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In 2009 all ECB publications feature a motif taken from the €200 banknote.

1 The opinions expressed herein are those of the author and do not necessarily reflect those of the European Central Bank or the Eurosystem.

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Abstract

This paper addresses the estimation of Phillips curve equations for the euro area while employing less stringent assumptions on the functional correspondence between price inflation, inflation expectations, and marginal costs. Expectations are not assumed to be an unbiased predictor of actual inflation and instead derived from the European Commission's Consumer Survey data. The results suggest that expectations drive inflation with a lag of about 6 months, which casts further doubt on the validity of the New Keynesian Phillips curve. Moreover, the tradeoff between inflation and real economic activity is not vertical in the short run. Non- and semiparametric estimates reveal an important nonlinearity in the sense that demand pressure on price inflation is not invariant to the state of the economy as it increases considerably at times of high economic activity. Conventional linear Phillips curves cannot capture this empirical regularity. Some implications for monetary policy are discussed.

JEL classification: C14, E31, E32,

Keywords: Inflation, Phillips Curve, Survey Expectations, Non- and Semiparametric Econometrics, Monetary Policy

Non-technical Summary

This study aims at assessing the appropriateness of various forms of Phillips curves for the euro area. Instead of presuming that expectations are rational, survey based measures thereof are used and thus one can refrain from assuming unbiasedness in expectations. The Phillips curve relationship between inflation, expected inflation, and some suitable measure of marginal costs will be cast in a hybrid New Classical and New Keynesian form. Overall, the analysis has two important features that separates it from previous work in this area.

First, as a complement to conventional parametric estimation techniques, nonparametric regression analysis is used to infer whether or not a linear functional form, as is usually invoked in Phillips curve equations, is indeed appropriate. Partial derivatives with respect to the set of covariates constituting the Phillips curve are being derived using nonparametric regression methods.

Second, for the sake of quantifying expectations, qualitative survey data is taken from the European Commission´s (EC) Business and Consumer Survey which has so far not been employed in the context of Phillips curve estimation. Unlike other surveys in Europe and the US that have been used in the related literature which are available at quarterly or lower frequency, the EC survey data is available on a monthly basis, hence making econometric analysis and subsequent inference more robust given a higher number of observations.

The results suggest that, as far as inflation expectations are concerned the Phillips curve is indeed well approximated by a linear function. As concerns the measure of real economic activity, however, the function turns out to be highly nonlinear, namely convex. Overall, the slope of the curve is positive on average over the output gap domain, suggesting that higher levels of economic activity generally entail higher levels of price inflation. This effect, however, is state dependent since it increases at times of high activity whereas at times of low activity the impact on price inflation vanishes. Within the conventional linear model framework this empirical regularity could not be revealed because the impact of real activity on prices is *constant* by assumption.

The results are in line with recent theoretical work on asymmetric loss functions and the conduct of monetary policy given a convex Phillips curve relation. Yet, since there is an ambiguity as to how certain nonlinearities possibly present in the Phillips curve may look like, e.g. whether it shall be convex or concave with respect to real activity, the use of nonparametric methods is especially appealing because one does not have to presume any particular functional form in the first place. The results clearly speak in favour of the function having a convex shape, which is in line with the predictions from the *capacity constraint model*. The idea is that capacity constraints, such as temporary labour, capital or material shortages, may limit the firms' ability to satisfy the level demanded at times of high economic activity so that price inflation accelerates as capacity is stretched.

For the conduct of monetary policy these findings matter in that the convex Phillips curve generally implies that the same policy measures pursued at different times can have different effects depending on the state of the economy. In particular, the convex model endorses more intense expansionary policy measures than the linear model at times of low economic activity, milder expansionary measures at times of high activity, respectively. This is because the linear model tends to underestimate demand side pressure on prices at times of high activity, and to overestimate it at times of low activity, e.g. during a crisis. A convex relation shall also motivate monetary authorities to act pre-emptively to try and dampen periods of excess demand, i.e. to impede inflationary pressures before they occur.

The empirical findings adduced in this study were found to be robust to the deployment of alternative output gap measures as well as to tests aimed at assessing sub-sample stability.

1 Introduction

This paper aims at analyzing the role of expectations and a measure of real economic activity in shaping the dynamics of price inflation in the euro area. To this end, various Phillips curve specifications are being approached empirically. Contrary to the majority of related work which bases its analysis on linear Phillips curve models, this study refrains from imposing functional form assumptions in the first place. Non- and semiparametric methods are employed to test whether the linear functional format is indeed appropriate. Unlike conventional parametric tests for correct model specification, that do not offer an alternative should the hypothesis of correct specification be rejected, nonparametric methods offer an alternative right away and can thereby help determining appropriate functional forms.

There is a small branch in the literature that suggests that the Phillips curve relation should be nonlinear. Stiglitz (1997) who puts forward his view on the natural rate hypothesis, e.g., contemplates the presence of nonlinearities in the relation. Although the traditional view on the curve is that its shape is actually convex, Stiglitz considers the possibility of a concave relation because concavity would, in fact, be consistent with the literature on asymmetric price adjustment. On the other hand, theoretical work also suggests that the curve should be convex. When looking at Phillips' (1958) original empirical work, the curve already appears not as linear but convex. Since then, research has proceeded and theories evolved that suggest convexity in the relation. Important references in this context are Eisner (1996) and Tambakis (1998). For an overview of various theoretical approaches, which imply different types of nonlinearities in the Phillips curve, see Dupasquier and Ricketts (1998). These authors find that short-run dynamics of inflation in Canada are characterized by a convex Phillips curve relation.

Given that there seems to be no clear consensus on what type of nonlinearity, if any, is present in the relationship, this study aims at employing nonparametric econometrics that allows modeling the curve without imposing any concrete linear or nonlinear form. Functional form assumptions are usually employed to make theoretical models tractable, as well as solvable. Approaching the Phillips curve nonparametrically involves no such assumption; It only involves the assumption that there *is* a relation.

A second difference with respect to related work concerns the forward-looking part of the model which is not modelled under the rational expectations hypothesis. Empirical estimates of the curve incorporate a survey based measure of expectations which is provided by the European Commission and has so far not been used in the context of Phillips curve estimation. Moreover, the use of the EC survey data allows one to conduct estimation with monthly data. From the point of view of nonparametric analysis this is helpful indeed as the sample comprises about 230 observations, opposed to only 72 observations that one would have if working with quarterly data for the same space of time. This helps making nonparametric modelling and inference much more robust and the conclusions more reliable.

The results show that the Phillips curve relation is indeed highly nonlinear (convex) as far as economic activity is concerned which is clearly in line with the shape of the curve predicted by the so-called *capacity constraint model* (see Macklem, 1997). The correspondence between inflation and expectations is, on the other hand, well approximated by a linear function and this in turn makes a semiparametric model the preferred choice. A classical format, in which expectations enter with a lag, seems more adequate than the New Keynesian curve. Moreover, empirical estimates clearly support the hybrid version as it captures inflation dynamics in the euro area more adequately.

Laxton et al. (1993) conduct an exercise using a macroeconomic model that captures key features of the policy process while assuming that the Phillips curve relation is either linear or nonlinear and they find, via simulation, that the cost of incorrectly presuming a linear structure of the economy is likely to exceed the cost of incorrectly assuming a nonlinear one. This suggests that, even if some model uncertainty will always remain, it is advantagous to assume the suitable nonlinear, say convex, format given that evidence in favour of this form has been adduced.

Section 2 will in the following be devoted to summarizing various forms of Phillips curves that have been discussed in the literature. Section 3 describes the data and the procedure employed for the quantification of expectations from survey data. In Section 4, a general model, that encompasses the traditional, New Keynesian, and hybrid form is then estimated using parametric and nonparametric regression methods. Section 5 concludes and discusses implications for monetary policy.

2 Phillips Curve Specifications

In principle, there are three different Phillips curve specifications that have been discussed in the literature and all of these have different underlying assumptions on how price inflation, price expectations and excess demand interact. In the sequel, they have quite different implications for the role of monetary policy. The three forms of curves can be referred to as the *Traditional* (or New Classical), the *New Keynesian*, and the *Hybrid Phillips curve*. In the following I discuss them briefly.

In the New Classical Phillips curve setting current inflation π_t is made a function of previously expected inflation $E_{t-1}\pi_t$ and a measure of excess demand $\widehat{y}_t$ that enters contemporaneously, that is,

$$\pi_t = E_{t-1}\pi_t + \varphi\widehat{y}_t \tag{1}$$

Theoretical work by Phelps (1967) suggests this New Classical kind of relationship in which current and recently expected inflation move one-to-one. The parameter attached to marginal costs indicates the degree to which prices are flexible; a higher coefficient hence implies less sticky prices while the curve becomes steeper.

Roberts (1997) shows that sticky price models, e.g. proposed by Calvo (1983), imply that inflation should have a forward looking structure which has led to an alternative specification in which current inflation is related to currently expected future inflation as well as some measure of excess demand. A fraction α of prices is assumed to stay constant in every period and only the remainder adjusts. The correspondence between actual and expected inflation is characterized by the discount factor, denoted as β in the following, which need not equal 1.

$$\pi_t = \beta E_t\pi_{t+1} + \kappa\widehat{y}_t \tag{2}$$

The reduced form parameter κ comprises more structure as it is composed of α and β. Lagged inflation may play a role in this context merely through its interaction with expected inflation at time t and it is not explicitly incorporated in the model. Moreover, when assuming rational expectations and iterating the model forward, it implies that actual inflation depends on the future path of excess demand, all the way to infinity, discounted by β.

$$\pi_t = \kappa\sum_{j=0}^{\infty}\beta^j E_t\widehat{y}_{t+j} \tag{3}$$

If the New Keynesian specification was correct, the inflation process should be free of serial correlation after having controlled for currently expected inflation and contemporaneously observed excess demand.

A third view on the dynamics of inflation is that current inflation depends, apart from excess demand, both on currently expected future as well as lagged realized price changes and this form of the Phillips curve is referred to as *hybrid*. A theoretical justification for such model is given e.g. in Galí and Gertler (1999). The theory rests on the assumption that not all firms are resetting prices in a forward-looking manner. Some agents may not get the chance to adjust prices optimally and rather use a simple rule that involves historic aggregate price behaviour, i.e. partial indexation to past inflation. Non-optimizing firms set prices to the average price level observed recently and this renders the dynamics of inflation to some extent forward- and backward-looking. The functional relation looks then as follows.

$$\pi_t = \omega^f E_t \pi_{t+1} + \omega^b \pi_{t-1} + \kappa \widehat{y}_t \tag{4}$$

where the degree of persistence in the inflation process is measured by ω^b.

An error term is attached to these models when approaching them empirically so as to allow explicitely for measurement error and/or the presence of variables that we omit but in fact have impact upon inflation. We shall assume that any omitted but relevant variable does not correlate with covariates that are included in the model since otherwise standard regression techniques yield parameter estimates that are biased and not consistent even if the number of observations went to infinity. The New Keynesian Phillips curve is especially prone to biases in estimation since it is likely that expectations, at the time when they are formed, are related to inflation contemporaneously. It is well understood, and emphasised e.g. by Rudd and Whelan (2005) that such bias can be severe. They stress that large estimates of ω^f can be obtained even if the true process was purely backward-looking. It is therefore important to account for the fact that some of the covariates in our model might be determined simultaneously with inflation.

The aim of this study is to determine what type of Phillips curve best explains inflation dynamics in the euro area. This endeavor has already been made by other authors, e.g. Galí et al. (2001) who assess the empirical performance of the Phillips curve for the euro area and compare it to the US. They find that euro area inflation has a stronger forward-looking component than US inflation, the latter thus being characterized by higher persistence. In their context, expectations are assumed to be rational. Paloviita (2002) analyzes two model sets, the Classical and the New Keynesian Phillips curve and uses, as in this study, direct survey based measures of expectations. This study conjectures that expectations play an important role and that the New Keynesian curve fits the data slightly better than the Classical specification.

