approach is adopted[32]. A Kalman-filter is used to form the likelihood of the system. Prior distributions for the parameters and maximize the posterior density function are specified with respect to the parameters[33]. As prior distribution we assume the gamma distribution with standard deviation of 0.2 for all of the parameters. β is restricted to lie between 0 and 0.95, with a prior mean of 0.80. The upper bound for this parameter is set to avoid unit-root output gaps. To obtain a value for λ_2 that yields cycles with duration of approximately eight years, a simple MATLAB optimizer tool is used[34].

[28] Consistent with empirical literature highlighting the information content of credit and property prices for business fluctuations and financial crisis (Drehmann et al., 2012; Claessens et al. 2011; Schularick & Taylor, 2009; Alessi & Detken, 2009; Borio & Low, 2000; 2004)
[29] In the appendix, unemployment rate neutral output gaps are estimated.
[30] Displayed in the R^2
[31] Displayed in the regression coefficient and corresponding t-statistic, at 1% and 5% significance level.
[32] An extended assessment of Bayesian statistics can be found in Koop et al. (2003).
[33] The IRIS toolbox add-on to MATLAB is used to perform these calculations.
[34] The optimizer contains a loop that finds the optimal value via automatic trial and error. Still, this is not the perfect method since by doing this a value for λ_2 is found which is very close to optimal (accurate to five decimal places), though not optimal. Given the fact that t-statistics are very sensitive to minor changes in λ_2, future research would do well to develop a tool that finds the optimal value for λ_2. This goes beyond the scope of this paper.

In this study the quality of the ex-post estimates of the output gap is not discussed extensively. From this point, we assume that the ex-post estimates are perfect[35], and we focus on the extent to which the real-time estimates follow the ex-post ones.

Remarks Previous Work

Some methodological remarks on previous empirical work using the Borio et al. (2013) approach need to be made. First, to my best understanding all the empirical work in this field, included the work of Borio et al. (2013) themselves, estimate real-time output gaps by using quasi real-time data. Hereby data uncertainty is neglected. Second, the optimal value for λ_2 , which is important to obtain a relative volatility of potential output that is comparable with the one obtained from the conventional HP-filter, is found by manual trial and error[36]. Third, all empirical works based on Borio et al. (2013) were to some extend looking for the optimal model for their particular sample using all the knowledge available that time[37]. That is, finding the optimal real-time model, using ex-post data. In other words, the optimal real-time model is determined ex-post and in real-time it is not clear which model is the optimal one. Although this is understandable from the particular researchers' point of view – this paper is also guilty – this approach is not perfect. Of course, in the real world it is not possible to use ex-post data. As a result, the approach to find the optimal model is not applicable in a real-world setting.

4.3 Real-time Robustness

The core of this paper focusses on the real-time usability of output gap estimates. Because of the substantial revisions output gap estimates are subject to, which are often larger in magnitude than the estimated output gaps themselves, they are surrounded by large uncertainty. In line with Borio et al. (2013, p. 18) the degree of robustness of real-time output gap estimates is measured. This is done by calculating the track-score, which answers the question; to which extend do the real-

[35] Author is aware of the ongoing academic discussion on the quality of output gap estimates in general, and especially the ones obtained via the HP-filter (i.e. Mc Morrow et al., 2015).

[36] Although none of the Borio a-like papers explicitly describe how the optimal signal-to-noise ratio is obtained, insight in the MATLAB codes shows me that it is done by trial and error which is obviously not the proper way to do so.

[37] This remark is based on the Turner (2013) paper which empirically show that the approach of Borio et al. (2013) work for some countries but fails for others, work for some periods in time and fails for others and also is sensitive to the choice of variables. It also raises a problem that it may only be clear with hindsight (i.e. after a major boom/bust episode) which financial variables are the most appropriate one to use (p. 21). The authors argue that it is important to find an estimation method for the output gap that works across a large number of countries before draw any conclusions about the reliability of the estimation method. Despite the fact that several papers did confirms Borio's approach in the years following his publication, results needs to be interpreted with caution since they all to a greater or lesser extend were looking for the optimal model for their particular sample. This is expressed in the different variables which are used to represent the financial cycle. Most commonly used are property prices and credit. Also different underlying data is used for the variables in the model, i.e. using private, non-private or residential property prices. Besides, variables are allowed to enter the model with a lag between zero and four to maximize statistical fit, which differs in every sample and is inconsistent among countries.

time estimates follow the ex-post ones? It displays the average error per percentage movement in the output gap. The track-score of a particular model is calculated by dividing the mean absolute deviation of the estimated real-time output gap by the standard deviation of the ex-post estimated output gap. The smaller the track score, the more robust the real-time estimates of the output gap are. In model (6) and (7); *rt,t* represent real-time estimate at time t and *ep* represent the ex-post one.

$$\text{Track score} = \frac{\frac{1}{n}\sum_{t=1}^{n}(\sqrt{x_{rt,t}-x_{ep,t}})^2}{\frac{1}{n}\sum_{t=1}^{n}(x_{ep,t}-\mu_{ep})^2} \quad (6)$$

Since the track score is based on the volatility of the ex-post estimates, which is not the main focus of this particular study, an additional indicator of real-time robustness is used which only focusses on the differences between the real-time and ex-post estimates; the mean absolute revisions (from real-time to ex-post) of output gap estimates are discussed (7). Both indicators need to point in the same direction, before any conclusion can be drawn.

$$\text{Mean Absolute Revision} = \frac{1}{n}\sum_{t=1}^{n}(\sqrt{x_{rt,t}-x_{ep,t}})^2 \quad (7)$$

4.4 Drivers of Real-time Uncertainty

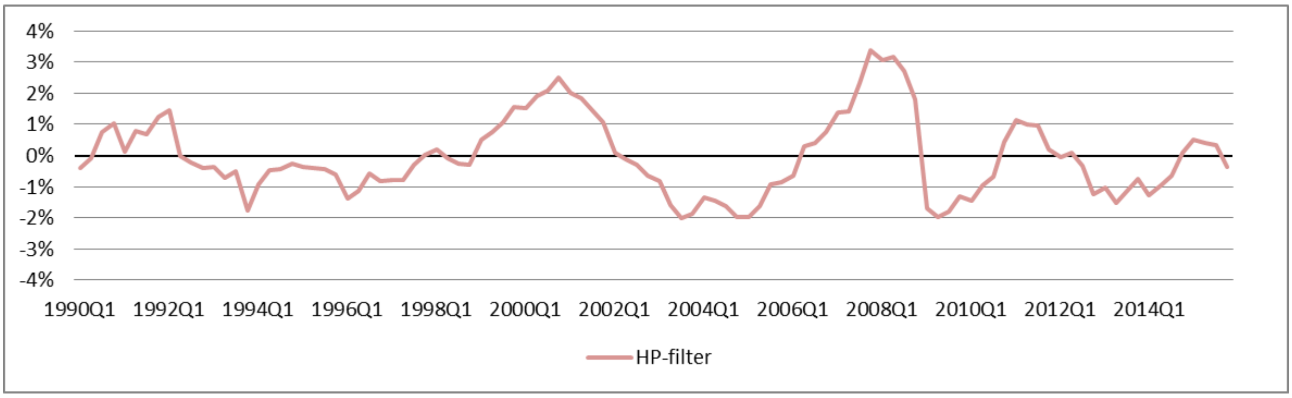
Three drivers of uncertainty are identified (section 2.3), of which data uncertainty and end-point uncertainty are more present in real-time estimates. Data uncertainty arises because the information available at the time is not the final vintage of that data. It is likely to become more accurate with time passes as more information from that time period becomes available and measurement methods improve. End-point uncertainties arise because the future path of output is unknown and it may contain information about the cyclical position of the economy now. Especially when using univariate filters (like the HP-filter), the end-point problem is substantial. It is expected that when extending the HP-filter with financial cycle information data uncertainty will increase and the end-point uncertainty will decrease. Financial cycle information contains predictive value about the future path of the business cycle. Data uncertainty can be isolated by focusing on the absolute difference between real-time and quasi real-time estimates of the output gap. The absolute difference between the quasi real-time and the ex-post estimates display the end-point uncertainty.

5. Estimation Results and Evaluation

In this section output gaps are estimated using the approach set in section 4.

5.1 Conventional Output Gap Estimation Method: The HP-filter

Results obtained via the HP-filter, using the GDP vintage of 2015Q4 (referred to as ex-post), displays expected movements. The findings are in line with empirical literature. As displayed in graph 5.1, in the sample period 1990-2015 two major output gap booms can be distinguished. The first one occurred during the early zero's (1999-2001), as a manifestation of the dot-com bubble. The highest estimated output gap this period was reached in the fourth quarter of 2000, in which the output gap noted 2.51% of potential output. The second output gap boom was prior to- and during the recent global financial crisis. It reached its peak in the fourth quarter of 2007, being 3.4% of potential output. With the boom comes the bust: After the dotcom bubble burst, also (estimates of) potential output decreased, leading to negative output gaps estimated in the period 2002Q2-2006Q1 with peaks at the third quarter of 2003 (-2% of potential output) and the fourth quarter of 2004 (-1.95%). The same applies to the bust period after the financial crisis, reaching an output gap of negative 2% of potential output in the second quarter of 2009.



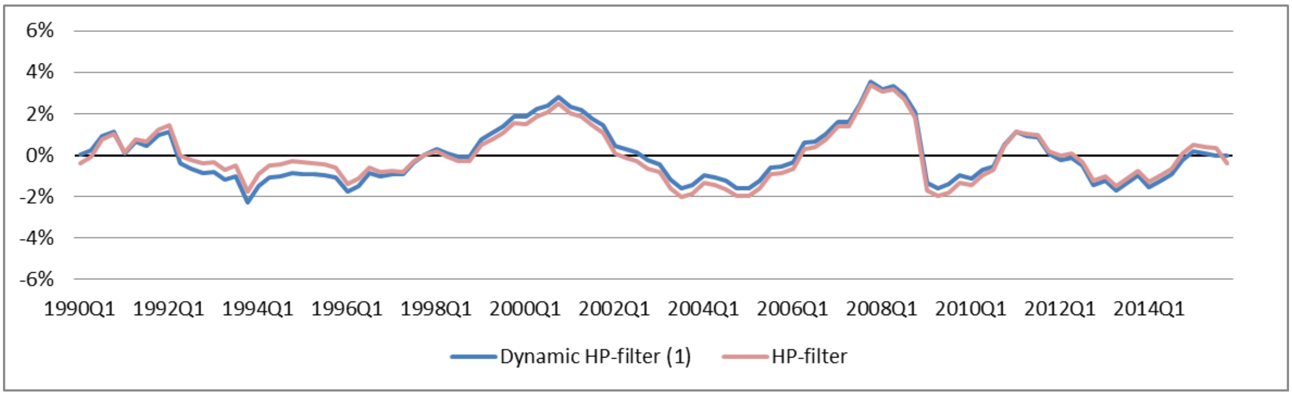
Graph 5.1 – HP-filtered (λ=1600) Output Gaps, Ex-post. Source: Authors Calculations

5.2 An Extension: Finance Neutral

Dynamic Output Gap

When estimating the finance neutral output gap, first, the by Borio et al. (2013) extended model will be determined without any additional variables except from the output gap estimate of the previous period, resulting in estimates named the *dynamic output gap*. Graph 5.2 compares this dynamic output gap (model 1 in table

5.1) with the conventional HP-filtered output gap. Modifying the conventional HP-filter by adding a lagged output gap makes hardly any difference to the point estimates. The corresponding output gap is virtually identical to the one constructed using the conventional HP-filter.



Graph 5.2 – Dynamic HP- and HP-filtered Output Gaps, Ex-post. Source: Authors Calculations

Finance Neutral Output Gap

Hereafter, explanatory variables are added to the model one-by-one, resulting in regression results as displayed in table 5.1, model (2) up until (9). In line with Borio et al. (2013) and empirical work based on their work, no economic and statistical significant effect of the interest rate is found[38]. All the other explanatory financial variables included do have a significant effect on potential output estimates. All coefficients are relatively large and clearly statistically significant in all cases. Especially private credit seems to have a substantial effect. The output gaps are highly persistent, very close to unit-root processes. The β-coefficient estimates reach the 0.95 upper boundaries in eight of the nine single variable models (table 5.1).

Graph 5.3 shows that adding financial variables to the model modify the estimated output gaps considerably, though they do qualitatively show the same pattern. Peculiar is that the estimated output gaps which include one explanatory financial variable, show larger positive output gaps in the years 1995-2004, but smaller gaps in the run up to- and the aftermath of the global financial crisis. This is contradictory to previous empirical findings, for other country samples. Previous findings show output gaps extended with equivalent financial variables, exceeding conventional HP-filtered output gaps in the run up to the global financial crisis. Besides, for most

[38] For Borio et al. (2013) the absence of a significant effect of this variable is important. They argue that financial factors, like credit and property prices, might do a better job of explaining business cycle fluctuations than interest rates. When the real interest rate is included as part of the model, equation (3) resembles something akin to an extended IS-curve.

countries tested, the years 1995-2004 show smaller finance neutral gaps relative to HP-filtered gaps[39]. Bernhofer et al. (2014) is the only one estimating the finance neutral output gap for the Netherlands. Their results differ slightly from the findings in this paper. For the period 1995-2004 they also find that finance augmented HP-filter estimates of the output gap are bigger in magnitude than HP-filtered gaps. In the period prior to and in the aftermath of the crisis, unlike findings in this paper, they find finance augmented output gaps that are slightly larger in magnitude than the HP-filtered ones. However, this is not reflected in solely credit-neutral output gaps, only through the property price neutral and finance neutral (credit & property prices) output gaps.