Although concerned with inflation in the US, another paper by Adam and Padula (2003) is worth mentioning. It uses survey measures of expectations, too, so that they can refrain from assuming that expectations are unbiased relative to actual inflation. The New Keynesian curve that they estimate explains inflation dynamics better when relying on survey expectations than if rationality was assumed. They let lagged inflation enter the model and find that it explains inflation, though the significance of this relation depends on the measure of marginal costs being used. From this one can conjecture that inflation is persistent, not only because lagged inflation is correlated with expectations that enter the equation contemporaneously. Overall, they adduce evidence against the validity of the New Keynesian specification; A hybrid form seems more plausible empirically.

Rumler (2005) has, more recently, provided estimates of the New Keynesian curve for the euro area while assuming rational expectations of agents. He extends the literature in that alternative measures of, e.g. costs of intermediate inputs, are incorporated in the estimation of the curve and he distinguishes between an open and a closed economy model.

Reduced form estimates suggest that the more appropriate model turns out to be the one for the open economy.

Two more studies that I shall refer to are Henzel and Wollmershaeuser (2008) and Paloviita (2008). Both aim at analyzing inflation in the euro area and both incorporate survey expectations instead of presuming rationality. Henzel and Wollmershaeuser (2008) find that when using survey expectations instead of realized future values when assuming rational expectations, backward-looking behaviour turns out to be more relevant for most European countries. Generally, when relying on survey expectations the slope of the curve with respect to marginal costs is positive. In contrast to Adam and Padula (2003) they extend the theory by allowing also for backward-looking agents, parallel to forward-looking ones. As a source for survey expectations they rely on the Ifo World Economic Survey (quarterly data). The general finding is, in line with previously mentioned studies, that when using survey expectations the slope estimate with respect to marginal costs is positive and significant and backward-looking behaviour is relevant for most European countries. The most recent work that I am aware of is Paloviita (2008) who uses survey expectations as well (Consensus Economics survey data). New Classical, New Keynesian, and Hybrid Phillips curves are being estimated and the findings suggest that the inflation process in Europe is not entirely driven by forward-looking expectations; Lagged inflation plays a role and thus the hybrid model captures inflation dynamics more adequately.

Studies which address the possible presence of nonlinearities in the Phillips curve relationship are Musso et al. (2009) and Baghli et al. (2007). The former analyze whether the linear functional form is appropriate empirically for the euro area by estimating a parametric time-varying smooth transition model which allows both for nonlinearity and time-varying parameters. The authors find no significant evidence of nonlinearity in the relation between inflation and excess demand, which stands in contrast to the evidence adduced in this paper and as well to the findings in Baghli et al. (2007). They conduct a similar exercise by estimating the Phillips curve for the euro area and selected euro countries nonparametrically. Their findings broadly confirm the ones from the present study in that the relation between price inflation and the output gap turns out to be convex. Their analysis and the present one differ, however, in one important respect: the authors do not explicitely model inflation expectations and instead assume that the inflation process is entirely backward-looking.

Capistrán and Timmermann (2009) present a theoretical model that can explain, inter alia, why inflation expectations can turn out to be biased. Their theory is based on the assumption that agents have asymmetric loss functions, thus making it more costly for them, e.g., to underpredict inflation than to overpredict it. The theory offers an intuitive explanation why biases as well as positive serial correlation in expectation errors may occur. From this point of view one shall rethink the meaning of *rationality*. If one accepts that loss functions are asymmetric, it is, in fact, *rational* to be biased, say, when forming expectations. Obviously, the terms *biased* and *rational* have the same meaning only if loss is symmetric. Otherwise *bias* will merely be a statistical measure but whenever statistically different from zero it should not be interpreted as expectations being irrational. Survey based measures derived in the following turn out to be biased on average and expectation errors exhibit positive serial correlation.

3 Preliminary Data Analysis

3.1 Quantifying Expectations

For subsequent empirical analysis and estimation of various Phillips curve equations a suitable measure of inflation expectations has to be available. Expectations will be derived from survey data that the European Commission (EC) provides on a monthly basis. The EC survey comprises two questions that are relevant in the following, one being related to previous price changes, and another one referring to future price developments. The survey is *qualitative* in nature as only the expected *direction of change* in prices is captured. The two relevant questions, question 5 and 6 from the survey to which I refer to as question A and B, read as follows.

Question A: *How do you think that consumer prices have developed over the past 12 months? They have...*

++ *risen a lot*
+ *risen moderately*
= *risen slightly*
- *stayed about the same*
- - *fallen*
N *don't know.*

Question B: *By comparison with the past 12 months, how do you expect that consumer prices will develop in the next 12 months? They will...*

++ *increase more rapidly*
+ *increase at the same rate*
= *increase at a slower rate*
- *stay about the same*
- - *fall*
N *don't know.*

From the raw sample proportions, i.e. the relative frequency of answers in respective categories for each question, one can derive a balance. The EC is providing a balance score which aggregates the percentages of answers by weighing them in the following way.

$$Balance = (PP + 1/2P) - (1/2M + MM)$$

where PP refers to '++', P to '+', M to '-', and MM to '- -'. The balance can thereby range from -100, when all respondents expect (have perceived) prices to fall, to +100, when all respondents expect (perceive) them to increase more rapidly[1]. For later use I shall refer to *Balance* computed from Question A as s_t^p (the *perception score*), and to the *Balance* from Question B as s_t^e (the *expectation score*).

In order to derive a quantitative estimate of inflation a number of methods have been developed, among them the Balance/Disconformity approach (henceforth BA approach) proposed by Theil (1952) and the Carlson-Parkin technique (referred to as CP approach), named after the two authors proposing the method (Carlson and Parkin 1975). By and large, the two techniques differ in terms of how restrictive they are in imposing assumptions on the

[1] For more detailed methodological notes on the EC Consumer Survey see the EC User Guide, EC (2007)

expectation distribution and response function of individuals. Batchelor (1986) summarizes the theory underlying these approaches. As concerns the underlying theory the reader is referred to the original papers by Theil, Carlson and Parkin.

Denoting the perception score observed at time t by s_t^p and the year on year percentage change in observed prices by π_t (where $\pi_t = \ln(p_t/p_{t-12})100$ where p_t is a price index), the correspondence between the perception score s_t^p and inflation π_t is assumed to be of the following form[2].

$$\pi_t = \alpha_o + \alpha_1 s_t^p + \epsilon_t \tag{5}$$

This equation is estimated recursively (i.e. parameters vary through time[3]), to generate fitted values, that is

$$\widehat{\pi}_t^p = \widehat{\alpha}_o + \widehat{\alpha}_1 s_t^p \tag{6}$$

At every point in time only past observations of π_t and s_t^p are used. The resulting fit, $\widehat{\pi}_t^p$, is called the consumers' *quantified perception* of inflation.[4]

To quantify also consumers' expectations, the conventional CP type approach is employed. Let $\{s_t^{e1}, s_t^{e2}, s_t^{e3}, s_t^{e4}, s_t^{e5}\}$ denote the shares in each of the five response categories in the question referring to expectations. Note that the sixth category ('don't know') has been excluded and the remaining five categories rescaled so that they sum to 1. The conditional expectation of inflation is made a function of these scores, that is,

$$\widehat{\pi}_{t+12|t}^e = -\widehat{\pi}_t^p \left[\frac{(Z_t^3 + Z_t^4)}{(Z_t^1 + Z_t^2 - Z_t^3 - Z_t^4)} \right] \tag{7}$$

where $Z_t^1 = N^{-1}\left[1 - s_t^{e1}\right]$, $Z_t^2 = N^{-1}\left[1 - s_t^{e1} - s_t^{e2}\right]$, $Z_t^3 = N^{-1}\left[1 - s_t^{e1} - s_t^{e2} - s_t^{e3}\right]$, $Z_t^4 = N^{-1}\left[s_t^{e5}\right]$ and $N^{-1}[\cdot]$ denotes the inverse of the standard normal distribution function[5]. The perceived inflation rate $\widehat{\pi}_t^p$ now scales the quantified measure of expected inflation, thus one does not, in fact, impose an assumption that would stipulate *unbiasedness* in expectations.

3.2 Bias in Expectations

Since the measure of aggregate expectations has been derived without imposing an unbiasedness assumption we shall now assess the extent to which agents systematically over- or underpredict inflation throughout the test period. The quantification procedure starts in 1985, when the survey data series begin, and ends in December 2008. Since the regression method which is used to quantify perceptions will need a number of observations in order to yield reliable estimates, fit respectively, the first 5 years of derived expectation data are being excluded from the analysis and the sample effectively starts in January 1990. In Figure 1 in the Appendix the derived expectation series is plotted along with actual inflation. To test for bias in expectations, the following equation is estimated

$$\pi_t = a_0 + a_1 \pi_{t|t-12}^e + \epsilon_t \tag{8}$$

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[2] The price index used to construct the inflation variable is the HICP overall index for the euro area that has been computed using fixed conversion rates as of 1990. The series has been seasonally adjusted. The choice of the overall HICP price index as a basis for quantifying perceptions and expectations has been done based on the assumption that the responses of individuals who participate in the survey are related to prices captured by the index.

[3] For the sake of parsimony the recursive estimation scheme is not made explicit in terms of notation.

[4] A *rolling* sampling scheme has been chosen, where the length of the rolling window has been set to 36 months.

[5] See Berk (1999) for a derivation of this set of equations.

and the Null hypothesis to be tested reads as

$$H_0 : (a_0, a_1) = (0, 1) \tag{9}$$

The empirical F-statistic from a Wald test for this restriction equals 37.2, the corresponding p-value being virtually zero and hence suggesting that when considering the full sample, expectations seem biased (see Table 1 in the Appendix for detailed test results). The unconditional bias that one can obtain by regressing the expectation error on a constant equals .18 percentage points, being statistically different from zero at the 10 percent level (see Table 2 for details). To see how expectation bias evolves over time, the test regression along with the F-statistic for the aforementioned hypothesis are estimated recursively, using a 5-year rolling window. The result is presented in Figure 2. The rolling F-statistic suggests strong evidence against the null most of the time, with a notable exception in the time period between October 1998 and December 1999 when the null cannot be rejected at conventional significance levels. Complementary to this, also the unconditional bias is estimated recursively (5-year window) which yields, in fact, a 5-year moving average of the expectation bias; the t-statistic corresponding to the hypothesis that bias equals zero is plotted in Figure 3. Until August 1997 bias was positive (significant at least at a 10 percent level), followed by a period in which it was not statistically different from zero until summer 2000. Thereafter, unconditional bias has remained significantly negative.

Yet another test confirms significant changes in bias in the middle of the sample. The Quandt-Andrews test for an unkown breakpoint indicates that the most significant change in bias occured in December 1999 (the LR F-statistic equals 42.3). Overall, the results concerning bias in expectations are in line with previous findings [see e.g. Forsells and Kenny (2002)].

4 Empirical Findings

4.1 Parametric Estimation

This section is devoted to conventional parametric estimation. From now on, the following general model specification serves as the benchmark for estimation.

$$\pi_t = \alpha_0 + \alpha_1 \pi^e_{t+h|t-s} + \alpha_2 \pi_{t-1} + \alpha_3 \widehat{y}_t + \epsilon_t \tag{10}$$

The term $\pi^e_{t+h|t-s}$ refers to inflation expectations formed at time $t-s$ for time $t+h$. Unless otherwise stated, the output gap $\widehat{y}_t$ is defined as the log difference between actual output (industrial production in the euro area) and a trend which is computed using an HP filter with smoothing parameter set to 14400.[6] The last 6 months (January - June 2009) are excluded from the sample to avoid end-of-sample effects resulting from the HP filter method. Before conducting more detailed econometric analysis, the index parameter s is now of interest. The idea is that, even though survey question B is explicit about the horizon

[6] The choice of industrial output rather than overall output (GDP) has been done to maintain the monthly frequency of the model. When converting the industrial output series (levels) to quarterly by taking period averages, and then comparing the resulting HP filtered gap with the GDP gap, they appear to follow very similar paths and correlate strongly (+86%). The question as to whether an output gap measure in general is a suitable proxy for marginal costs has been addressed e.g. in Neiss and Nelson (2005); see also references therein. Without variable capital, the relation between the two should be proportionate. In Section 5, this issue will be addressed by conducting a robustness check based on quarterly data, involving a GDP based output gap.

by asking to state expectations over 'the next 12 months', the actual horizon of expectations may deviate and, in fact, be shorter or longer than 12 months. This issue is being addressed by estimating the parameters from the above equation repeatedly for all $s = \{0, 1, 2, ..., 12\}$. When $s = 0$ and $\alpha_2 = 0$ then the model has the New Keynesian form and h is not, in this case, set to a particular value. As s is set equal or larger 1, h will be zero by assumption, meaning that with s increasing, one can think of expectations formed at time $t - s$ being targeted directly at time t. By examining the profile of t-statistics related to α_1 across all s one can infer the actual horizon of expectations.