Possible explanation of this finding is that the Netherlands is a small and open country, highly dependent on international trade. In the run up to the global financial crisis, it could be the case that the Netherlands was partly lifting on (unsustainable financial) booms of other countries. A result is that Dutch actual output boomed, reflected in the relative large output gaps obtained via the HP-filter. The same period finance neutral estimates are relatively small because the unsustainable financial boom in the Netherlands was smaller than the one abroad.

In this study the quality of the ex-post estimates of the output gap is not discussed extensively. From this point, we assume that the ex-post estimates are perfect[40], and we focus on the extent to which the real-time estimates follow the ex-post ones.

[39] This applies for the U.S.A., U.K., Spain (Borio et al., 2013), South Africa (Kemp, 2014), Colombia (Amador-Torres, et al., 2015) and Ireland (De Manuel Aramendia & Raciborski, 2015), but not for The Netherlands (Bernhofer et al. 2014), Chile and Mexico (Amador-Torres, et al., 2015)

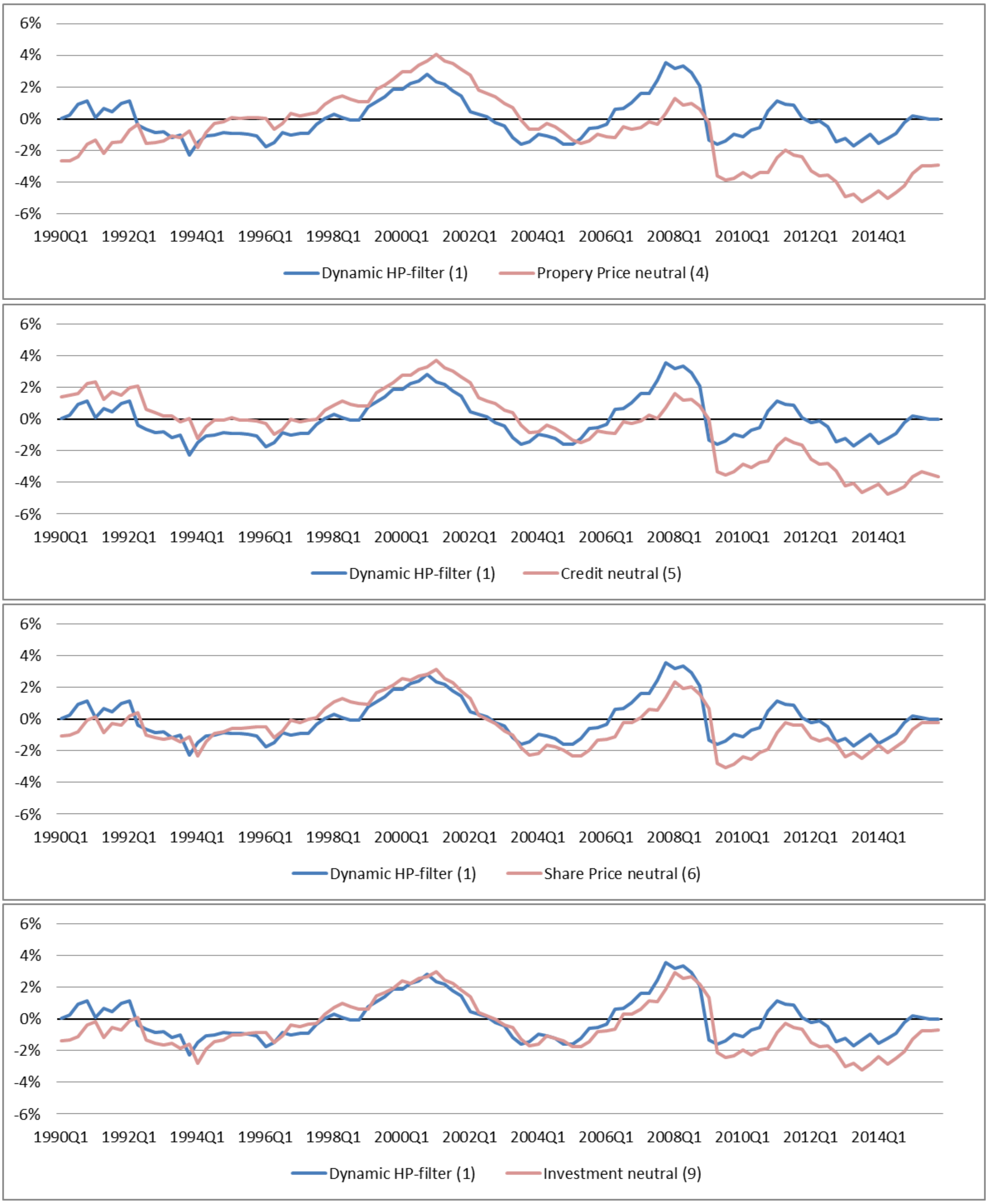
[40] Author is aware of the ongoing academic discussion on the quality of output gap estimates in general, and especially the ones obtained via the HP-filter (i.e. Mc Morrow et al., 2015).

Table 5.1 – Regression Results Finance Neutral

Model	lag	1	2	4	5	6	7	8	9
β		0.95** (19.5)	0.95** (16)	0.84** (17.1)	0.95** (72.5)	0.95** (40.2)	0.95** (59.5)	0.95** (54.7)	0.95** (46.1)
Interest Rate	0		0.00** (8.1)						
Property Prices	2			0.24** (4.2)					
Private Credit	0				0.42** (13.3)				
Share Prices	1					0.03** (4.5)			
Market Value on Euronext	1						0.03** (3.4)		
Private Investment	0							0.11** (5.0)	
Total Investment	0								0.13** (10.6)
R^2		0.32	0.32	0.49	0.51	0.50	0.47	0.52	0.52

Dependent variable is the output gap (actual output minus potential output). Results based on ex-post data (2015Q4 vintage). Figures in parenthesis are t-statistics; with *-significant at .05, **-significant at .01. Optimal lag between 0 and 4 based on highest coefficient and significance. β is restricted to lie between 0 and 0.95, with a prior mean of 0.80. Observations: 102 (each model).

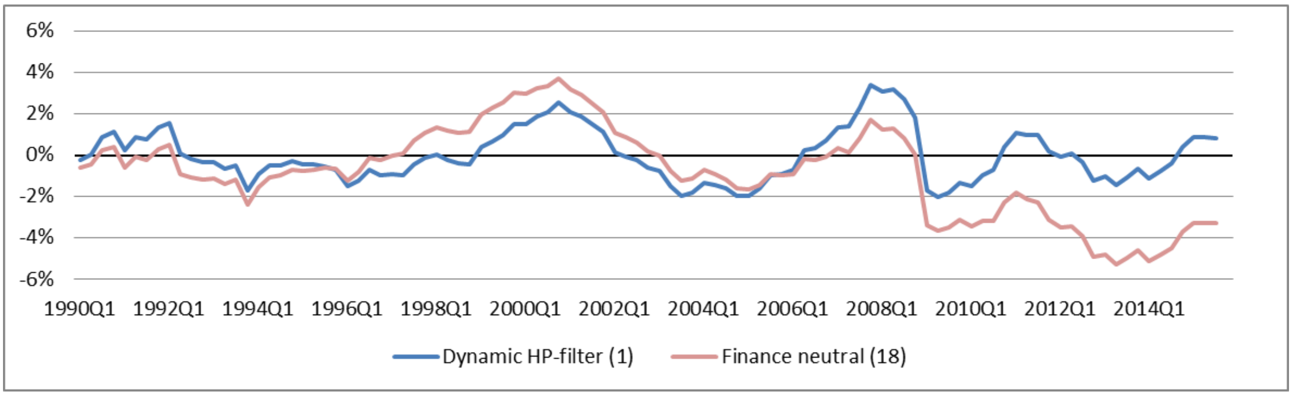
Graph 5.3 – Output Gaps Estimates (Ex-post)



Source: Authors calculations

Contradictory to the majority of empirics in this field, the optimal model found (table 5.2) does not include credit and property prices, but credit and total investment[41]. At the moment that credit and property prices are included together, the coefficient of property prices tends to zero and the statistical significance disappears. It seems that all explanatory value of property prices is absorbed by credit. Because of the high correlation between the two variables (appendix 3, table A3.3), this can be expected[42]. Besides, a relative large part of the properties in the Netherlands is mortgage-finance; it is plausible that the property prices increase is largely fueled by credit growth. In general, credit seems to be very dominant over all other variables, absorbing most of the explanatory value out of the share prices- and Market Value on Euronext variables. The investment variables seem to be more robust.

Based on the regression results, the optimal finance neutral model for this particular dataset is the one with private credit and total investment included. Both variables are included without any lag[43 44]. As displayed in graph 5.4 below, finance neutral output gap estimates based on this model show similar movements and deviations from the HP-filtered ones, as the models with one explanatory variable included. In this study the ex-post estimates of the output gap are not discussed extensively. Above, some potential explanations of the deviation are provided. However, from this point, we assume that the ex-post estimates are perfect, and we focus on the extent to which the real-time estimates follow the ex-post ones.



Graph 5.4 – Full specification Finance Neutral Output Gap (Ex-post). Source: Authors calculations

[41] Only Amador-Torres et al. (2015) estimate output gaps using a model with credit, asset prices and exchange rate variables included. The remainder of the empirical work in this field, all uses a proxy of (private or total) credit and property/house prices.
[42] The correlation between credit and property prices in the dataset of Kemp (2014) is from comparable magnitude. In his model some of the explanatory value of property prices is absorbed in credit, though not all (p. 8).
[43] Optimal lags are found by including financial variable isolated to the model, using ex-post data (2015Q4 GDP vintage). Though, lags seem to be robust when included in a model with more than one financial variable too. Lags are also robust for other GDP vintages (tested for 2002Q1; 2006Q1; 2012Q1).
[44] When adding more financial information to the model (model (19), table 5.2), explanatory value evaporates and statistical significance disappears.

Table 5.2 – Regression Results Finance Neutral, Jointly

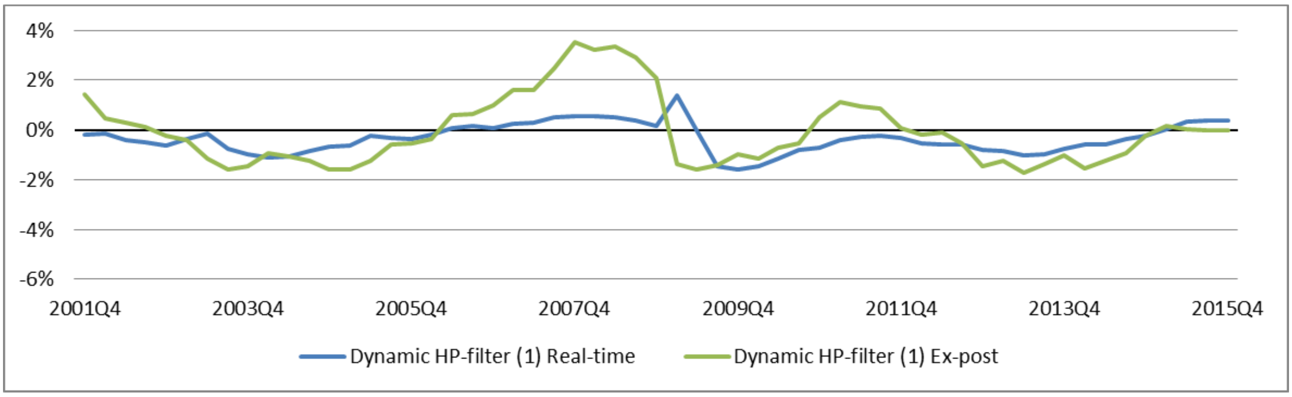
Model	lag	10	11	12	13	14	15	16	17	**18**	19
β		0.95** (75.5)	0.94** (35.6)	0.95** (73.9)	0.83** (7.4)	0.88** (18.5)	0.95** (14.3)	0.95** (116.5)	0.95** (100.3)	**0.95**** **(30.1)**	0.94** (111.3)
Property Prices	2	0.00 (0.0)	0.14** (12.5)	0.16** (19.9)	0.22** (2.8)	0.22* (2.4)					
Private Credit	0	0.46** (27.8)					0.36** (18.3)	0.35** (14.9)	0.33** (22.6)	**0.32**** **(8.7)**	0.17** (22.2)
Share Prices	1		0.03** (4.9)					0.03** (4.0)			0.00 (0.0)
Market Value on Euronext	1			0.03** (3.0)			0.02* (2.6)				
Private Investment	0				0.09** (4.5)				0.08** (8.3)		
Total Investment	0					0.11** (4.6)				**0.10**** **(4.7)**	0.00 (0.0)
R^2		0.51	0.59	0.59	0.61	0.62	0.57	0.61	0.61	**0.62**	0.45

Dependent variable is the output gap (actual output minus potential output). Regression results based on ex-post data (2015Q4 vintage). N=57. Figures in parenthesis are t-statistics; with *-significant at .05, **-significant at .01. Optimal lag between 0 and 4 based on highest coefficient and significance. β is restricted to lie between 0 and 0.95, with a prior mean of 0.80. Observations: 154 (model 10-18), 206 (model 19). Source: Authors Calculations

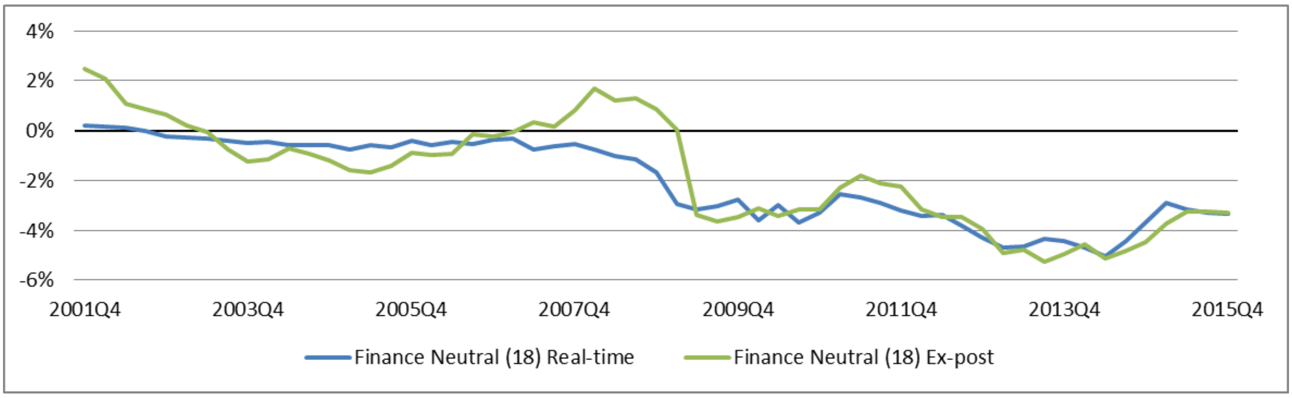
5.3 Real-time Robustness

As can be seen in graph 5.5 and 5.6, the results via both estimations methods have in common that they produce relative reliable estimates real-time during stable economic conditions: Apart from the period 2006-2008 both lines follow each other closely. Another similarity observed, is that both output gap series do show relative large differences in output gap' estimates in the run up to the global financial crisis. In real-time both methods did not foresee a relative large output gap occurring in the years 2006-2008, which both methods did see with hindsight (using ex-post data).