Figure 4 shows the empirical t-statistics for the α_1 coefficient for $s = \{0, 1, 2, ..., 12\}$. The set of estimates suggests that expectations have positive impact on contemporaneous inflation, which is significant at conventional levels only when displacing expectations by 0 to -1, and -5 to -6 months. When considering the setting in which s is small, say 1 or 0, expectations enter the equation almost or entirely contemporaneously and hence other forces which are not explicitly modelled might determine inflation as well as expectations *simultaneously*; When $s = 0$, possibly present reverse causality running from inflation to expectations may also cause estimates to be biased. Therefore, a test for endogeneity (á la Durbin-Wu-Hausman) is conducted, both for expectations as well as the output gap measure, for $s = 0$ and $s = 1$. Table 3 and 4 contain the test results for expectations and the output gap. When $s = 0$ (expectations enter contemporaneously) there is evidence of endogeneity in expectations (p-value close to zero). There is very weak evidence against the Null of exogeneity of the output gap with the corresponding p-value equaling 15.6 percent. When displacing expectations by one period ($s = 1$) the test indicates that both expectations and the output gap are exogenous at conventional significance levels. Only for the case when $s = 0$ I will therefore address the issue of simulateneity by conducting Generalised Method of Moments (GMM) estimation of the above general model.

Two GMM methods are being employed, a standard 2-step GMM as well as a Generalised Empirical Likelihood (GEL) method. The latter has recently been developed and used e.g. in Martins and Gabriel (2009) who estimate the New Keynesian Phillips curve for the US. The advantage of GEL is that it is an identification-robust method. Estimation results do not depend on the specification of moment conditions in this setting, i.e. estimates are invariant to the normalisation of moment conditions. Martins and Gabriel (2009) employ GEL to show that empirical estimates of the New Keynesian Phillips curve in Galí and Gertler (1999) and Galí et al. (2005) may not be entirely valid. In the following, GEL is employed, in particular the so-called continuous-updating estimator (henceforth CUE) [for more details see e.g. Newey and Smith (2004) and Anatolyev (2005)]. As regards the choice of the weighting matrix for CUE, which is likely to affect the estimation results, I choose a data dependent method proposed by Andrews (1991). Just as in Martins and Gabriel (2009), a Bartlett kernel with fixed bandwidth is used. The set of instruments comprises lags of inflation and at least one lag of all covariates (the list of instruments is reported in respective tables showing results in the Appendix). Estimates for the reduced form parameters obtained via CUE and 2-step GMM are reported in Table 5 and 6 and they suggest that the coefficient on expectations turns out to be less significant compared to conventional OLS estimates.

After having reconsidered the plausibility of an OLS estimate for the coefficient and t-statistic related to expectations when $s = 0$, which has been corrected downwards after GMM and CUE have been applied, from Figure 4 one can finally infer that variation in inflation is best explained by variation in expectations when the latter are displaced in time by about 6 months. Table 7 shows final estimation results for the model with $s = 6$.

Both expectations and the output gap are exogenous from a statistical viewpoint, thus OLS should yield reliable estimates. A lag of inflation is included to capture persistence. Also the constant has turned out to be statistically significant[7]. The estimates show that inflation is highly persistent, with $\widehat{\alpha}_2 = .88$. A 1 percentage point (pp) increase in the output gap is associated with about $\widehat{\alpha}_3 = .03$ additional pp of inflation and this effect is significant at the 1 percent level. Expectations have somewhat higher impact on inflation compared to the output gap with $\widehat{\alpha}_1 = .07$ which is as well highly significant at least at the 1 percent level. The DW statistic indicates positive serial correlation ($DW = 1.50 < 2$) in the residuals. Nonetheless, no further lags of inflation are included; instead, t-statistics are computed from Newey-West robust standard errors so as to make inference robust to serial correlation in the model residuals.

4.2 Nonparametric Estimation

The model estimates so far rely on the assumption that the correspondence between inflation and the set of covariates is well characterized by a linear function. The exact same model setup will be examined in this section; The functional correspondence between variables, however, will be left unspecified and generically represented as follows.

$$\pi_t = g\left(\pi^e_{t|t-6}, \pi_{t-1}, \widehat{y}_t\right) + \epsilon_t \tag{11}$$

Less restrictive assumptions are now imposed on the relation between variables. The functional relation $g(\cdot)$ is merely presumed to *exist* and to be at least twice continuously differentiable. The aim is to reveal the structure of $g(\cdot)$ using a kernel method, in particular by estimating the conditional expectation of inflation $E\left(\pi_t|\pi^e_{t|t-6}, \pi_{t-1}, \widehat{y}_t\right)$. The nonparametric regression estimate will therefore have three conditioning variables and interest lies in determining the partial derivatives with respect to $\pi^e_{t|t-6}$, π_{t-1}, and $\widehat{y}_t$. In generic notation they read as follows.

$$\frac{\partial E(\pi_t|\pi^e_{t|t-6}, \pi_{t-1}, \widehat{y}_t)}{\partial \pi^e_{t|t-6}}, \frac{\partial E(\pi_t|\pi^e_{t|t-6}, \pi_{t-1}, \widehat{y}_t)}{\partial \pi_{t-1}}, \frac{\partial E(\pi_t|\pi^e_{t|t-6}, \pi_{t-1}, \widehat{y}_t)}{\partial \widehat{y}_t} \tag{12}$$

Note that in the parametric model these partial derivatives are all *constants* by assumption. In a nonparametric model, the coefficient attached to an explanatory variable is allowed to vary freely over its domain. The type of nonlinearity between variables is in no way constricted except for it being continuous.

A local linear kernel approach is used to conduct the nonparametric regression. For details the reader is referred to Stone (1977) and Cleveland (1979) who propose the local linear method, and Fan and Gijbels (1996) who provide an overview of nonparametric methods, including, inter alia, local linear and polynomial regression methods. The following minimization problem is the starting point for the local linear regression.

$$\min_{\{a,b\}} \sum_{i=1}^{n} \left(\pi_t - a - (\widetilde{\pi}_t - \widetilde{\pi})' \, b\right)^2 K\left(\frac{\widetilde{\pi}_t - \widetilde{\pi}}{h}\right) \tag{13}$$

where $\widetilde{\pi}_t$ is a vector comprising the right-hand-side variables from the model, here inflation expectations, the lag of inflation, and the output gap. $K(\cdot)$ is a product kernel function

[7] Both the model including and the one exluding a constant suggest that s should equal 6 months. The profile of t-statistics across different s as well as GMM estimation results yield very similar estimates when exluding the constant.

that delivers weights which depend on a window-width vector h as well as on the distance between the data $\widetilde{\pi}_t$ and the point $\widetilde{\pi}$ at which one intends to estimate the conditional mean of π_t. The product kernel has the following form.

$$K\left(\frac{\widetilde{\pi}_t - \widetilde{\pi}}{h}\right) = k\left(\frac{\pi^e_{t|t-6} - \pi^e}{h_1}\right) \times k\left(\frac{\pi_{t-1} - \pi}{h_2}\right) \times k\left(\frac{\widehat{y}_t - \widehat{y}}{h_3}\right) \tag{14}$$

where h_1, h_2, and h_3 are individual scalar bandwidth parameters. The function $k(\cdot)$ is the univariate second-order Epanechnikov kernel, that is,

$$k(u) = \begin{cases} \frac{3}{4\sqrt{5}}\left(1 - \frac{1}{5}u^2\right) & \text{if } u^2 < 5 \\ 0 & \text{otherwise} \end{cases} \tag{15}$$

The classic statistical tradeoff is between bias and variance in a finite sample and the smoothing parameters play an important role in balancing the two. As h increases, the estimator tends to have smaller variance but larger bias, i.e. the estimate becomes smoother. The opposite is true when h is small. The variance increases, bias is reduced and the estimate becomes more erratic in this case. In the following, the smoothing parameters $h_{1,2,3}$ are determined via least-squares cross-validation. For details see, e.g., Li and Racine (2007) or Stone (1974).

A first preliminary nonparametric estimate of the Phillips curve is presented in Figure 5. Actual inflation is regressed on the output gap and lagged expectations and the resulting nonparametric fit is the surface in Figure 5. For the time being, lagged inflation is excluded from the regression so as to make a graphic presentation of the model in three dimensions feasible. The surface is clearly upward sloping along both the output gap and the expectation dimension which is in line with parametric estimates that suggest positive impact of either variable on average over their domains. When lagged inflation terms are not included in the model, the Durbin-Watson statistic computed from the residuals equals .58, indicating high positive serial correlation therein. This calls for the inclusion of lagged inflation.

Estimates of the nonparametric partial derivatives given in equation (12), now including also the lag of realized inflation are presented in Figure 6. To see how these derivatives compare to the linear estimates the graphs show both parametric and nonparametric derivatives. As concerns expectations and lagged inflation, the nonparametric derivatives turn out to be positive on average (over respective domains) and correspond closely to the parametric point estimates for α_1 and α_2. The mean nonparametric derivative with respect to lagged expectations equals .066 (compared to $\widehat{\alpha}_1 = .066$ in the parametric model). For lagged actual inflation the average nonparametric derivative is .885 (compared to $\widehat{\alpha}_1 = .881$ in the linear model). When turning to the output gap, the nonparametric derivative reveals a highly nonlinear, though very stable, relationship in that the slope is increasing in the level of the output gap. Unlike for lagged inflation and expectations whose impact seems being well characterized by a linear function (horizontal lines in Figure 6) with a single α_1 and α_2 summarizing the impact of these variables well over their domain, the influence of marginal cost pressure on inflation is *not* invariant to the level of the output gap. At low levels, say, when actual output is about -3.5 percent below potential, a 1 pp increase in the output gap is associated with a .007 pp increase in inflation. At times of high economic activity, say, 4.5 percent above potential, the marginal impact upon inflation equals .03 pp. When output is right at potential, a marginal 1 pp increase in the output gap entails a .02 pp increase in inflation. The Durbin-Watson statistic now equals 1.63, thereby indicating that residuals from the model that includes lagged inflation are much less serially correlated.

Also compared to the linear model (DW=1.50), the nonparametric residuals are less afflicted with serial correlation.

The nonlinearity in the output gap is, in fact, visible already in Figure 5. The plotted surface along the output gap dimension increases its slope as output attains levels higher above potential. To further illustrate this nonlinearity, Figure 7 shows the partial derivative with respect to the output gap over time, along with the actual path of the output gap. The impact (shown on the secondary axis) clearly increases at times of high economic activity. As output falls farther below potential, its impact on inflation gets muted. This feature could not be revealed when one was imposing a linearity assumption in the first place, thus rendering partial derivatives constant (horizontal lines in Figure 6 and 7).

Although the partial derivative with respect to the output gap is quite stable in the sense that it is smooth and constantly upward sloping, the associated standard error is, in fact, large relative to the estimated derivative. The estimated standard error is .07 pp on average over its domain, thus the effect cannot be distinguished from zero. This issue will be addressed in the following section which aims at making estimation more efficient and parametric and nonparametric estimates more precise.