One the eye, the ex-post and real-time estimates of the output gap obtained via the finance neutral method seems to be slightly better matched compared to the HP-filtered ones. Resulting in real-time estimates of the output gap which are more robust in real-time when extending the HP-filter with financial cycle information.



Graph 5.5 – Dynamic HP-filtered Output Gaps. Source: Authors calculations



Graph 5.6 – Finance Neutral Output Gaps. Source: Authors calculations

Indeed, as expected and in line with previous empirical findings[45], the track score of the finance neutral output gap is smaller than the one obtained via the HP-filter (table 5.3), which implies that real-time estimates are more robust when including financial variables. The finance neutral track score is smaller for all periods, excluding the global financial crisis. Based on the track score, the real-time and ex-post gap follow each other more closely when financial variables are added to the model for all periods, excluding the global financial crisis.

	Mean Absolute Revision		Track Score	
	HP-filter	Finance Neutral	HP-filter	Finance Neutral
2001Q4-2004Q4	0,60%	0,81%	0,80	0,73
2005Q1-2009Q4	1,35%	1,11%	0,75	0,67
2010Q1-2015Q4	0,55%	0,42%	0,67	0,41
GFC	1,72%	1,35%	1,15	1,63
Excluding GFC	0,58%	0,57%	0,67	0,28
2001Q4-2015Q4	0,85%	0,76%	0,62	0,37

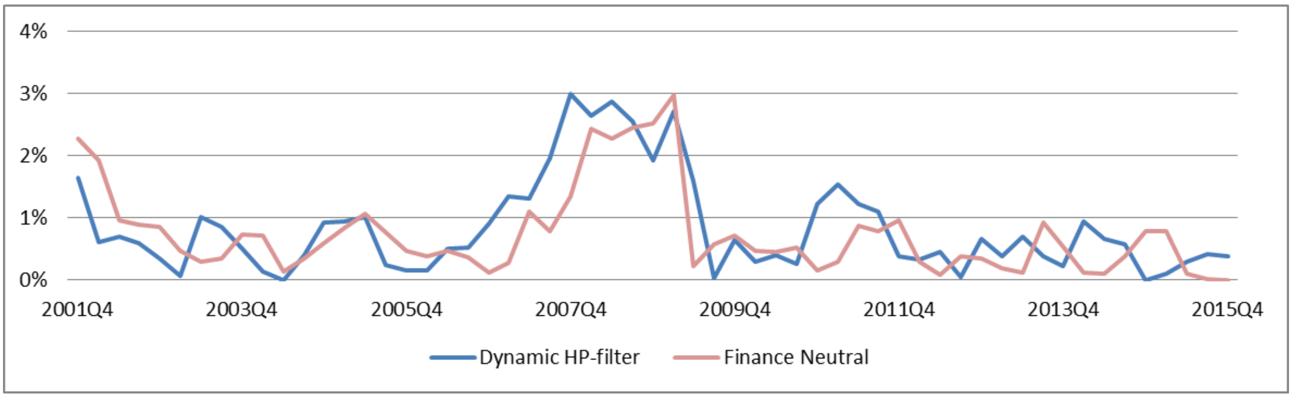
GFC (2006Q1-2009Q1); using a t-test author found that the mean absolute revision for the periods '2001q4-2015q4' and 'excluding GFC' significantly (1% significance level) differ from zero for both methods: t-values of 8.33 and 8.95 (HP-filter) and 8.12 and 8.47 (Finance Neutral) respectively. The period’s 2001Q4-2004Q4, 2005Q1-2009Q4 and 2010Q1-2015Q4 contain too little observations to conduct a t-test individually. Source: Authors Calculations.

Table 5.3 – Track Scores and Mean Absolute Revisions. Source: Authors Calculations

When looking at the mean absolute revisions (from real-time to ex-post) for the whole sample period, a typical revision using the HP-filter is around 0.85%-point. When estimates are obtained via the finance neutral approach the typical revision is 0.10%-point smaller: around 0.76%-point. A closer look shows us that the mean absolute revisions during the sample period excluding the global financial crisis are almost the same for both methods. However, since the standard deviation of the ex-post finance neutral gap is larger, the track score is smaller. The same thing applies for the period 2001Q4-2004Q4, in which the mean absolute revision using the HP-filter even is 0.21%-points smaller than the ones obtained via the finance neutral approach.

[45] Borio et al. (2013) find track scores via the HP-filter of 0.61 (United States), 0.42 (United Kingdom) and 0.68 (Spain), and via the finance neutral method 0.12 (United States), 0.24 (United Kingdom) and 0.38 (Spain). Kemp (2014) find HP-filtered track scores of 0.70, and finance neutral of 0.40 (South Africa).

Turner et al. (2016) argues that revisions of output gap estimates typically tend to be markedly larger around turning points. This holds for the Netherlands in the sample period, whereby absolute revisions prior to- and during the global financial crisis are the largest ones. The mean absolute revisions are substantially larger in magnitude for both methods in this period. The mean absolute revisions for the HP-filtered output gaps are typically 1.72%-point; against 1.35% for the finance neutral ones. The biggest revision is observed using the HP-filter in the fourth quarter of 2007, when the absolute revision was 3%, from a positive output gap of 0.5% real-time to a positive output gap of 3.5% ex-post. The finance neutral method displays a similar maximum revision, in the first quarter of 2009.



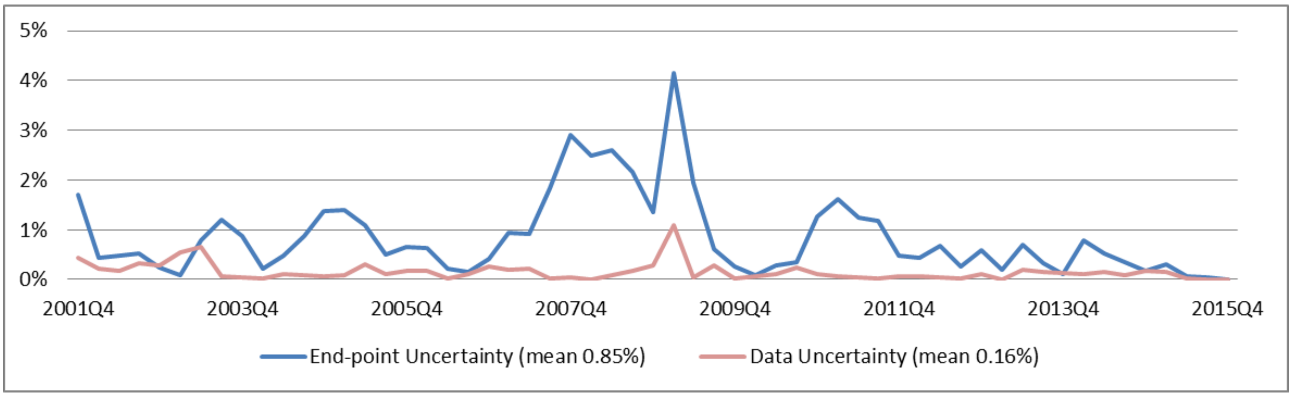
Graph 5.7 – Absolute Revisions (Real-time to Ex-post) Output Gaps. Source: Authors Calculations

In general the real-time robustness of output gap estimates slightly increase when financial information is added to the model. However, including financial information did not improve the robustness of real-time output gap estimates prior to- and during the recent global financial crisis.

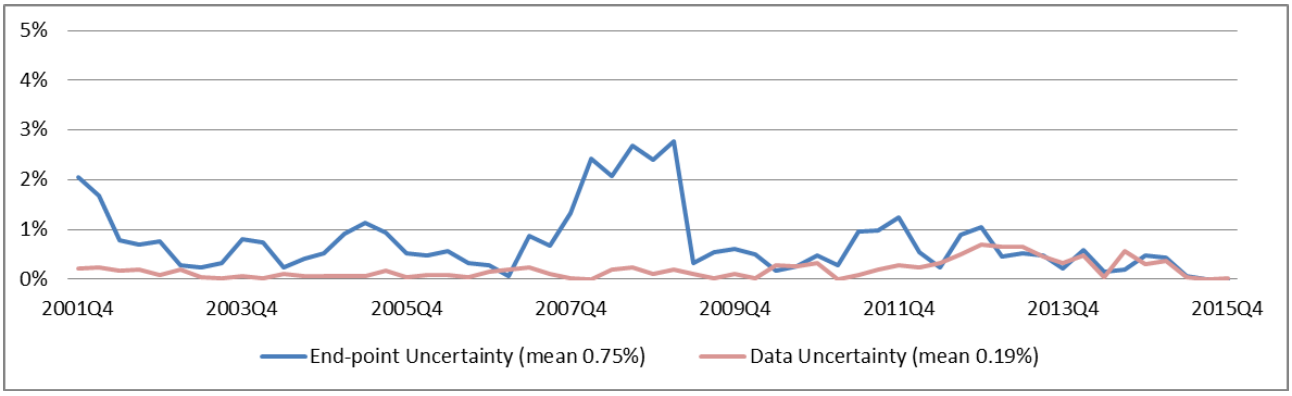
5.4 Drivers of Real-time Uncertainty

Within a particular model, two sources of uncertainty are identified: data uncertainty and end-point uncertainty. Graph 5.8 and 5.9 display that, independent from the method used, the end-point uncertainty is larger in magnitude than the data uncertainty. These findings are in line with previous empirical findings[46]. Graph 5.10 displays that adding financial variables decreases the end-point uncertainty of output gap estimates. The magnitude of data uncertainty increases slightly when adding financial variables (graph 5.11).

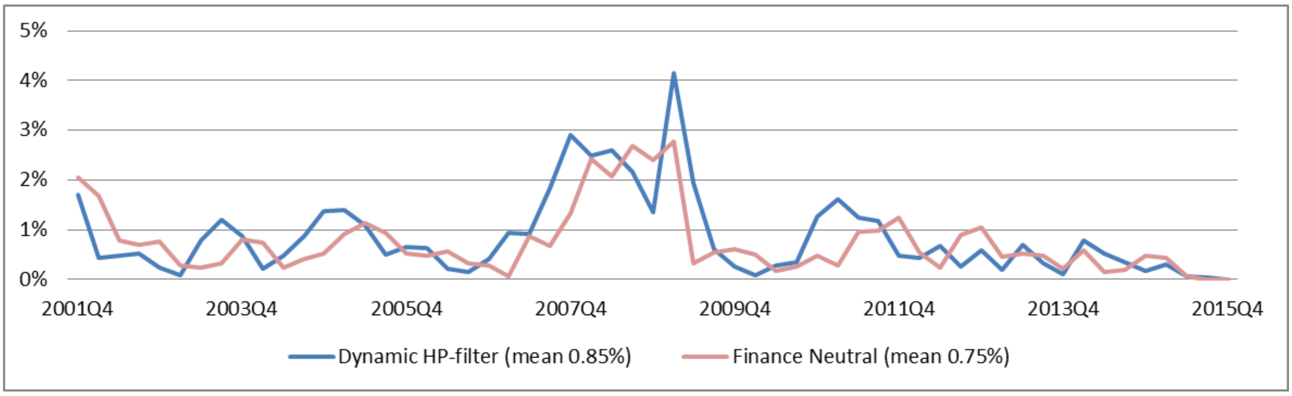
[46] i.e. Murray (2014), Orphanides & van Norden (2002) and Camba-Mendez & Rodriguez (2001).