4.3 Semiparametric Estimation

Nonparametric estimation results from the previous section clearly suggest that the relation between inflation and lags thereof, as well as with previously formed expectations is well approximated by a linear function. With respect to the measure of marginal costs, however, a highly nonlinear relation has been revealed. This leads to the idea of treating the model as only partially linear. One reason for not leaving it at the provision of fully nonparametric estimates is that their partial derivatives are estimated with too low precision. In the following it will therefore be assumed that the Phillips curve is linear in expectations and lags of inflation but nonlinear in the output gap. There is now a finite number of parameters characterising the linear part, and an infinite dimensional set of parameters shaping the nonparametric part of the model. For a detailed discussion of semiparametric models see, e.g., Härdle et al. (2004) or Li and Racine (2007) and references therein. The model now reads as

$$\pi_t = \alpha_1^{sp}\pi^e_{t|t-6} + \alpha_2^{sp}\pi_{t-1} + h\left(\widehat{y}_t\right) + \omega_t \tag{16}$$

where the superscript sp highlights that the model parameters α_1^{sp} and α_2^{sp} are estimated from a semiparametric model. Let $\widetilde{\pi}_t$ be a column vector containing $\pi^e_{t|t-6}$ and π_{t-1}, and let α^{sp} be the row vector comprising α_1^{sp} and α_2^{sp}. The model can now be rewritten as follows.

$$\pi_t = \widetilde{\pi}_t'\alpha^{sp} + h\left(\widehat{y}_t\right) + \omega_t \tag{17}$$

Then $\widetilde{\pi}_t'\alpha^{sp}$ constitutes the parametric (linear) part, and $h(\widehat{y}_t)$ the nonparametric part of the model. It is assumed that $E\left(\omega_t|\widetilde{\pi}_t, \widehat{y}_t\right) = 0$. Note that $\widetilde{\pi}_t$ must not contain an intercept term; if it was included it could not be identified because it is impossible to separate it from $h(\widehat{y}_t)$. An estimate of α^{sp} and $h(\widehat{y}_t)$ is obtained as follows.

First, condition the above equation on $\widehat{y}_t$.

$$E\left(\pi_t|\widehat{y}_t\right) = E\left(\widetilde{\pi}_t|\widehat{y}_t\right)'\alpha^{sp} + h\left(\widehat{y}_t\right) \tag{18}$$

Now subtract this expression from equation (17), that is,

$$\pi_t - E\left(\pi_t|\widehat{y}_t\right) = \left(\widetilde{\pi}_t - E\left(\widetilde{\pi}_t|\widehat{y}_t\right)\right)'\alpha^{sp} + \omega_t \tag{19}$$

Next, redefine terms such that $\pi_t - E(\pi_t|\widehat{y}_t) \equiv \pi_t^*$ and $\widetilde{\pi}_t - E(\widetilde{\pi}_t|\widehat{y}_t) \equiv \widetilde{\pi}_t^*$. Before α^{sp} can be estimated from the equation, one has to have an estimate of $E(\pi_t|\widehat{y}_t)$ as well as $E(\widetilde{\pi}_t|\widehat{y}_t)$ available where the latter term comprises, in fact, two regressions because $\widetilde{\pi}_t$ contains two variables. The three conditional expectation terms are estimated using the exact same nonparametric kernel approach as in the previous section. A second order Epanechnikov kernel along with a local linear bandwidth selection scheme is employed and bandwidths are determined using a least-squares cross-validation method. Let the estimates of these objects be denoted as

$$\widehat{m}_{1,t} = \widehat{E(\pi_t|\widehat{y}_t)} \text{ and } \widehat{m}_{2,t} = \widehat{E(\widetilde{\pi}_t|\widehat{y}_t)} \tag{20}$$

The final semiparametric estimate of α^{sp} can then be computed using the least-squares method, that is,

$$\widehat{\alpha}^{sp} = \left(\sum_{t=1}^{T} \widetilde{\pi}_t^* \widetilde{\pi}_t^{*\prime}\right)^{-1} \times \left(\sum_{t=1}^{T} \widetilde{\pi}_t^* \pi_t^*\right) \tag{21}$$

The asymptotic distribution of $\widehat{\alpha}^{sp}$ reads as follows [for details see Li and Racine (2007)].

$$\sqrt{T}\left(\widehat{\alpha}^{sp} - \alpha^{sp}\right) \xrightarrow{d} N\left(0, \Phi^{-1}\Psi\Phi^{-1}\right) \tag{22}$$

where $\Psi = E\left(\sigma^2\left(\widetilde{\pi}_t^* \pi_t^*\right)\widetilde{\pi}_t^*\widetilde{\pi}_t^{*\prime}\right)$, $\Phi = \left[E\left(\widetilde{\pi}_t^*\widetilde{\pi}_t^{*\prime}\right)\right]$, and σ^2 is the error variance.

Interest lies also in revealing the shape of $h(\widehat{y}_t)$, which one can obtain from equation (18) by rearranging and substituting for the conditional expectation terms by their estimates. The $\widehat{h(\widehat{y}_t)}$ estimate looks then as follows.

$$\widehat{h(\widehat{y}_t)} = \widehat{m}_{1,t} - \widehat{m}_{2,t}^{\prime}\widehat{\alpha}^{sp} \tag{23}$$

The steps towards obtaining the semiparametric estimates can be summarized as follows. First, conduct three nonparametric regressions in which inflation, expectations and lagged inflation are all regressed on the output gap. The resulting fitted values are then subtracted from respective variables to partial out the effect of the output gap. The adjusted inflation variable is then regressed on the adjusted expectation and lagged inflation term using ordinary least-squares so as to obtain estimates for the parametric (linear) part of the model.

The empirical estimates from the semiparametric model are summarized in Table 8 (upper part of the table). The $\widehat{\alpha}_1^{sp} = .0661$ is indeed very close to the parametric estimate $\widehat{\alpha}_1 = .0667$; The p-value corresponding to the semiparametric coefficient estimate for expectations is 1.59 percent (compared to 1.52 percent in the linear model). The coefficient on lagged inflation again indicates strong persistence in inflation, with $\widehat{\alpha}_2^{sp} = .882$ ($\widehat{\alpha}_2 = .881$ in the linear model).[8]

An estimate of the nonparametric part $h(\widehat{y}_t)$ of the model is presented in Figure 9 which shows an estimate of the conditional mean function along with two standard error point-wise confidence bounds. Figure 10 plots the partial derivative with respect to the output gap, i.e. it measures the slope of the function in Figure 9. Finally, Figure 11 and 12 illustrate how the fit generated by the nonparametric part of the model, its partial derivative respectively, evolve over time. Concerning the shape of the function and its derivative, results are in line with findings reported for the nonparametric model in the previous section. One major

[8] Figure 8 shows the nonparametric regressions from the first step in which the effect of the output gap is partialled out from all other variables. The 1st-step regression results will not be discussed and are reported for the sake of completeness.

difference though is that estimated standard errors for the function and its derivative are much smaller when conducting the semiparametric regression. Standard error bounds have, in fact, not been plotted for the nonparametric case because they were too large. The standard error estimate for the semiparametric derivative for the output gap now turns out to be much lower, with .004 pp on average over the output gap domain. Following a semiparametric approach has therefore proven helpful as coefficients have been estimated with higher precision compared to the ones obtained from the nonparametric model.

4.4 Robustness Checks

In an attempt at checking the robustness of the results, three additional exercises are conducted.

First, the output gap measure is being replaced by an alternative one which is constructed as the log-difference between actual and potential output, where the latter is now a quadratic time trend estimated from the actual path of output. The semiparametric model is then re-estimated including the alternative output gap variable. Results are summarized in Table 7 (the lower part).

Compared to the model that employs the HP filtered output gap, the parametric part of the model changes slightly in that expectations are somewhat less significant, though still significant at the 10 percent level. The estimated degree of persistence has essentially stayed at the same level and along with its corresponding p-value (≈ 0) indicate that the hybrid form of the model should be the preferred format.

In Figure 13, the nonparametric estimate that relates to the alternative output gap measure is presented. In comparison to the derivative for the HP filtered output gap, the average derivative (over its domain) has changed only very little. The derivative seems somewhat less dependent on the level of the output gap, though it is still positive.

To test further the robustness of the results, the stability of the estimates through time is being assessed. To this end, the semiparametric model is now re-estimated for two sub-samples. A rolling breakpoint test for the model including expectations, lagged inflation and the output gap indicates that the most significant break occures in July 1999 (which does not invalidate the test result reported in Section 3.2, since a different test equation is now employed). This point happens to devide the sample in two parts of almost equal lengths; The first one comprises 109, and the second one 111 observations.

Semiparametric estimation results for the two samples are summarized in Table 9 and the nonparametric function and derivative estimates are presented in Figure 14 and 15. As concerns the magnitute of coefficient estimates in the two samples, the impact of expectations has remained almost unchanged ($\widehat{\alpha}_1^{sp} = .102$ and $\widehat{\alpha}_1^{sp} = .107$ in sub-sample 1 and 2, respectively). Its significance has diminished, however, to some extent, with its p-value increasing from 3.8 to 12.2 percent when switching to the second sample. Regarding persistence, the model estimates are very stable and indicate rather strong serial correlation in inflation dynamics in both parts of the sample.

Figure 14 and 15, which show the partial derivatives for the output gap, reveal that the slope of the Phillips curve has, in fact, increased. The average derivatives over the output gap domain in the first and second half of the sample equal .007 pp and .026 pp, respectively. In sub-sample 1, real activity starts putting significant pressure on price inflation when output exceeds potential by about 1 percent, whereas in sub-sample 2 the effect is significantly different from zero along the entire output gap domain. In line with full-sample estimates, the slope of the curve is increasing with economic activity.

A third and final check for robustness concerns the choice of industrial area-wide output as a basis for computing the output gap. To see how sensitive the parametric benchmark estimates are, all variables have been converted to quarterly by taking period averages. Thereafter, the level GDP and industrial production series for the euro area are detrended using the HP filter to obtain an output gap measure. Estimates for the two quarterly models are presented in Table 10. The results suggest that inflation expectations, which still enter optimally with a lag of 6 months, 2 quarters in this case respectively, relate positively to actual inflation, though the significance of this relation is somewhat lower when the GDP based output gap is included in the model (p-values equal 6.3% and 11.6% respectively). Coefficients on the constant and lagged inflation change only very little and the significance of the output gap variable itself is comparable with t-statistics equalling 2.40 and 2.32 respectively.

By and large, these results confirm the robustness of findings from previous full-sample estimation results.

5 Conclusions

This paper has been aimed at providing empirical Phillips curve estimates for the euro area while refraining from imposing too strong assumptions on the functional correspondence between variables. Moreover, it was not presumed that agents' expectations are an unbiased predictor of actual future inflation. Four main findings emerge from the analysis.

First, consumers' inflation expectations turn out to be biased relative to actual inflation, first upwards by about .25 pp on average until December 1999. A rolling test scheme has revealed that bias in expectations has fallen since the millenium change and become somewhat negative (-0.5 pp). Moreover, expectation errors are positively serially correlated. Future work aiming at estimating Phillips curve relationships shall therefore refrain from assuming unbiasedness in expectations and rather incorporate survey based measures thereof.

Second, from an empirical perspective, the classical type of Phillips curve is more appropriate than the New Keynesian format for explaining inflation dynamics in the euro area. Moreover, inflation dynamics are characterized by relatively high persistence, making the hybrid form the preferred choice. The results suggest that expectations have impact upon actual inflation and variation therein is best explained by variation in expectations when the latter are being lagged by about 6 months. This is seen as empirical evidence against the New Keynesian format of the curve in which expectations influence actual price changes contemporaneously.

Third, all model estimates, whether parametric, nonparametric, or semiparametric, reveal a statistically positive slope of the Phillips curve on average. More intense economic activity is therefore associated with higher levels of price inflation.

Forth, non- and semiparametric model estimates reveal that a linearity assumption is appropriate as far as lagged inflation as well as the expectation variable are concerned. The impact of real economic activity on inflation, however, varies depending on the level of the output gap, i.e. the relation is *not* linear and inflation does not change simply proportionally with lower/higher economic activity. As output grows relative to potential, its impact on price inflation *increases*. As output falls off, possibly below potential, its impact on inflation abates, i.e. the Phillips curve flattens out. If one was to instead cast the Phillips curve in the conventional linear model, one was not able to uncover this empirical regularity as the impact of real activity on inflation is *constant* by assumption.

The estimation results were found to be robust to the deployment of an alternative measure of the output gap as well as to the conduct of sub-sample analysis.

The empirical evidence in favour of nonlinearities, namely convexity, in the Phillips curve relation has implications for monetary policy. There are at least two channels through which monetary policy can potentially influence price inflation, through expectations and by setting policy rates so as to stimulate/dampen aggregate demand. Apart from the fact that the results suggest a positive tradeoff between price inflation and real activity in the short run, the difference between linear models and a convex one is that this tradeoff depends on the state of the economy if the curve is convex. A marginal increase in aggregate demand, say, induced by expansionary monetary policy, entails higher rates of inflation at times of already high economic activity. At times of low activity, e.g. during a recession, the same policy would cause prices to accelerate less quickly, if at all. If monetary policy was indeed establishing its understanding of how output and inflation interact solely on the Phillips curve (which it certainly does not), in particular either a linear or convex one, a convex relation would endorse relatively sharper expansionary policy measures at times of low activity (e.g. in times of a crisis), and more cautious expansionary or rather tighter contractionary measures at times of high activity. A convex relation also suggests, as pointed out in Macklem (1997) that monetary policy shall act pre-emptively to avoid periods of excess demand, the reason being that at higher levels of activity inflation will tend to rise more rapidly.

When exploring the results in light of the determination of a sacrifice ratio, which measures the cost of reducing inflation in terms of output growth, the results imply that such ratio, too, is state dependent, which can be seen as the inverse of the partial derivative that has been derived with respect to the output gap. Unlike in the linear model where the sacrifice ratio is a constant, the convex model now implies that the ratio is a *decreasing* function of economic activity so that contractionary policy that aims at reducing inflation by 1 percentage point at times of high inflation would entail a *lower* loss in terms of output growth than at times of already low inflation. In the sequel, pre-emptive policy is also beneficial when time is ripe to slow down growth and inflation because the sooner such policy is pursued the less costly it is in terms of lost output.

Overall, this reasoning is in line with the typical Keynesian's view that the answer on whether expansionary (contractionary) policy will raise (lower) output and employment via demand or just accelerate (decelerate) inflation depends on circumstances; the circumstance being the economy's state in the business cycle.

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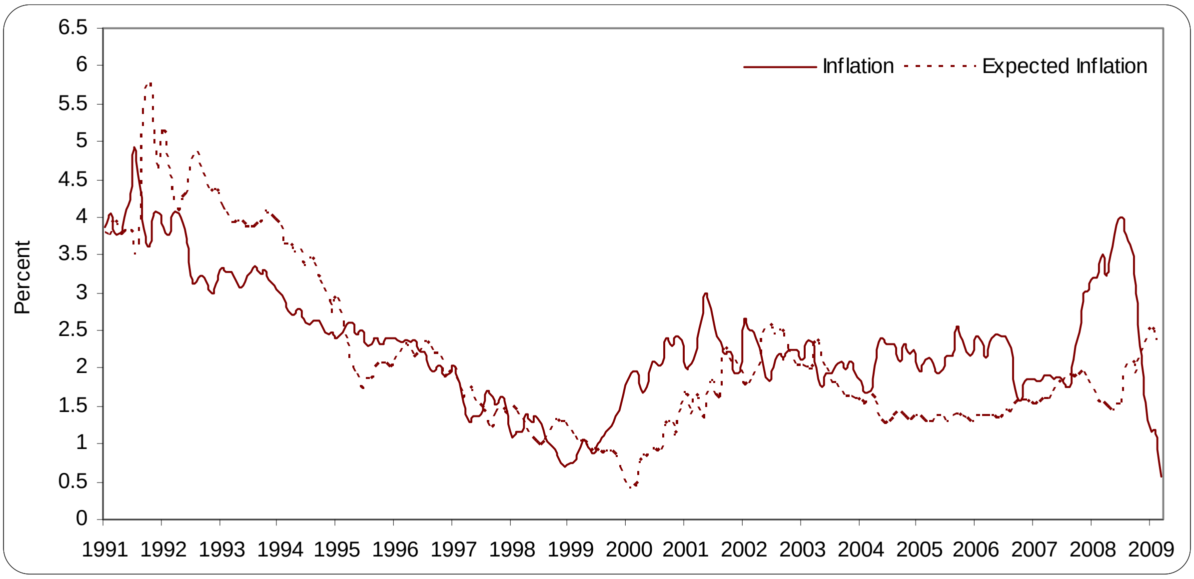
ANNEX 1: FIGURES

FIGURE 1

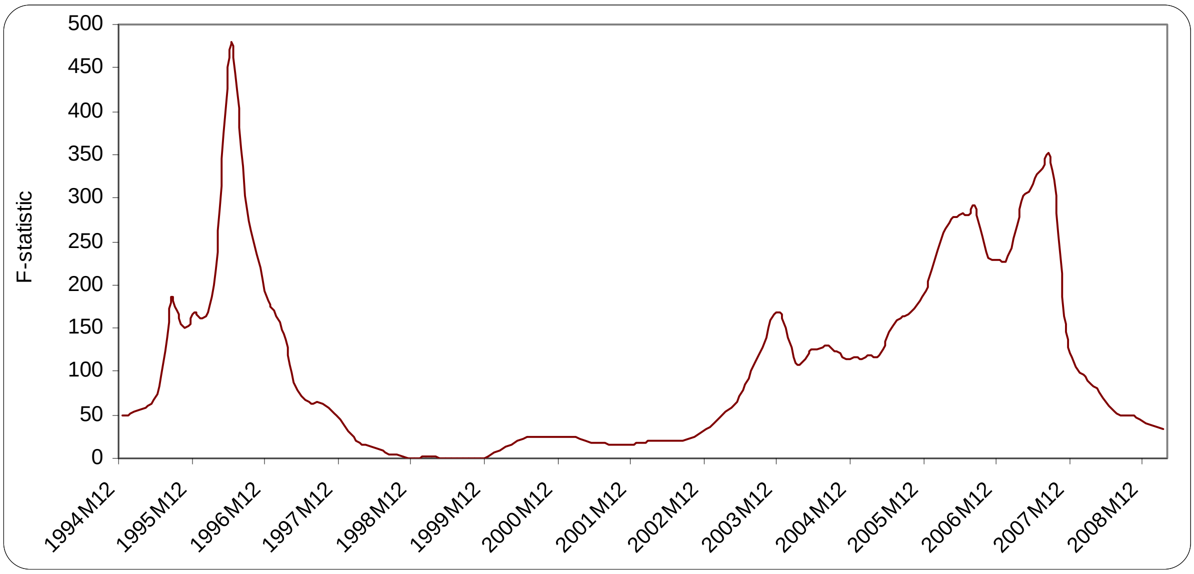
INFLATION EXPECTATIONS IN THE EURO AREA



Note: The graph plots Expected Inflation with a lag of 12 months. Expected Inflation in, e.g., January 2000 (0.40%) refers to consumer expectations formed in January 1999.

FIGURE 2

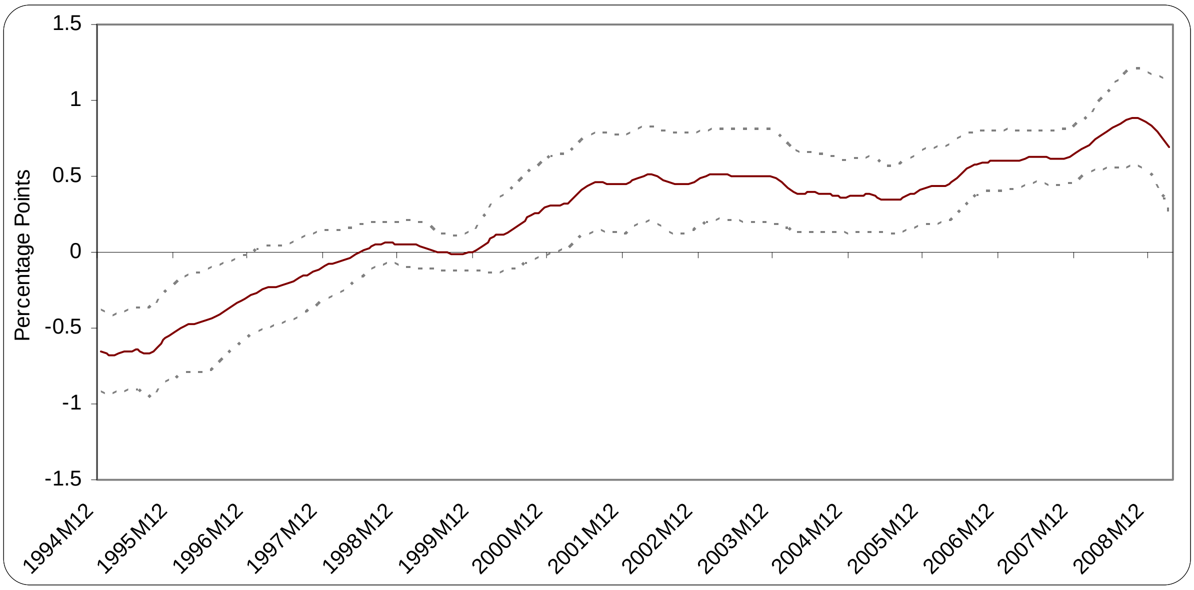
TEST FOR BIASEDNESS IN EXPECTATIONS



Note: The F-statistic is computed recursively using a 5-year rolling sample of data. Dates in the graph refer to the end of the rolling sample at every point in time.

FIGURE 3

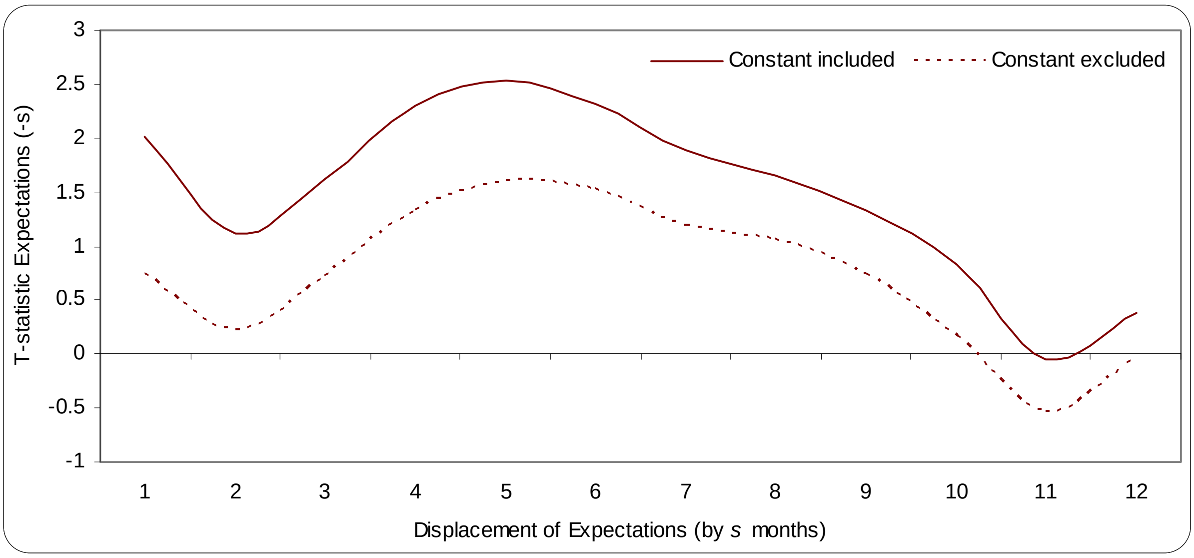
UNCONDITIONAL BIAS IN EXPECTATIONS



Note: The bias is estimated from a regression of expectational errors on a constant, using a 5-year rolling sample. Two standard error point-wise confidence bounds are plotted (dotted lines) along with the actual estimate for the constant.