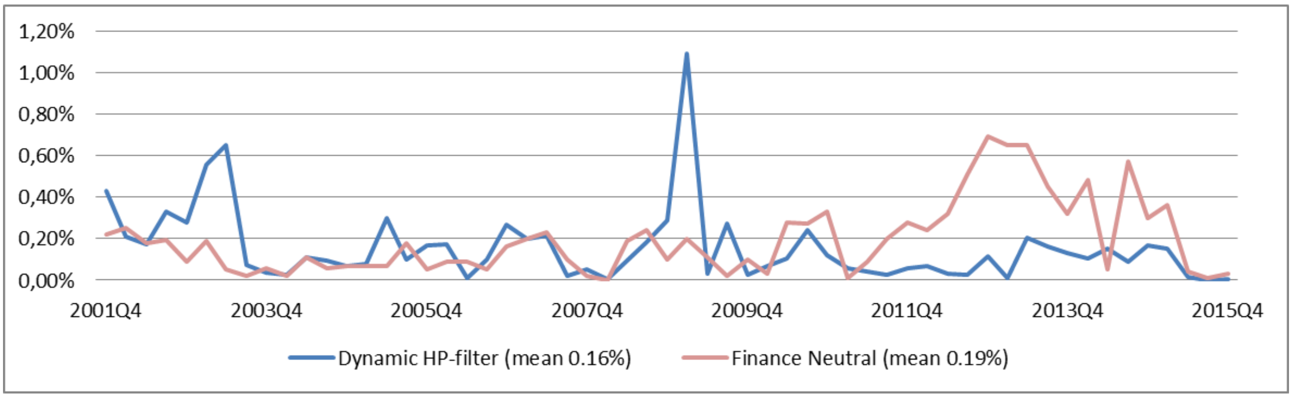
Graph 5.8 – Dynamic HP-filtered Output Gap Uncertainty. Source: Authors Calculations



Graph 5.9 – Finance Neutral Output Gap Uncertainty. Source: Authors Calculations



Graph 5.10 – End-point Uncertainty. Source: Authors Calculations



Graph 5.11 – Data Uncertainty. Source: Authors Calculations

6. Conclusion and Discussion

This study tested the stated hypothesis by Borio et al. (2013) that extending the conventional HP-filter with financial cycle information increases the real-time robustness of output gap estimates. Previous studies in this field confirmed this hypothesis for several countries. However, to my best knowledge, this is the first study providing real-time finance neutral estimates for the Netherlands. The main research question of this study is*: To what extent does the finance neutral estimate of the Dutch output gap provide more accurate information for policy makers real-time relative to estimates obtained via a conventional method?* In order to address this question, a new dataset containing real-time GDP vintages for the period 2001Q4 up until 2015Q4 is constructed. Hereby, it is the first time the Borio et al. (2013) approach is applied to a real-time GDP dataset. Three hypotheses are identified, jointly providing an answer on the main research question.

The first hypothesis set, is whether using conventional methods to estimate output gaps for the Netherlands, these are indeed misspecified in the way that the ex-post and real-time estimates are highly inconsistent. Results show that this first hypothesis holds using the dynamic HP-filter: A modified conventional HP-filter, adding a lagged output gap. Although, the real-time and ex-post estimates of the output gap qualitatively follow the same path during stable economic conditions, a typical (absolute) revision still is about 0.85%-points. Besides, prior to- and during the recent global financial crisis revisions were much larger.

The second hypothesis tested is if financial variables do have explanatory value to potential output and the corresponding output gap estimates. Regression results obtained via the extended HP-filter confirm this hypothesis. When added independently to the model, the financial variables *private credit*, *share prices* and *property prices* display the highest explanatory value to output gap estimates. When financial information is added to the model jointly, the optimal model is the one including *private credit* and *total investment*. This is inconsistent with previous empirical work in this field, which mainly found optimal models including *private credit* and *property prices.*

The third hypothesis tested is if these finance neutral estimates of the output gap provide more reliable information real-time. In general, also this third hypothesis is confirmed. In general the real-time robustness of output gap estimates increase slightly when financial information is added to the model. A typical absolute revision using the finance neutral approach introduced by Borio et al. (2013) is around 0.10%-point smaller than the ones excluding financial information. Also, when comparing the track score (absolute revision divided by the standard deviation of the ex-post gap) the finance neutral estimates outperform the dynamic HP-filter. Especially the end-point problem of the HP-filter is reduced substantially. However, including financial information did not improve the robustness of real-time output gap estimates prior to- and during the recent global financial crisis.

Herewith, the answer on the main research question is that finance neutral estimates of the Dutch output gap do provide more accurate information real-time, although this improvement in accuracy is small in magnitude and not robust during the recent global financial crisis. Table 6.1 provides a recap of table 1.1; the mean revision decreased, the outlier in revisions did not decrease.

HP-Filter	Real-time Estimation	Ex-post Estimation	Revision
2007Q4 (max)	0,54%	3,53%	2,99%-point
Mean			0,85%-point

Finance Neutral	Real-time Estimation	Ex-post Estimation	Revision
2009Q1 (max)	-2,96%	0,01%	2,97%-point
Mean			0,76%-point

For HP-filter estimates; see table 1.1. Finance Neutral estimates are obtained following the approach explained in section 4.3

Table 6.1 - Uncertainty of Real-time Estimates of the Output Gap. Source: Authors calculations

Some additional remarks need to be made. Finding the optimal real-time model using the Borio et al. (2013) approach requires ex-post data. Of course, this is not possible in the real world in which data is – in perfect conditions – available up until that very same moment. Additionally, for every sample (country and period) a different model seems to be the optimal one. This applies to both the choice of the financial variables as their appertained optimal lag. As a result the optimal model found is this study for this particular period and country is not automatically the optimal model in the future, neither for other countries samples. Another remark is that results show that when extending the HP-filter with unemployment rate information, which do not represent the financial cycle directly, output gap estimates performance also improve (appendix 2). Unemployment rate neutral estimates even outperform the finance neutral ones in terms of real-time robustness. One of the drawbacks of this particular study is that the new constructed dataset only contains real-time GDP vintages, neglecting the real-time data for other variables. Although the data revisions of the financial variables are generally smaller in magnitude compared to the revisions in GDP series, it can be the case that certain data is only available one or two periods later.

From a theoretical point of view it makes sense to include financial cycle information to output gap estimation models: The financial cycle amplifies the business cycle, unnoticed by inflation and estimates of potential output based inflation as the key symptom of sustainability. Besides, Borio et al. (2013) and following empirical work in this field – including this paper – show that applying this finance neutral approach in most cases lead to output gap estimates which are more precise and robust in real-time relative to the HP-filter. However, considering the drawbacks of the general finance neutral approach and the specific results found in this specific paper, the by Borio et al. (2013) proposed approach is above all usable as a starting point for future research. Finance neutral estimates can also be used as an additional indicator for fiscal- and monetary policy making. Though, it should not be used as an omniscient instrument and neglecting other output gap estimation methods and supplementary indicators. There is a risk of misjudging the economic situation.

A general recommendation for future research following the Borio et al. (2013) approach is to test the hypotheses while simulating a real world setting. That is, using a dataset which include real-time vintages of all explanatory variables. In the same line of reasoning, it is interesting to see if – when finding the optimal model using only real-time data – the finance neutral approach still produces more precise and robust output gap estimates. Additionally, it is more usable to make a more broad comparison between more and other (conventional) estimation methods.

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Appendix 1 – Production Function Method

To illustrate that it is not only the HP-filter' estimates which are surrounded by uncertainty, here the estimates obtained using the European Commission Production Function Approach are shown.

Instead of making statistical assumptions on the time series properties of trends and their correlation with the cycle, the production function approach makes assumptions based on economic theory. The European Commission approach[47] focuses on the supply potential of an economy and has the advantage of giving a more direct link to economic theory but the disadvantage is that it requires assumptions on the functional form and the representative utilization of production factors. With a production function, potential GDP can be represented by a combination of factor inputs, multiplied with the technological level or total factor productivity (TFP). The parameters of the production function essentially determine the output elasticities of the individual inputs, with the trend components of the individual production factors, except capital, being estimated. Since the capital stock is not de-trended, estimating potential output amounts therefore to removing the cyclical component from both labor and TFP. In more formal terms, with a production function, GDP (Y) is represented by a combination of factor inputs - labor (L) and the capital stock (K), corrected for the degree of excess capacity (U_L, U_K) and adjusted for the level of efficiency (E_L, E_K). A Cobb Douglas specification is chosen for the functional form. This greatly simplifies estimation and exposition. Thus potential GDP is given by:

$$Y = (U_L L\, E_L)^{\alpha}(U_K K E_K)^{1-\alpha} = L^{\alpha} K^{1-\alpha} * TFP$$

where total factor productivity (TFP), as conventionally defined, is set equal to:

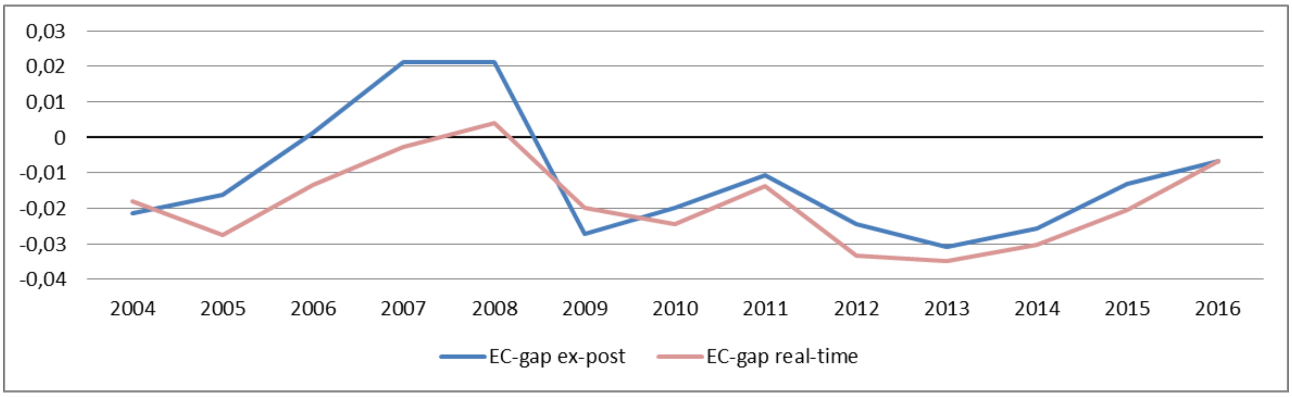
$$TFP = (E_L^{\alpha} E_K^{1-\alpha})(U_L^{\alpha} U_K^{1-\alpha})$$

which summarizes both the degree of utilization of factor inputs as well as their technological level (Havik et al., 2014).

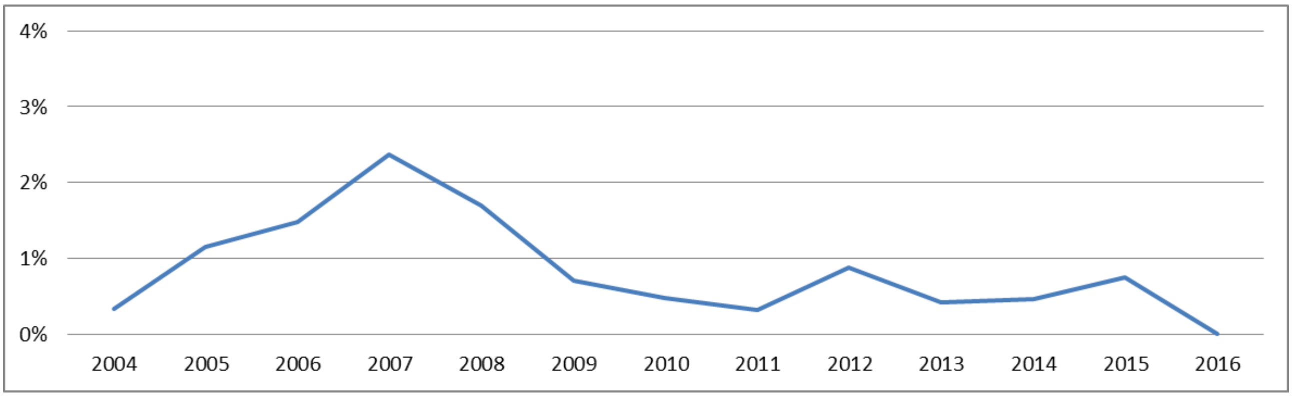
It is important to note that real-time estimates obtained via the PF-method are based on GDP forecasts from (underlying factor inputs) the concerning period itself (t). This is different to HP-filter estimates. Since the PF-method needs factor inputs to estimate potential output and corresponding output gaps, which are not directly

[47] Havik et al. (2014) provide an extensive assessment of the EC production function method.

available, these underlying factors needs to be estimated first. This potentially creates additional uncertainty in the real-time estimates.



Graph A1.1 – PF-method Output Gaps. Source: European Commission (2016)



Graph A1.2 – Absolute Revisions PF-method Output Gaps. Source: European Commission (2016)

The PF-method mostly overestimated potential output in the Netherlands during 2004-2016, resulting in upwards revisions in the corresponding output gaps. Only exception is in 2009, in which with hindsight, the economy was operating more below potential than considered real-time. The real-time estimates did not observe that the Dutch economy was operating above potential in the run op to the crisis, only 2008 showed a small positive output gap. On the other hand, from 2009 onwards, real-time estimates via the PF-method were not subject to substantial revisions. Note that the estimates obtained via the PF-method use annual data. The estimates obtained via the HP-filter and PF-method, and the revisions they were subject to, therefore are not comparable quantitatively. However, qualitatively we can conclude that both methods' real-time estimates are surrounded by uncertainty. The HP-filter shows both over- and underestimations of the output gap which are from comparable magnitude. The PF-method particularly underestimates the output gap.

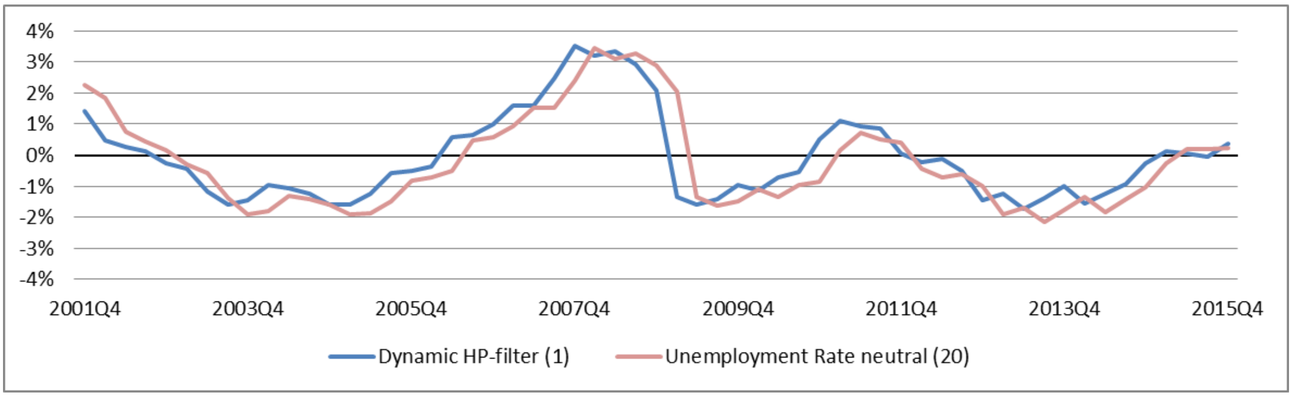
Appendix 2 – Extension: Unemployment Neutral

In this section output gaps are estimated using the approach set in section 4, including the explanatory variable unemployment rate [48]. By doing this, the hypothesis set by Borio et al. (2013) – extending the conventional HP-filter with financial cycle information increase the precision and real-time robustness of output gap estimate – is tested in the way if it is the actually the financial cycle information that improves the estimates, or that adding economic information in general does the job too. Table A2.1 display the regression results of the unemployment rate model[49].

Model	lag ↓	1	20
β		0.95** (19.5)	0.86** (22.5)
Unemployment Rate	0		-0.07** (4.1)
R^2		0.32	0.28

Regression results are based on ex-post data (2015Q4 vintage). N=104. Figures in parenthesis are t-statistics; with *-significant at .05, **-significant at .01. Optimal lag between 0 and 4 is based on highest coefficient and significance. β is restricted to lie between 0 and 0.95, with a prior mean of 0.80.

Table A2.1 – Regression Results Economic Neutral
Source: Authors calculations



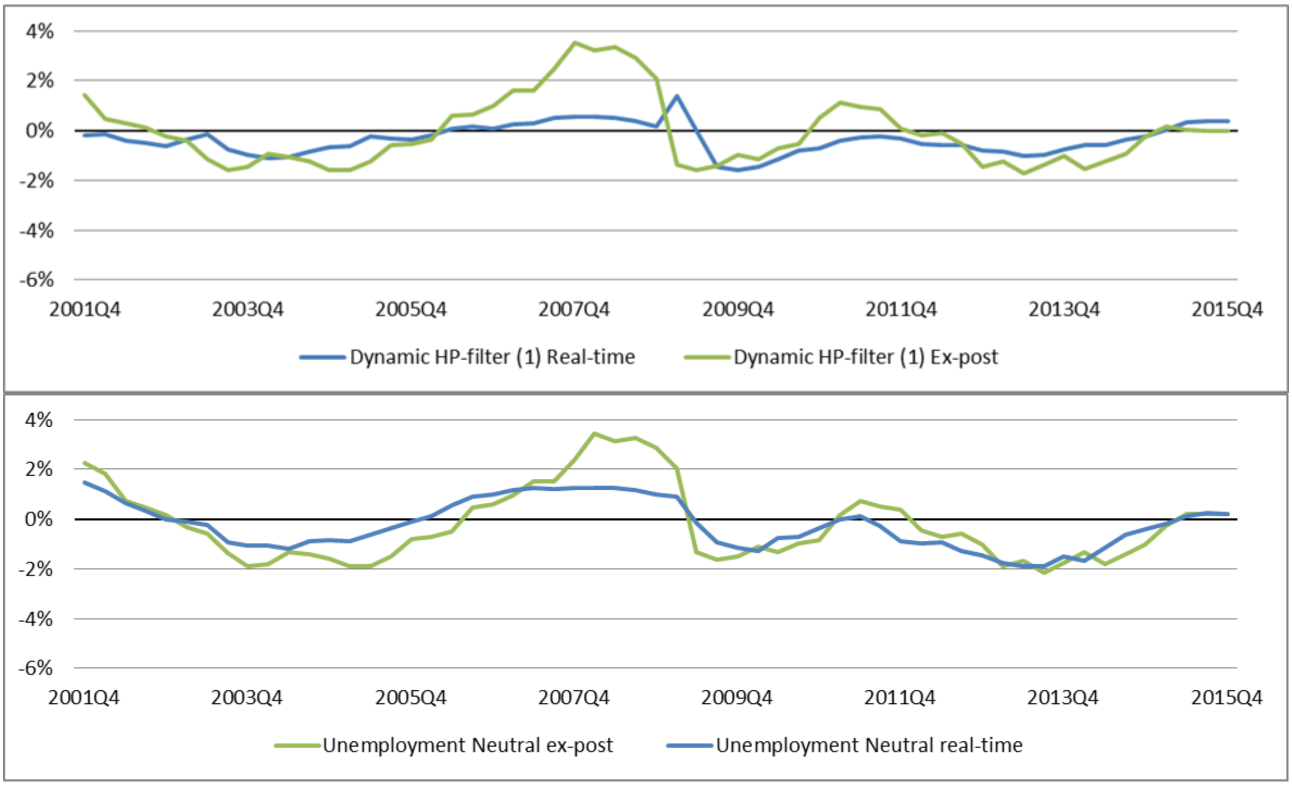
Graph A2.1 – Unemployment Rate Neutral Output Gap (Ex-post). Source: Authors calculations

[48] Unemployment rate represent the harmonized unemployment rate. Harmonized unemployment rates define the unemployed as people of working age who are without work, are available for work, and have taken specific steps to find work. This indicator is measured in numbers of unemployed people as a percentage of the labor force and it is seasonally adjusted. The labor force is defined as the total number of unemployed people plus those in civilian employment. The data used in this section are all obtained from the OECD (2016) online database. The data is added in differences, and as natural logarithm.

[49] Also, extensions of the dynamic HP-filter with consumer confidence and industrial confidence information are tested. Although they did outperform (in terms of precisions and real-time robustness) both the dynamic HP-model as the finance neutral model, the estimated output gaps were highly unrealistic, displaying gaps between -10% and -15% of potential output.

Real-time Robustness

On the eye, the real-time output gap estimates obtained via unemployment rate neutral model follows its ex-post line more closely than the HP-filtered ones (graph. A2.3). Table A2.2 confirms this: The track score calculated over the whole sample period is smaller for the unemployment rate neutral output gaps than the HP-filtered ones. Besides, they hold for all periods, including the global financial crisis. This implies that real-time estimates are more robust when including unemployment data. When looking at the mean absolute revisions (from real-time to ex-post) for the whole sample period, a typical revision using the HP-filter is around 0.85%-point. When estimates are obtained via the unemployment rate neutral approach the typical revision is 0.22%-point smaller: around 0.63%-point. Note that this is even 0.13%-point smaller than the finance neutral ones (section 5.4). A closer look shows us that the unemployment rates mean revisions are smaller in all sample periods relative to the HP-filtered ones. Besides, they outperform the mean absolute deviations obtained via the finance neutral model in all periods, only in the period 2005q1-2009q4 both extended models perform equally.



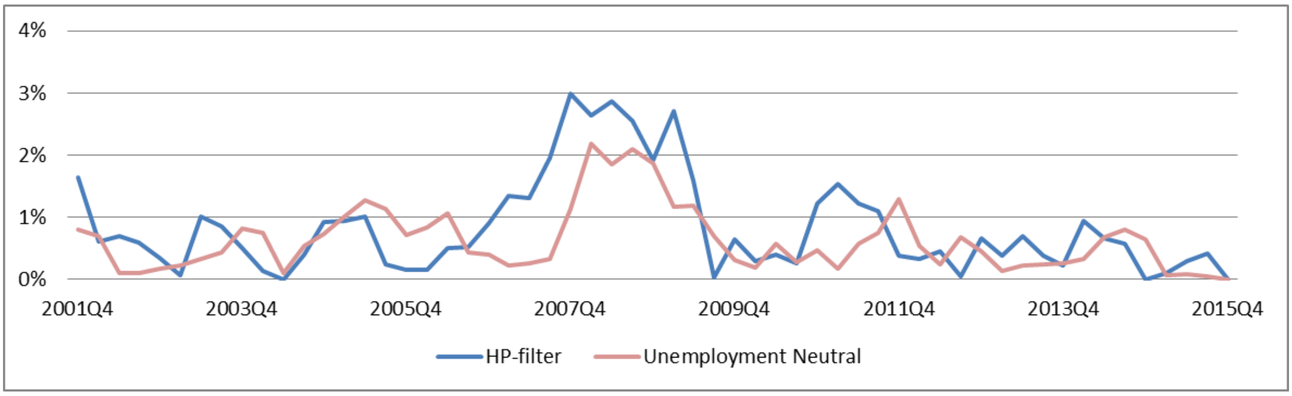
Graph A2.2 – Output gaps Ex-post and Real-time. Source: Authors calculations

The mean absolute revisions (graph A2.3) are substantially larger in magnitude in the period prior to- and during the global financial crisis. The mean absolute revisions for the HP-filtered output gaps are typically 1.72%-point; against 1.07% for the unemployment neutral ones. The biggest revision is observed using the HP-filter in the fourth quarter of 2007, when the absolute revision was 3%. The unemployment rate neutral method displays a smaller maximum revision; 2.2% in the first quarter of 2008.

	Mean Aboslute Revision		Track Score	
	HP-filter	Unemployment Neutral	HP-filter	Unemployment Neutral
2001Q4-2004Q4	0,60%	0,45%	0,80	0,38
2005Q1-2009Q4	1,35%	1,01%	0,75	0,55
2010Q1-2015Q4	0,55%	0,42%	0,63	0,48
GFC	1,72%	1,07%	1,15	0,77
Excluding GFC	0,57%	0,50%	0,66	0,47
2001Q4-2015Q4	0,85%	0,63%	0,62	0,42

GFC (2006Q1-2009Q1), Source: Authors Calculations

Table A2.2 – Track Scores and Mean Absolute Revisions. Source: Authors Calculations

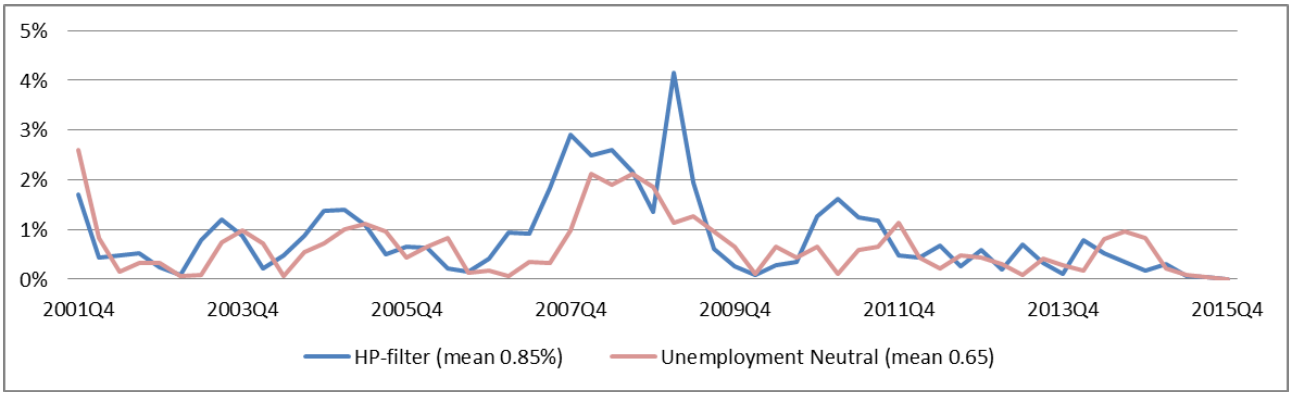


Graph A2.3 – Absolute Revisions (Real-time to Ex-post) Output Gaps. Source: Authors Calculations

Drivers of Uncertainty

Graph A2.4 display that adding unemployment rate information decreases the end-point uncertainty of output gap estimates. The magnitude of the end-point uncertainty of HP-filtered output gaps is 0.85%, while the ones obtained using the unemployment rate neutral model is only 0.65%[50].

[50] Finance neutral end-point uncertainty is 0.73%.