FIGURE 4

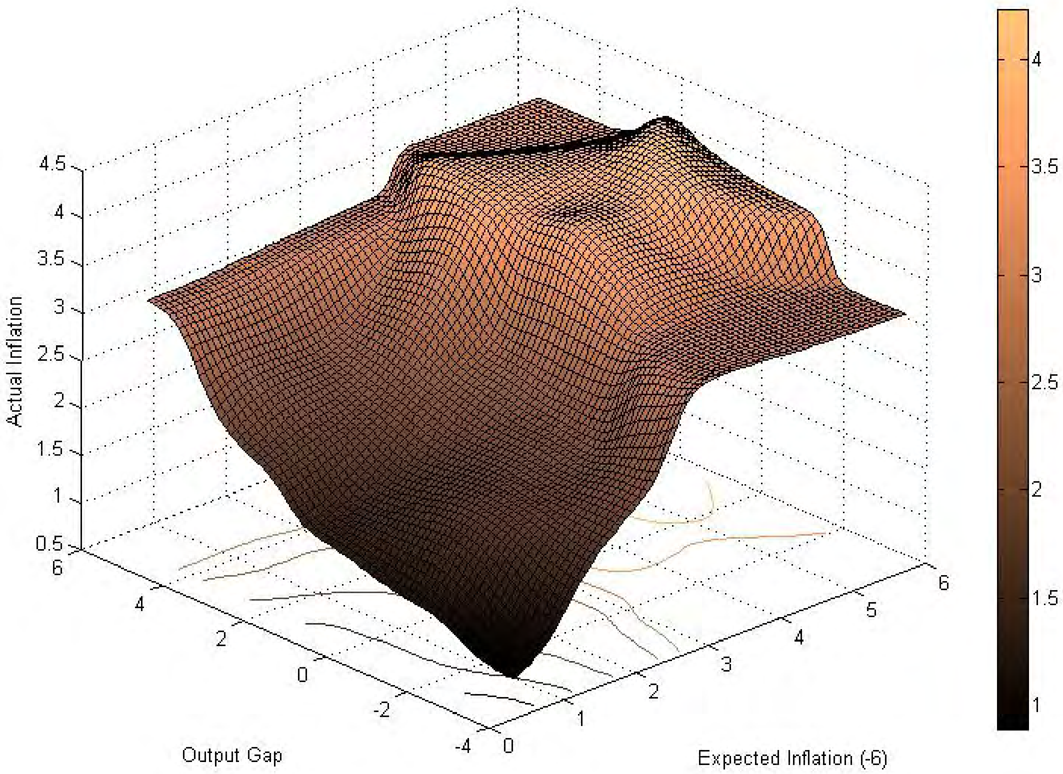
PARAMETRIC PHILLIPS CURVE ESTIMATES (COEFFICIENT ON EXPECTATIONS) FOR *s={1,2,…,12}*



Note: The plotted t-statistic is the one related to the coefficient on expected inflation in a regression of inflation on expected inflation, the output gap, lagged inflation, and a constant if indicated. The t-statistic is based on Newey-West HAC standard errors.

FIGURE 5

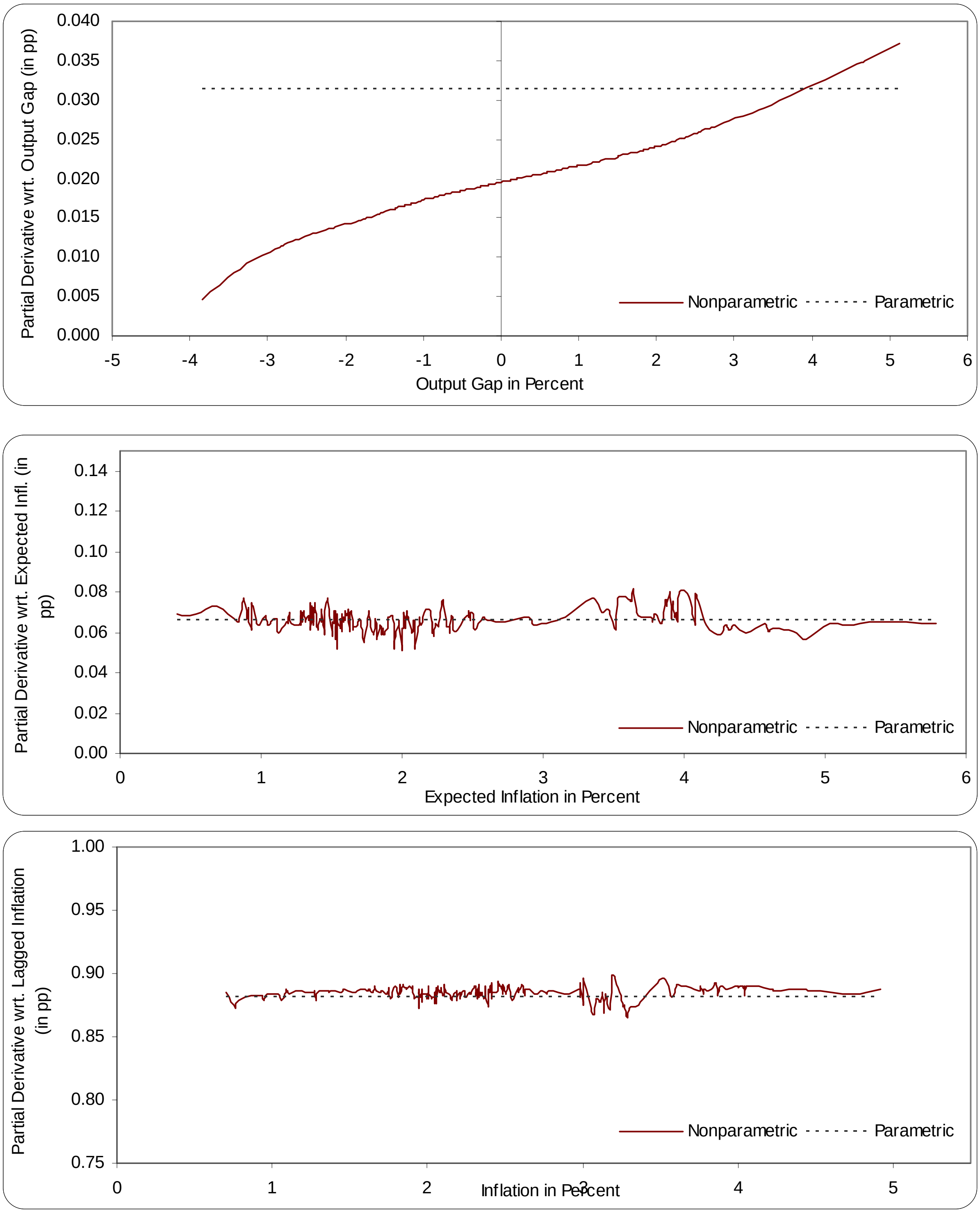
NONPARAMETRIC PHILLIPS CURVE ESTIMATE



Note: All variables in Percent. The plotted surface is the fit from a nonparametric regression of inflation on lagged expected inflation and the output gap. Details concerning the nonparametric regression procedure are given in Section 4.2.

FIGURE 6

PARAMETRIC VERSUS NONPARAMETRIC PARTIAL DERIVATIVES

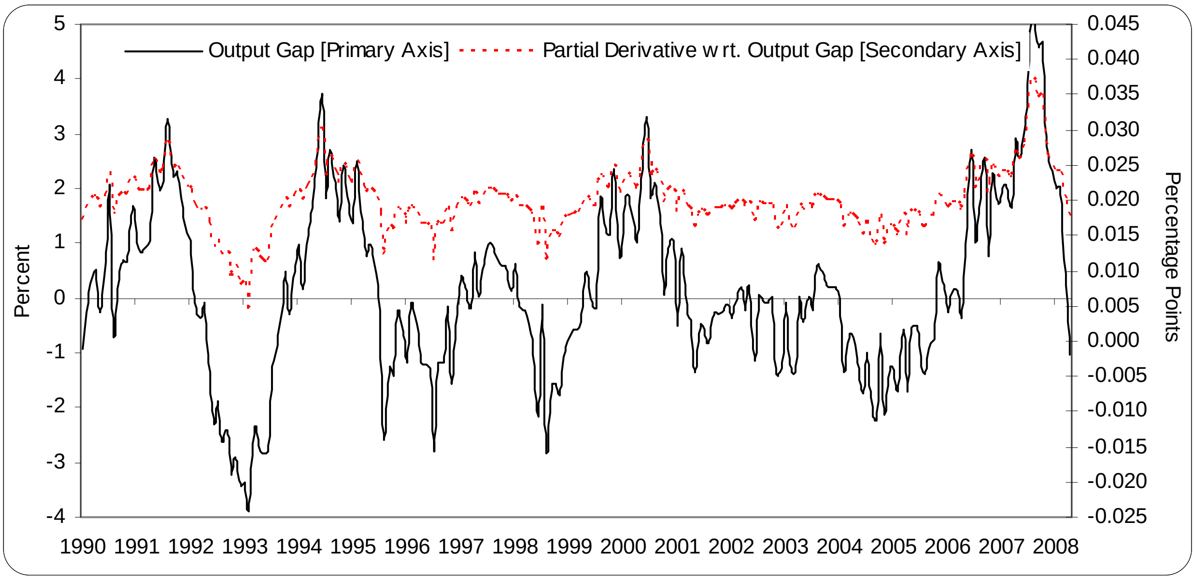


Note: Partial derivatives have been computed from a nonparametric regression of inflation on lagged expected inflation, the output gap, and lagged actual inflation. A second order Epanechnikov kernel along with a local linear bandwidth selection procedure has been used. The bandwidth parameters have been determined via least-squares cross-validation.

FIGURE 7

OUTPUT GAP VERSUS PARTIAL DERIVATIVE WITH RESPECT TO THE OUTPUT GAP OVER TIME

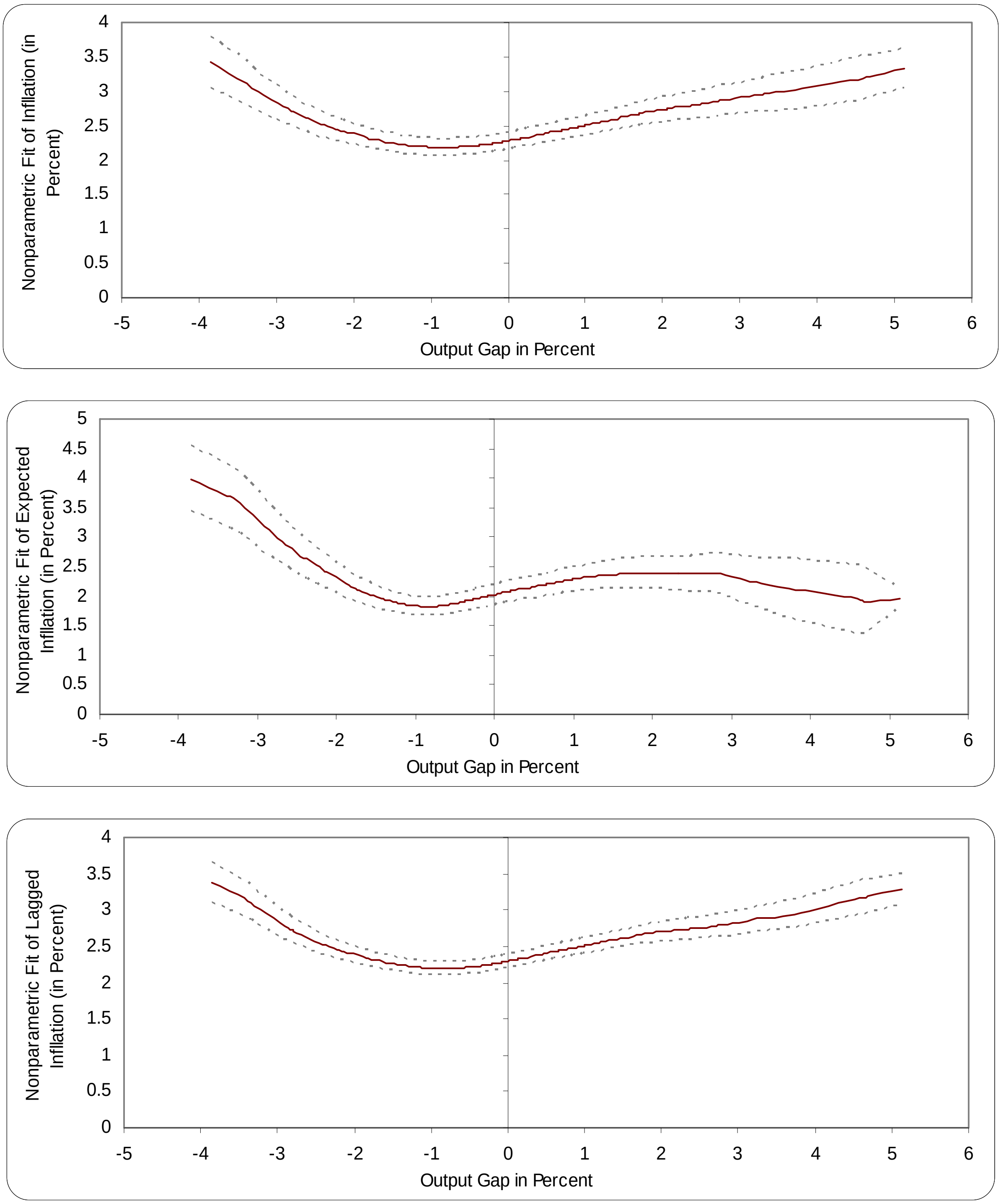
(NONPARAMETRIC MODEL)



Note: The graph shows the level of the output gap (primary axis) along with the partial derivative with respect to the output gap (secondary axis). The partial derivative has been computed from a nonparametric regression of inflation on lagged expected inflation, the output gap, and lagged actual inflation. A second order Epanechnikov kernel along with a local linear bandwidth selection procedure has been used. The bandwidth parameter has been determined via least-squares cross-validation.

FIGURE 8

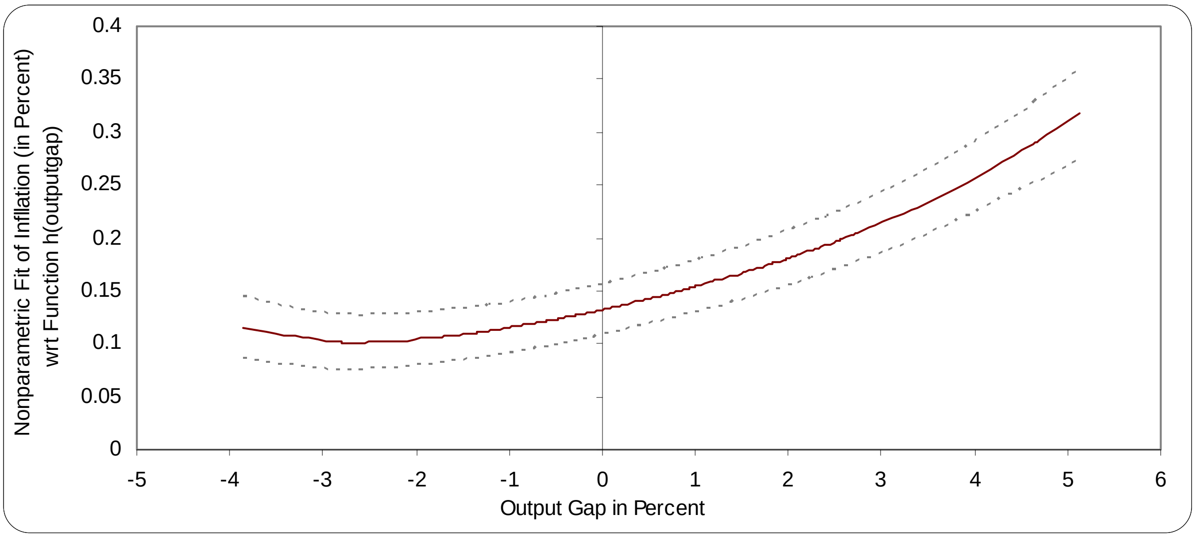
SEMIPARAMETRIC REGRESSION (1ST PART)



Note: The three graphs show the fit from a nonparametric regression of inflation, lagged expected inflation, and lagged inflation on the output gap. A second order Epanechnikov kernel along with a local linear bandwidth selection procedure has been used. The bandwidth parameters have been determined via least-squares cross-validation. Two standard error point-wise confidence bounds are plotted (dotted lines) along with the actual function estimate.

FIGURE 9

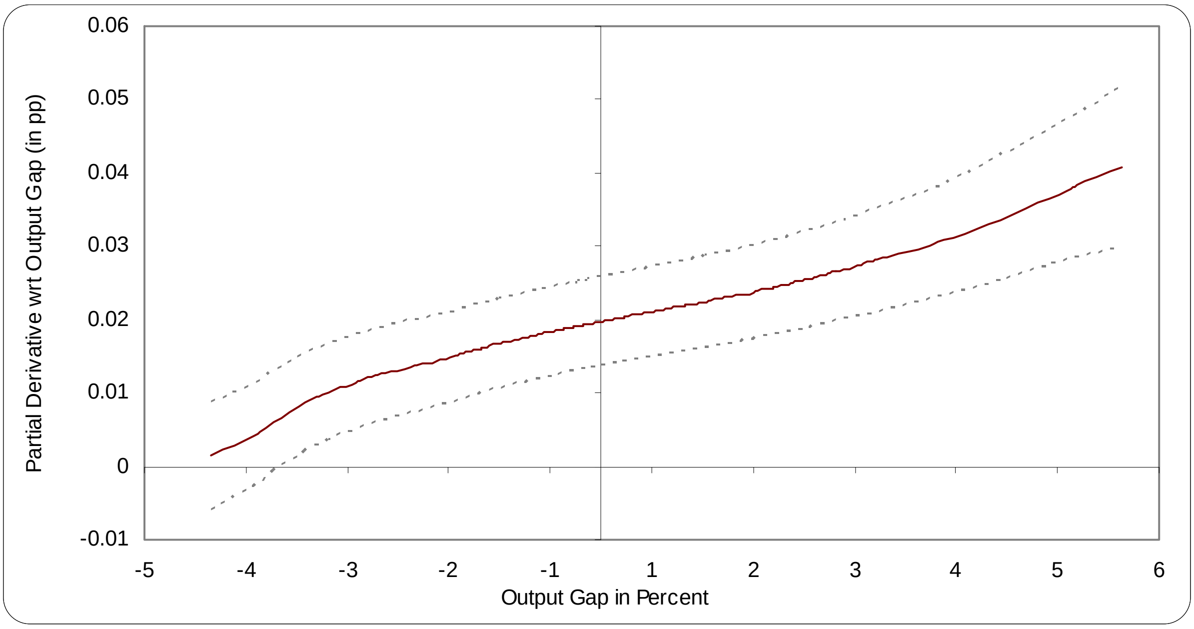
NONPARAMETRIC FUNCTION ESTIMATE FOR OUTPUT GAP (SEMIPARAMETRIC MODEL)



Note: The graph shows the fit from the nonparametric part of the Semiparametric Model for inflation. The fit (vertical axis) is not to be interpreted as the final level of inflation implied by the model but as the portion of inflation corresponding to varying levels of the output gap. Two standard error point-wise confidence bounds are plotted (dotted lines) along with the function estimate.

FIGURE 10

PARTIAL DERIVATIVE WITH RESPECT TO THE OUTPUT GAP (SEMIPARAMETRIC MODEL)

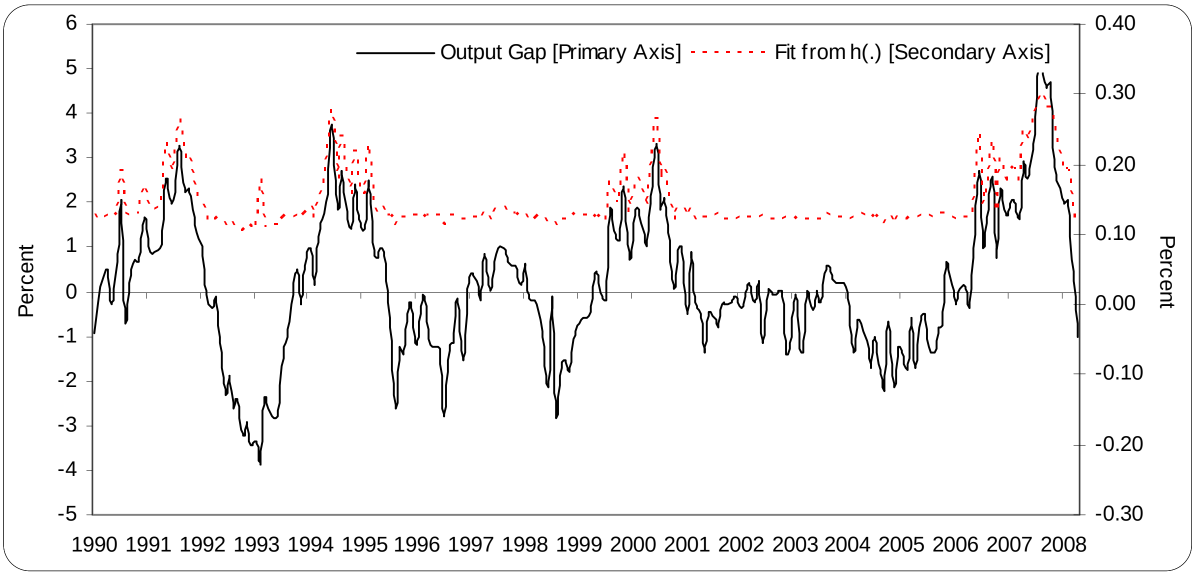


Note: The graph shows the partial derivative with respect to the output gap from the semiparametric model. A second order Epanechnikov kernel along with a local linear bandwidth selection procedure has been used. The bandwidth parameters have been determined via least-squares cross-validation. Two standard error point-wise confidence bounds are plotted (dotted lines) along with the estimate.

FIGURE 11

OUTPUT GAP VERSUS NONPARAMETRIC FIT FROM OUTPUT GAP OVER TIME

(SEMIPARAMETRIC MODEL)

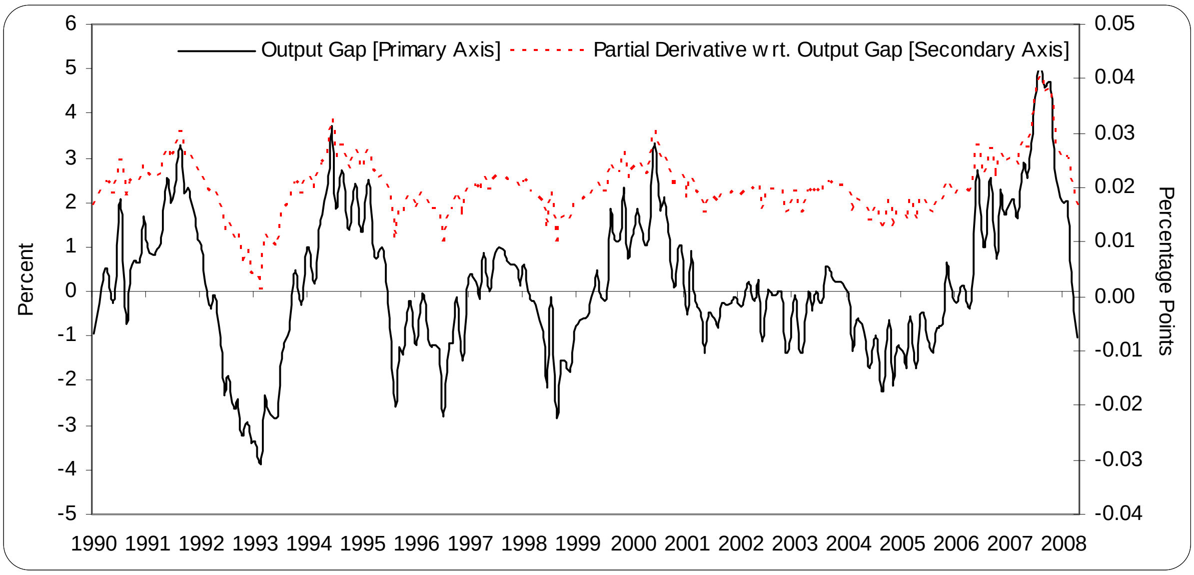


Note: The graph shows the fit from the nonparametric part of the Semiparametric Model for inflation. The fit (secondary axis) is not to be interpreted as the final level of inflation implied by the model but as the portion of inflation corresponding to varying levels of the output gap (primary axis).