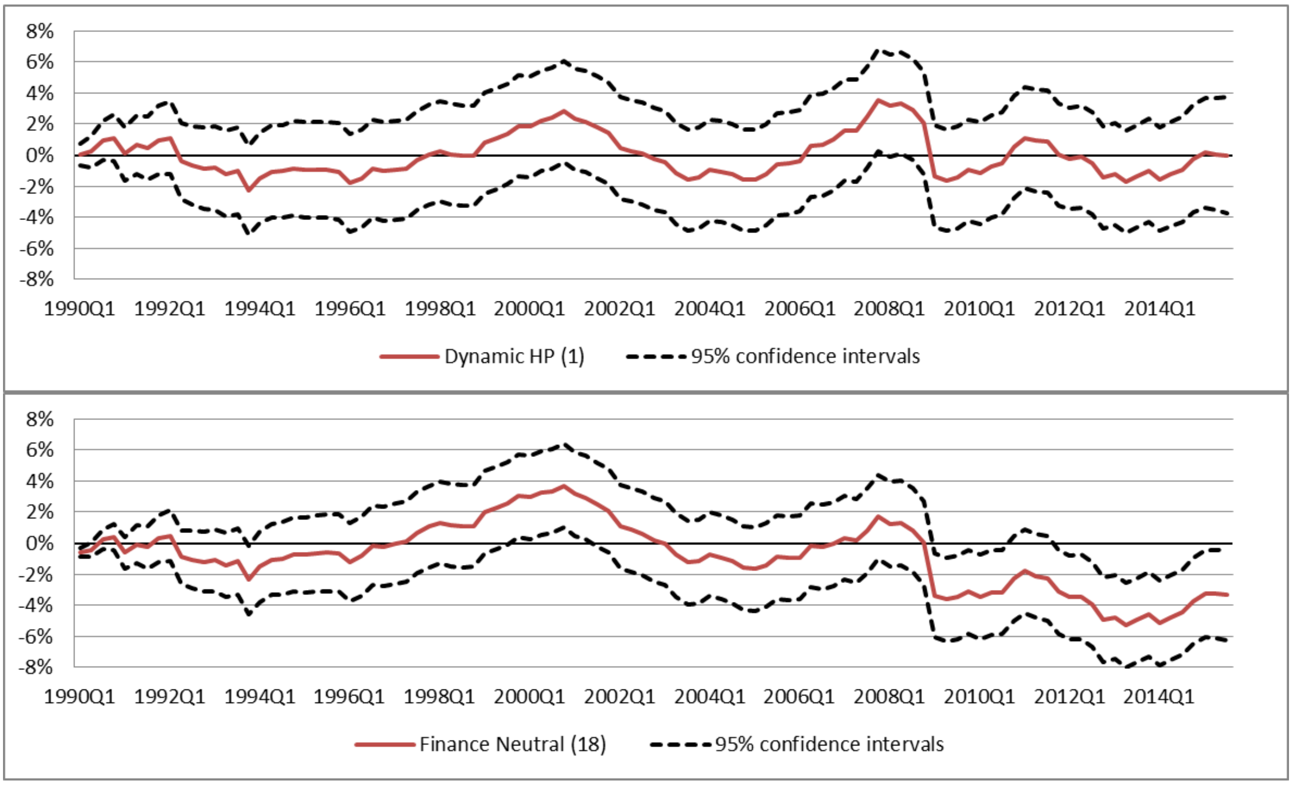
Graph A2.4 – Uncertainty Unemployment Rate Neutral Output Gaps. Source: Authors Calculations

Overall, the real-time robustness of output gap estimates increase when information on unemployment is added to the model. Relative to the HP-filtered ones, this holds for all periods including the global financial crisis. While still substantial, the absolute revisions prior to- and during the global financial crisis are substantially smaller. Additionally, the unemployment rate neutral output gap estimates outperform the finance neutral ones in terms of precision and real-time robustness. Especially the end-point uncertainty decreased substantially when the model is extended with unemployment rata data.

Appendix 3 – Statistical Precision

To evaluate the statistical precision of the ex-post output gap estimates, confidence intervals are constructed and compared to those obtained from the dynamic HP-filter[51]. This is done using the ex-post estimates for the (dynamic) HP-filter, finance neutral and unemployment neutral ones. Two points are compared. First, the absolute width of both the 95%-confidence bands. The wider the bands, the more uncertain the estimated gaps are. Second, whether the whole confidence band deviates from the zero-line, which implies that the produced output gaps are statistically different from zero.

Finance Neutral



Graph A3.1 – Statistical Precision Ex-post Output Gaps. Source: Authors calculations

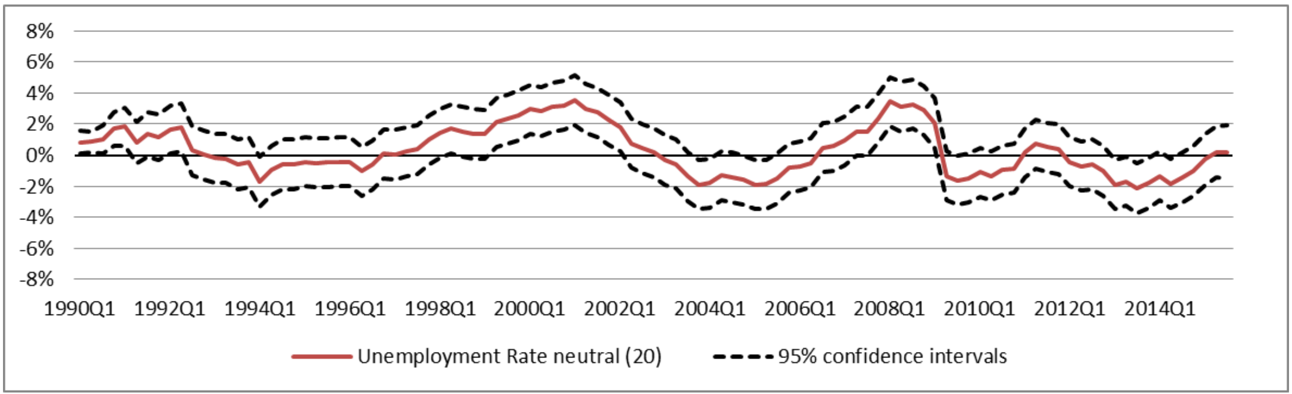
While still quite wide, the size of the confidence band in the finance neutral estimates is much smaller than the dynamic HP-filtered one; around 4.9 against around 6.1. Additionally, in contrast to the dynamic HP-filter, the finance neutral confidence bands are narrow enough to produce output gap estimates that are statistically different from zero[52]. These findings are in line with existing empirical findings.

[51] The dynamic hp-filtered gap is used for comparative purposes because one needs to take into account the underlying persistence in the output gap variable in order to construct reliable confidence intervals.
[52] If for one period the zero line falls outside the conf. band, one may conclude that the gap is statistically different from zero.

However, the absolute magnitude of the difference (20% for the Netherlands), is much smaller than found in similar research[53].

Unemployment rate Neutral

To evaluate the statistical precision of the ex-post estimates, confidence intervals are constructed and compared to those obtained from the dynamic HP-filter.



Graph A3.2 – Statistical Precision Ex-post Output Gaps, Unemployment Rate Neutral. Source: Authors calculations

The size of the confidence band in the unemployment rate neutral estimates is smaller than with the dynamic HP-filtered one; around 3.1 against around 6.1. Besides, the difference in confidence bands from the dynamic HP-filter and the extended HP-filter is much larger compared to the ones obtained including financial cycle information. Additionally, in contrast to the dynamic HP-filter, the unemployment rate confidence bands are narrow enough to produce output gap estimates that are statistically different from zero. These findings are in line with existing empirical findings.

[53] Borio et al. (2013) find confidence bands from dynamic HP-filtered output gaps of 3.50 (United States), 3.85 (Spain) and 2.95 (United Kingdom), and confidence bands for the finance neutral ones of 1.35, 2.10 and 1.80. Kemp (2014) find dynamic HP confidence bands of 4.40 for South Africa, and finance neutral ones of 2.36. Absolut change in confidence band from dynamic to finance neutral is between 61% and 39%.

Appendix 4 – Descriptive Statistics and Overview of Variables

A4.1 Descriptive Statistics

As displayed in table A4.1, the real-time GDP vintages start with the 2001Q4 vintage and end with the 2015Q4 vintage. This 2015Q4 is also used as ex-post data series. The most outdated vintage contains 48 quarterly observations (1990Q1-2001Q4). Every vintage after this period, contains one additional observation. This leads to the 2015Q4 vintage, containing 104 quarterly observations (1990Q1-2015Q4). With this increasing number of observations, the variation and standard deviation in the sample increases too. Due to economic growth and upwards revisions of GDP estimates, the minimum, maximum and subsequently the mean of the sample increases gradually. The relative large changes in GDP observations are due to the change in base year.

All explanatory variables include the period 1990Q1 – 2015Q4, which equal 104 quarterly observations. Descriptive statistics are displayed in table A4.2. Property Prices, Share Prices, Private Investment and Total Investment are all included as indexes, hence the mean observations are around 100. Property Prices and Share Prices display a relative large deviation in their observations. This is because both these variables showed relative low numbers in the beginning of the sample period.

Table A4.2 - Descriptive statistics

Variable	Obs	Mean	Var	SD	Min	Max
GDP 2015Q4	104	137603	457731087	21395	98952	163229
Interest rate	104	2,56	3,35	1,83	-1,22	6,69
Property Prices	104	71	753	27	27	106
Private Credit	104	288608	7903245148	88900	140611	401682
Share Prices	104	100	1589	40	32	184
Market Value on Euronext	104	442259	39300000000	198353	114112	861054
Private Investment	104	97	205	14	73	124
Total Investment	104	93	211	15	68	119

Source: Authors calculations

Table A4.3 - Correlation Matrix

	short	GDP	r	PP	Cpr	SP	MVEUR	INVp	INVt
GDP (2015Q4)	**GDP**	x	-0,24	0,71	0,76	0,57	0,53	0,73	0,75
Interest Rate	**r**		x	-0,25	-0,18	0,00	0,03	-0,36	-0,36
Property Prices	**PP**			x	0,81	0,29	0,29	0,42	0,50
Private Credit	**Cpr**				x	0,47	0,48	0,44	0,49
Share Prices	**SP**					x	0,97	0,41	0,37
Market Value on Euronext	**MVEUR**						x	0,35	0,31
Private Investment	**INVp**							x	0,99
Total Investment	**INVt**								x

Correlation based the growth rate (t-4). Source: Authors calculations.

Table A4.1 - Descriptive statistics real-time GDP

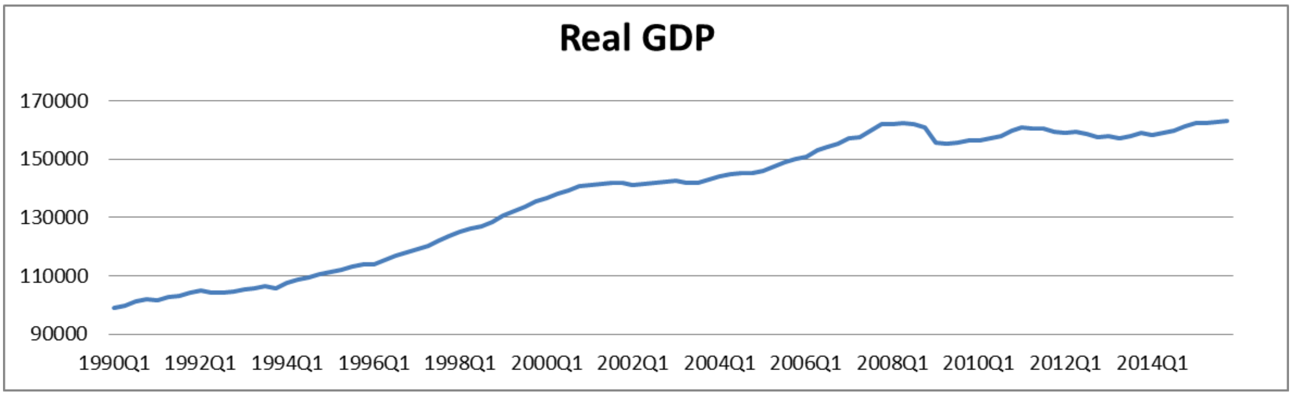
Vintage	Obs	Mean	Var	SD	Min	Max
2001Q4	48	78481	65402482	8087	66983	91642
2002Q1	49	78746	67486400	8215	66982	91660
2002Q2	50	79009	69579003	8341	66984	91746
2002Q3	51	79303	72732544	8528	66956	91904
2002Q4	52	79560	74716302	8644	66958	92207
2003Q1	53	79787	76018734	8719	66956	92159
2003Q2	54	80001	77062339	8779	66959	92214
2003Q3	55	80220	78415563	8855	67285	92274
2003Q4	56	80419	79207824	8900	67286	92332
2004Q1	57	80628	80270746	8959	67286	92364
2004Q2	58	80911	83105560	9116	67284	92868
2004Q3	59	81122	84282371	9181	67279	92877
2004Q4	60	81331	85468910	9245	67288	93156
2005Q1	61	81529	86430202	9297	67282	93240
2005Q2	62	99456	129695664	11388	81874	114625
2005Q3	63	99710	131460433	11466	81881	115029
2005Q4	64	99973	133700585	11563	81884	116446
2006Q1	65	100275	135721586	11650	81930	116382
2006Q2	66	100741	144058369	12002	81935	118982
2006Q3	67	101038	147717294	12154	81936	120130
2006Q4	68	95399	155412862	12466	76234	115159
2007Q1	69	95683	159373284	12624	76201	115683
2007Q2	70	95947	169468380	13018	75325	116566
2007Q3	71	96278	174737740	13219	75325	118921
2007Q4	72	96617	180570350	13438	75325	120482
2008Q1	73	96948	186000157	13638	75331	120662
2008Q2	74	97442	197891048	14067	75323	121850
2008Q3	75	97769	203229162	14256	75323	121878
2008Q4	76	98079	207850353	14417	75324	122242
2009Q1	77	98333	210111402	14495	75325	122548
2009Q2	78	98583	212336654	14572	75325	122622
2009Q3	79	98815	213868491	14624	75325	122718
2009Q4	80	99048	215503207	14680	75325	122733
2010Q1	81	99277	217084349	14734	75324	122665
2010Q2	82	99576	221450180	14881	75334	122880
2010Q3	83	99816	223501999	14950	75333	122910
2010Q4	84	100059	225793990	15026	75334	122885
2011Q1	85	100312	228528738	15117	75334	122867
2011Q2	86	115792	307146428	17526	86757	141267
2011Q3	87	116065	310142408	17611	86754	141299
2011Q4	88	116322	312224135	17670	86760	141306
2012Q1	89	116565	314037644	17721	86757	141306
2012Q2	90	116775	314144508	17724	86769	141293
2012Q3	91	116997	315142366	17752	86769	141313
2012Q4	92	117214	316025251	17777	86769	141311
2013Q1	93	117415	316369168	17787	86766	141307
2013Q2	94	117545	314135734	17724	86792	141298
2013Q3	95	117738	314293280	17728	86792	141297
2013Q4	96	117940	314935793	17746	86790	141293
2014Q1	97	118114	314616581	17737	86790	141283
2014Q2	98	135633	424944649	20614	99362	162028
2014Q3	99	135790	428061681	20690	99334	162028
2014Q4	100	136023	429164281	20716	99334	162028
2015Q1	101	136269	430975450	20760	99334	162028
2015Q2	102	137103	453665190	21299	98952	162506
2015Q3	103	137354	455707989	21347	98952	162797
2015Q4	104	137603	457731087	21395	98952	163229

GDP data in millions of euro. Source: Authors calculations, via CBS (2016)

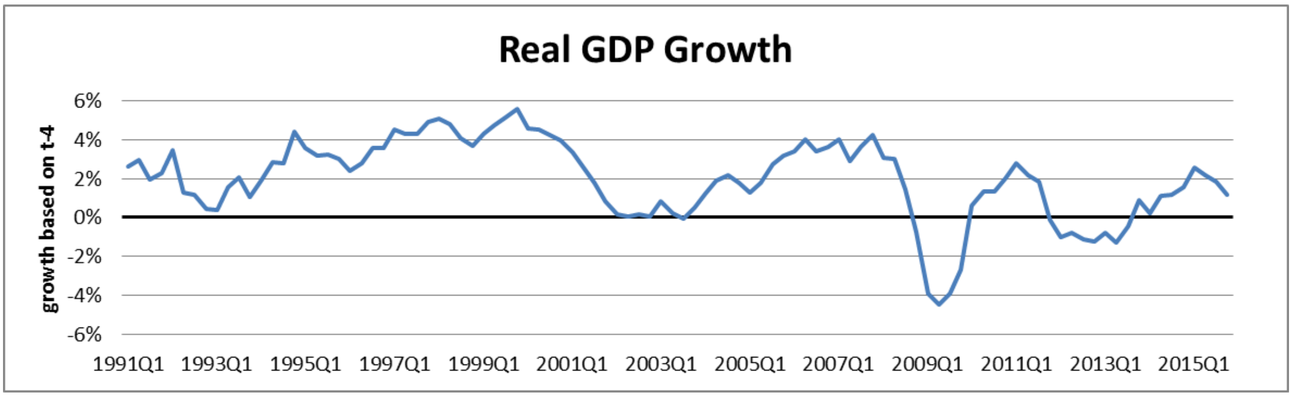
A4.2 Overview Variables

A4.2.1 Gross Domestic Product

In the period 1990q1 – 2015q4 real GDP increased from €99 billion to €163 billion which account for a 65% growth in the total period (graph A4.1). The period ’95-’00 showed the biggest increase in GDP level with 1999Q4 as positive outlier (see graph A4.2). In the fourth quarter of 1999 real GDP grew with 5.1% relative to the same quarter in 1998. Biggest negative outlier was during the global financial crisis in the second quarter of 2009, in which real GDP decreased with 4.47% relative to the same quarter in 2008.



Graph A4.1 – Real GDP (2015Q4 vintage). Source: CBS (2016)

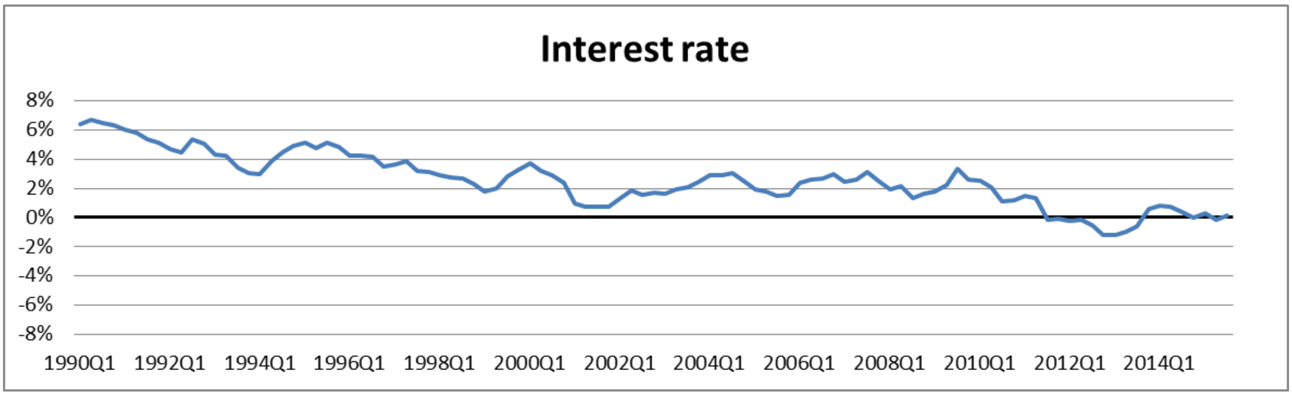


Graph A4.2 – Percentage Change Real GDP (2015Q4 vintage). Source: CBS (2016)

A4.2.2 Interest rate

In the sample period, interest rates gradually converge towards zero. From the fourth quarter in 2011 until the third quarter in 2013, interest rates even became negative. The same applies for the second quarter of 2015. It is beyond the scope of this paper to elaborate extensively on this negative interest rate, which occurred not only in the Netherlands but throughout in (western) Europe and Japan.

However, it is important to stress the relationship between interest rate and potential output. Monetary policymakers often think in terms of a concept known as the real equilibrium rate or the natural rate of interest (Cœuré, 2016). This equilibrium rate is the interest rate that is consistent with stable inflation and output at its potential level. Thus, potential output estimated using the conventional concept of non-inflationary output. Setting short-term interest rates above this equilibrium rate puts downward pressure on activity and inflation. Setting them below this rate of course has the opposite effect. While this real equilibrium interest rate is difficult to estimate precisely, and while there are competing explanations for it, there is a broad consensus that it has declined in advanced economies over the past two decades[54].



Graph A4.3 – Interest Rates. Source: OECD (2016)

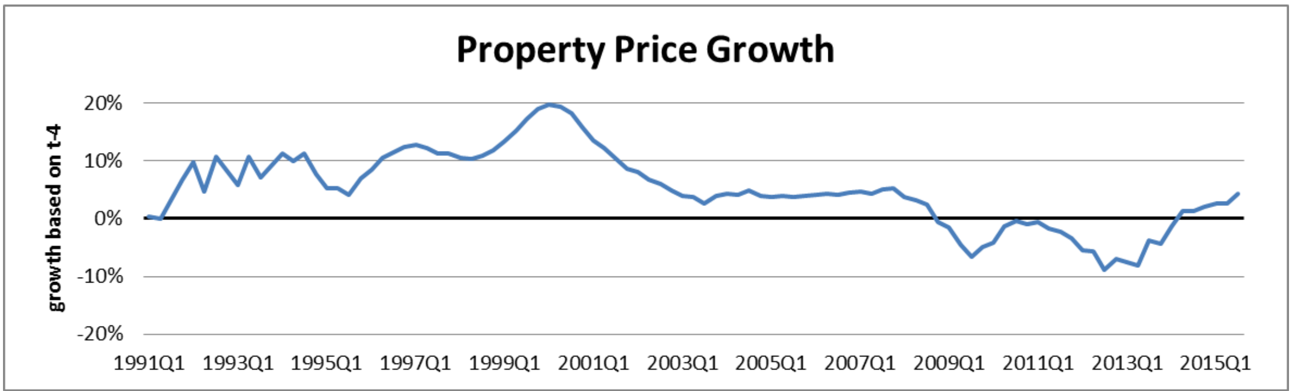
A4.2.3 Property Prices

During the nineties property prices in the Netherlands increased significantly. From the first quarter of 1992 onwards, property prices increased continuesly with more than 5% every quarter compared to the same quarter the previous year[55] until the thrid quarter in 2003. This enermous growth of property prices reached its peak in the first and second quarter from 2000. During that time, property prices increased with 19% relative to the same quarter the year before. From that moment on, property price continioud to grow around a – for those time relative low rate - 5 percent quartely until the house market bubble bust in 2008. To illustrate, the average selling price of houses doubled in only 6 years in the period 1994-2002, hereafter again increasing with 30% in total till 2002. The global financial crisis reduced the average Dutch house prices in 2013 to its 2002 price level, falling with 20% in total in only 5 years. In the first quarter of 2013, house prices decreased with

[54] A range of structural factors have been proposed for this secular decline in the rate of return on safe assets including demographic changes, a slowdown in the rate of technological progress, and a high demand for safe assets relative to their supply (Bean, Broda, Ito, & Kroszner, 2015).
[55] Except from 1995Q2 when property prices increased with 4.6% relative to same quarter the year before.

8.1% relative to the same quarter the previous year. The property market in the Netherlands showed bigger growth and decline rates prior- and following the global financial crisis compared to other European countries. This is because of several reasons. Without giving a full assessment of the Dutch housing bubble56, it is clear that the generous mortgage interest deductability and low taxation of home ownership contributed to the house price upsweep. Mortgage interest payments are fully deductible from taxable income. With high marginal income tax rates up to 52%, the government subsidizes a large part of the mortgage servicing costs. There is not only a strong incentive to obtain a high mortgage loan, but also to delay repayment of the principal over the length of the mortgage loan until maturity. Additionally, Bernhofer et al. (2014) conclude that innovations and liberalization in mortgage financing played a more important role in the Netherlands than in other European countries. The Netherlands scores high in terms of mortgage debt. In fact, with a mortgage debt stock equaling 108% of gross domestic product in 2010, the Netherlands ranked number one in the European Union (Leeuwen & Bokeloh, 2012).

Graph A4.4 – Property Prices in The Netherlands. Source: CPB/Land Registry Office (2016)

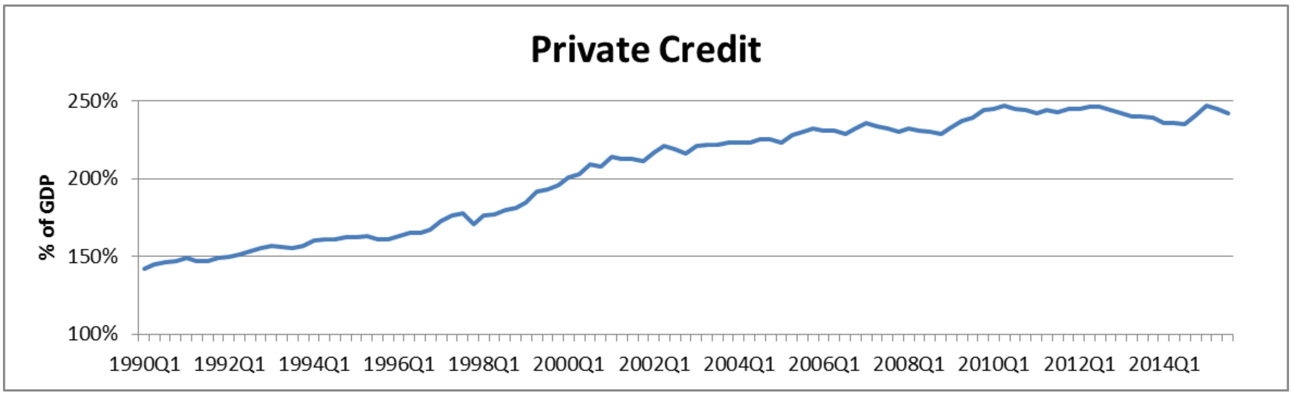


Graph A4.5 –Property Prices Growth. Source: CPB/Land Registry Office (2016)

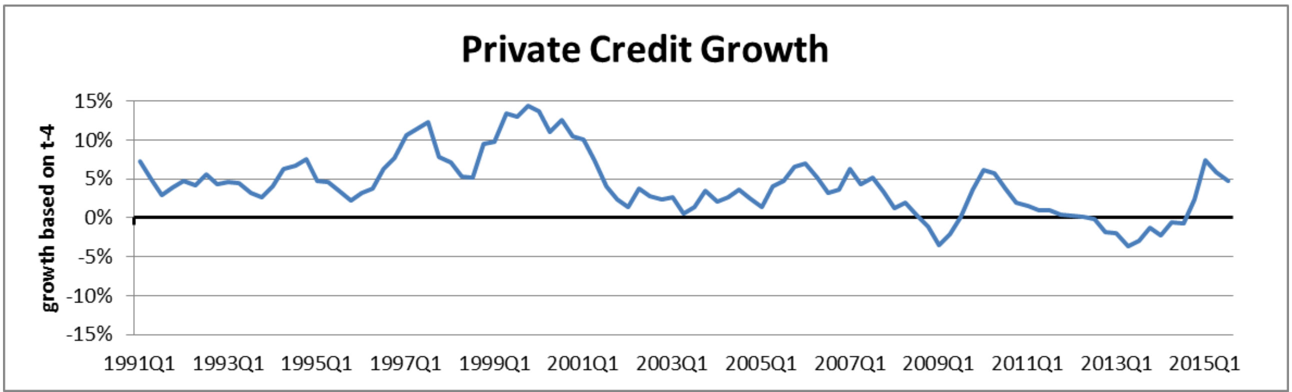
[56] Vandevyvere & Zenthöfer (2012) provide an extensive assessment of the Dutch housing market.

A4.2.4 Private Credit

For credit, data is obtained from the Bank of International Settlement (2016), specifically using total credit to the non-financial private sector provided by all sectors[57], valuated at market value. Private credit shows a steady growth in the Netherlands in the period 1990-2015. In the first quarter of 1990, private credit covers 147% of GDP (graph A4.6). Around 25 years later, this number has increased to 240% of countries' GDP. At the same time GDP also increased substantial. As a result private credit in volume increased from €140 billion in 1990 to €390 billion in 2015, equal to an increase of 180% percent.



Graph A4.6 – Private Credit as % of GDP. Source: BIS (2016)



Graph A4.7 – Private Credit Growth. Source: BIS (2016)

The growth rate of private credit was highest in the period 1999-2001. In the second quarter of 1999 private credit increased relative to the same quarter the year before with 13.5% and stayed above a 10% growth until the first quarter of 2001. In volume this implies a growth of almost €50 billion in only 2 years. This is equal to an increase over €3000 in private credit per inhabitant. In 2015 this increased to €23000 of private credit per Dutch inhabitant, or a total of €393 billion.

[57] All lending sectors are covered, i.e., with the SNA classification numbering: Non-financial corporations (S11), Financial corporations (S12), General government (S13), Households (S14) and Non-profit institutions serving households (S15) and Rest of the world (S2). Source: BIS (2016).

When looking to the debt side of credit, Dutch households are frontrunners in Europe. Average mortgage debt of all households which own a house was in 2013, at its peak, €158 000. When excluding households without mortgage debt this number was €190 000 in 2013 (CBS, 2016) which equals 450% of household disposable income and 250% of gross household income.

A4.2.5 Share price variables

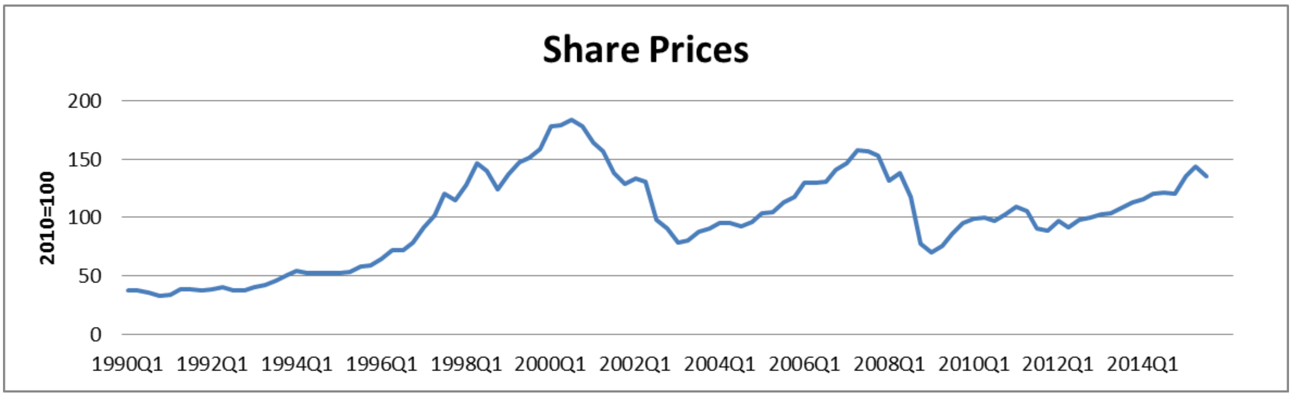
Based on Goodhard & Hofmann (2000) who empirically show the effect of share prices on output gap estimates, two share prices variables are considered; the Share Price Index and Market Value on Euronext Amsterdam.

First, Share Price Index (SPI), obtained from OECD (2016) is calculated from the prices of common shares of companies traded on national stock exchanges, using the closing daily values for the monthly data. The SPI measures changes in the market capitalization of the basket of shares in the index.

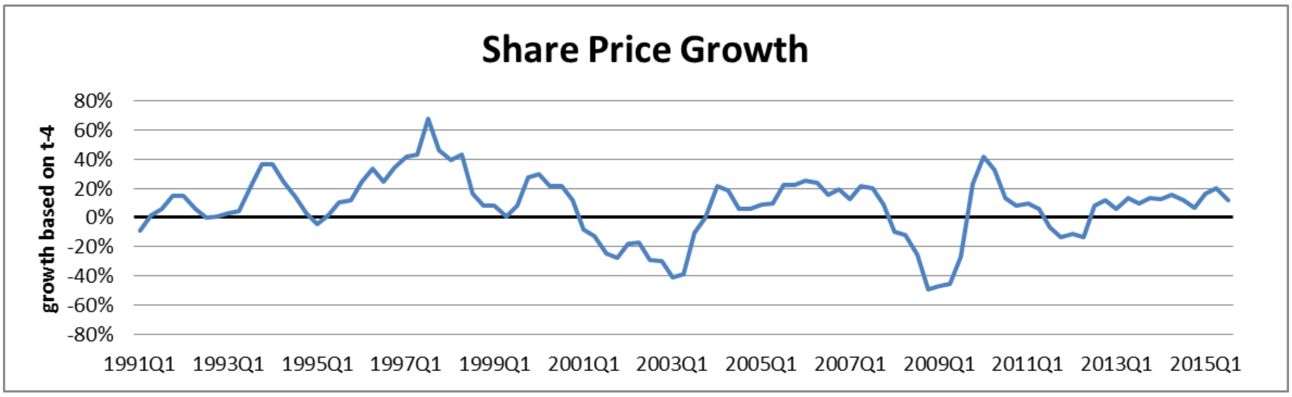
Second, Market Value on Euronext (MVEUR) which concerns the exchange value of all outstanding common shares of all Dutch companies and funds listed on Euronext Amsterdam at the end of every month. The value of the total market is the sum of the official and the new market values. The market value is calculated by multiplying the number of outstanding shares of a company by the share price. Data is obtained from Statistics Netherlands (CBS, 2016). The statistics only deal with stocks that provide an equal right in the control of the company. Other kinds of stocks, such as preferred stocks, are not included.

As can be seen (graph A4.8 and A4.10), both variables show qualitatively the same information. From the start of the nineties, especially from 1994 onwards, share prices increased rapidly up until the beginning of 2000. This is when the dot-com bubble burst[58]. The second boom that can be distinguished concerns the prior global financial crisis period, busting at the end of 2007. From the lowest level since thirteen years in the first quarter of 2009, a gradually increase in both share prices as total market value on Euronext is displayed, up until the moment of writing this paper.

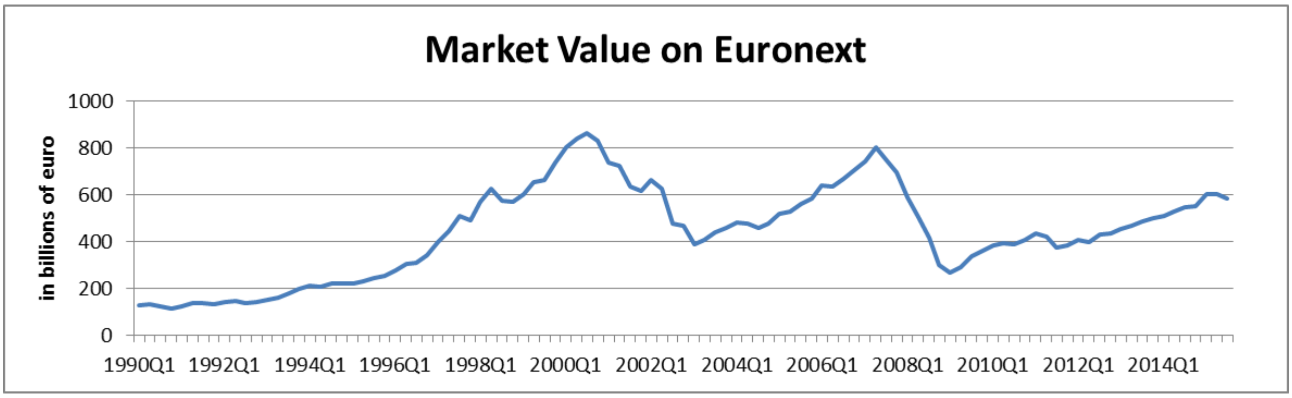
[58] See Ofek & Richardson (2003) for an extensive of the dot-com bubble.



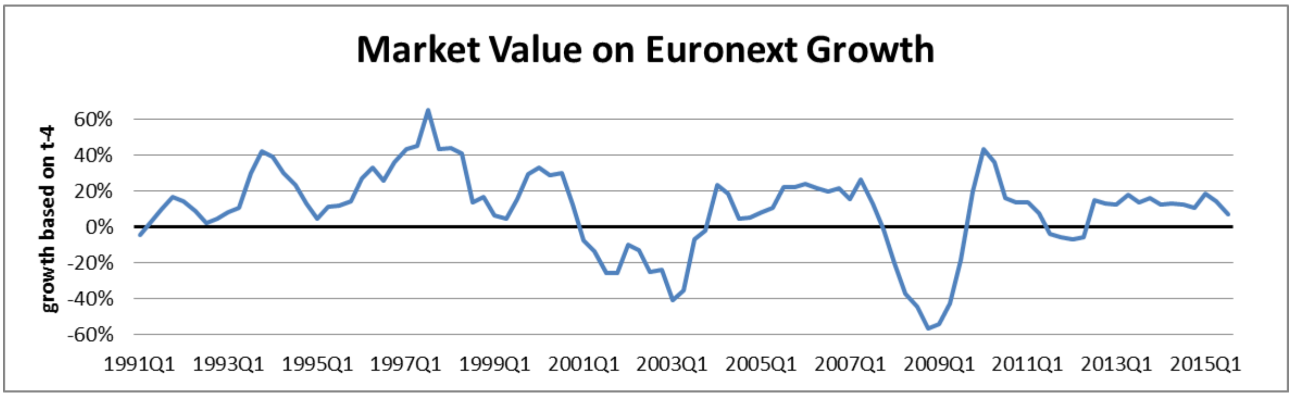
Graph A4.8 – Share Price Index. Source: OECD (2016)



Graph A4.9 – Share Price Index Growth. Source: OECD (2016)



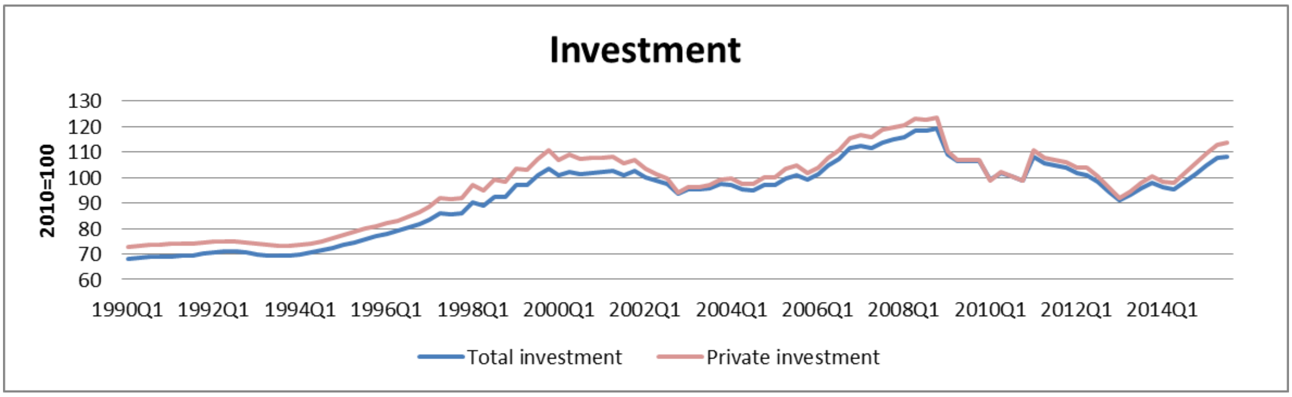
Graph A4.10 – Market Value on Euronext Amsterdam. Source: CBS (2016)



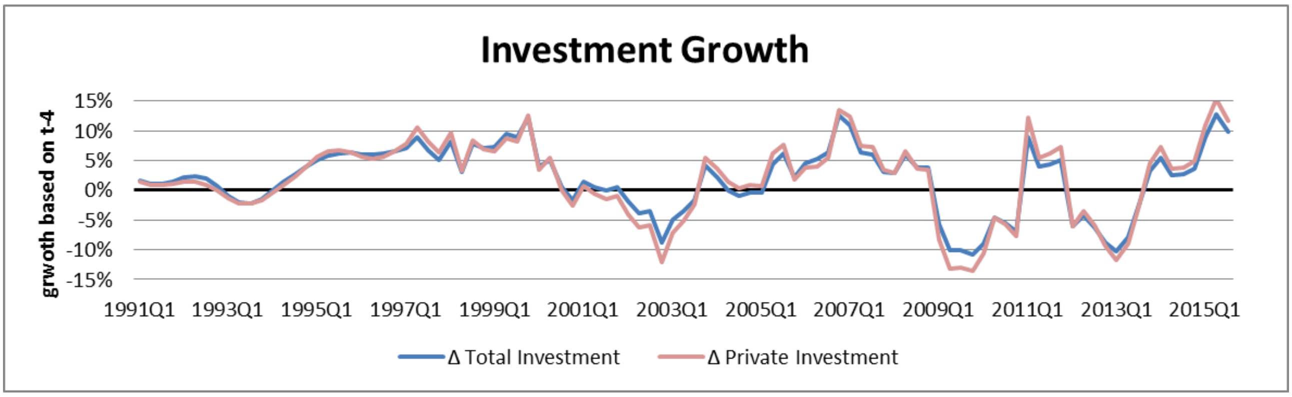
Graph A4.11 – Market Value on Euronext Amsterdam Growth. Source: CBS (2016)

A4.2.6 Investment

Both private and public investments are obtained from Statistics Netherlands (CBS, 2016) and displayed as index. These indexes account for the gross investments in fixed assets (used for more than one year), hereby is not accounted for depreciations of the assets. Roughly, two cycles can be determined. First, from the start of the sample period in the beginning of the nineties, investments show a steady increase (private and total) until the start of the zeros. Investments slightly decrease until 2003, at which 1998 levels occurred again. From 2003 up until a year after the start of the global financial crisis, investments increase substantially. Hereafter falling with some shocks until in 2013 again more-or-less 1998 investment levels are reached.



Graph A4.12 – Total & Private Investment Index (2010=100). Source: CBS (2016)



Graph A4.13 – Total & Private Investment Growth. Source: CBS (2016)