FIGURE 12

OUTPUT GAP VERSUS PARTIAL DERIVATIVE WITH RESPECT TO THE OUTPUT GAP OVER TIME

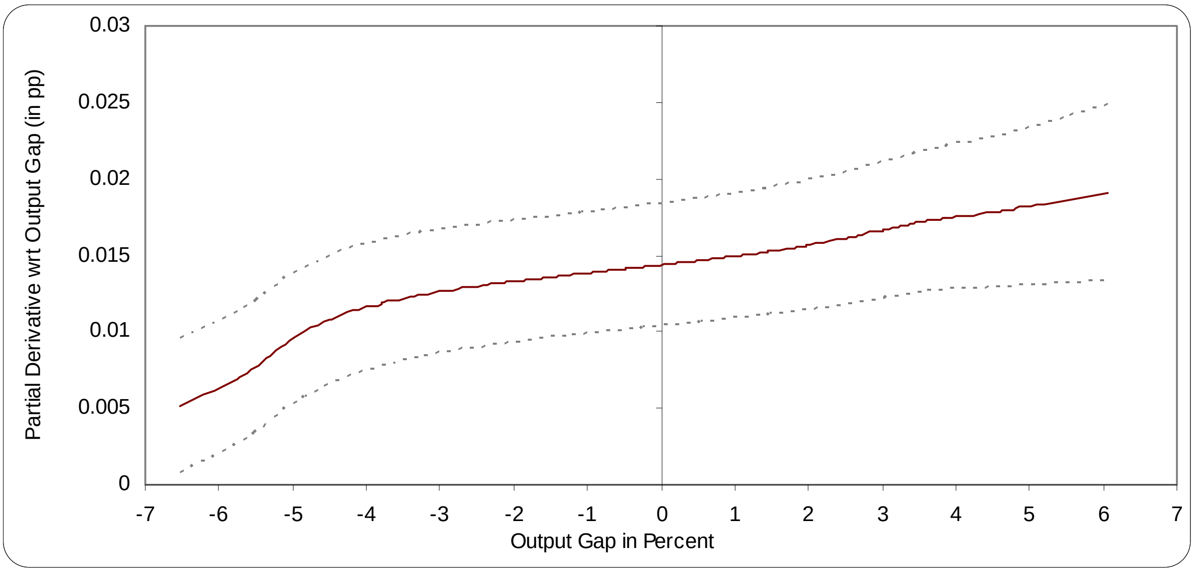
(SEMIPARAMETRIC MODEL)



Note: The graph shows the level of the output gap (primary axis) along with the partial derivative with respect to the output gap (secondary axis). A second order Epanechnikov kernel along with a local linear bandwidth selection procedure has been used. The bandwidth parameter has been determined via least-squares cross-validation.

FIGURE 13

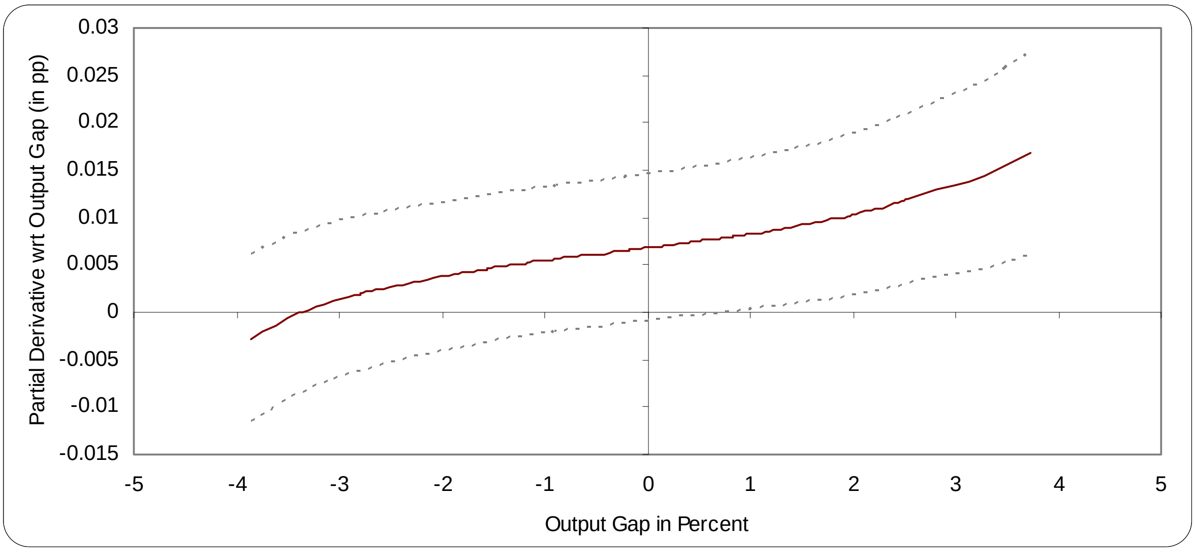
PARTIAL DERIVATIVE WITH RESPECT TO THE OUTPUT GAP FOR AN ALTERNATIVE OUTPUT GAP MEASURE (QUADRATIC TIME TREND) (SEMIPARAMETRIC MODEL)



Note: The graph shows the partial derivative with respect to the output gap from the semiparametric model. A second order Epanechnikov kernel along with a local linear bandwidth selection procedure has been used. The bandwidth parameters have been determined via least-squares cross-validation. Two standard error point-wise confidence bounds are plotted (dotted lines) along with the estimate.

FIGURE 14

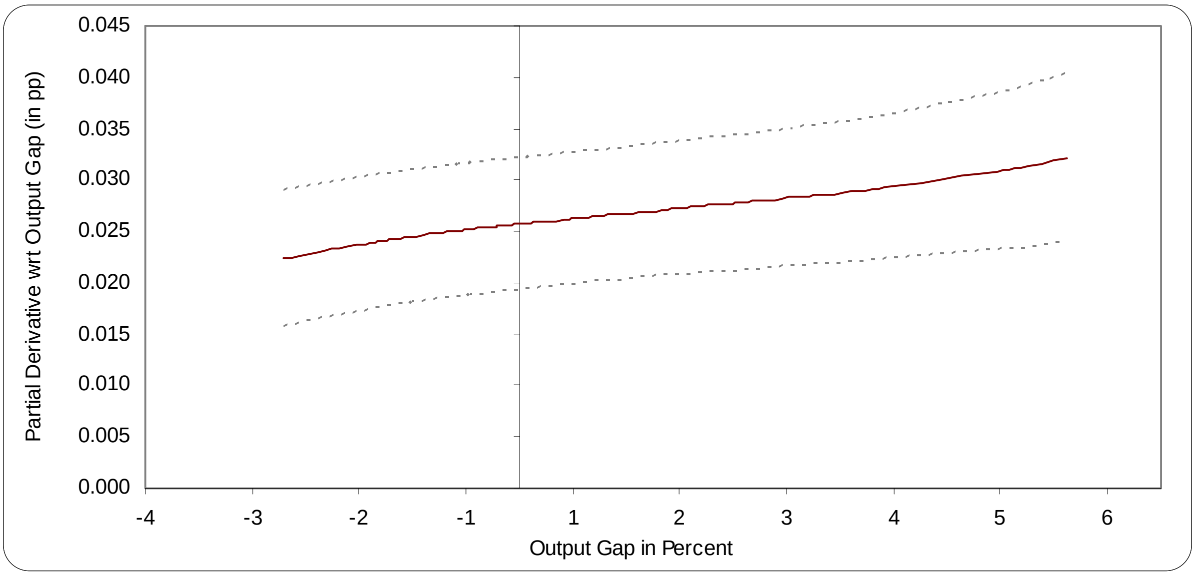
PARTIAL DERIVATIVE WITH RESPECT TO THE OUTPUT GAP FOR SUB-SAMPLE 1: JULY 1990 – JULY 1999 (SEMIPARAMETRIC MODEL)



Note: The graph shows the partial derivative with respect to the output gap from the semiparametric model. A second order Epanechnikov kernel along with a local linear bandwidth selection procedure has been used. The bandwidth parameters have been determined via least-squares cross-validation. Two standard error point-wise confidence bounds are plotted (dotted lines) along with the estimate.

FIGURE 15

PARTIAL DERIVATIVE WITH RESPECT TO THE OUTPUT GAP FOR SUB-SAMPLE 2: AUGUST 1999 – OCTOBER 2008 (SEMIPARAMETRIC MODEL)



Note: The graph shows the partial derivative with respect to the output gap from the semiparametric model. A second order Epanechnikov kernel along with a local linear bandwidth selection procedure has been used. The bandwidth parameters have been determined via least-squares cross-validation. Two standard error point-wise confidence bounds are plotted (dotted lines) along with the estimate.

ANNEX 2: TABLES

TABLE 1

TEST FOR BIASEDNESS IN EXPECTATIONS

Test Equation $\pi_t = a_0 + a_1 \pi^e_{t\|t-12} + \varepsilon_t$				
Sample (adjusted): 1991:01 – 2008:12 (216 observations)				
Dependent variable: Inflation (Year-on-year)				
Variable	**Coefficient**	**Std. Error***	**t-statistic**	**p-value**
Constant	1.2213	0.1599	7.6383	0.0000
Expectation (-12)	0.5160	0.0561	9.1964	0.0000
R-squared	0.4973	DW-statistic	0.2235	
R-squared adjusted	0.4950	F-statistic	214.6451	
Log-likelihood	-190.7030	p-value (F-stat)	0.0000	

Null Hypothesis $H_0 : (a_0, a_1) = (0,1)$

Wald Test	Value (df)	p-value
F-statistic	37.1983	0.0000

* Newey-West HAC Standard Errors (lag truncation=4)

TABLE 2

UNCONDITIONAL BIAS IN EXPECTATIONS

Test Equation $\pi_t - \pi^e_{t\|t-12} = a_0 + \varepsilon_t$				
Sample (adjusted): 1991:01 – 2008:12 (216 observations)				
Dependent variable: Inflation (Year-on-year)				
Variable	**Coefficient**	**Std. Error***	**t-statistic**	**p-value**
Constant	0.1827	0.1075	1.6990	0.0907
R-squared	0.0000	DW-statistic	0.1966	
R-squared adjusted	0.0000	F-statistic	2.8866	
Log-likelihood	-259.2480	p-value (F-stat)	0.0907	

* Newey-West HAC Standard Errors (lag truncation=4)

TABLE 3

DURBIN-WU-HAUSMANN TEST FOR ENDOGENEITY IN INFLATION EXPECTATIONS

Sample (adjusted): 1990:03 – 2008:12 (226 observations)

Auxiliary regression (dependent variable: inflation expectations)

Variable	Coefficient	Std. Error	t-statistic	p-value
Constant	-0.0221	0.0442	-0.4995	0.6179
Output Gap	0.0164	0.0071	2.3033	0.0222
Inflation Expectation (-1)	0.9229	0.0316	29.1639	0
Inflation (-1)	0.3197	0.0691	4.6271	0
Inflation (-2)	-0.2468	0.0667	-3.7016	0.0003

R-squared	0.9673	DW-statistic	1.9092
R-squared adjusted	0.9668	F-statistic	1658.8670
Log-likelihood	45.7268	p-value (F-stat)	0.0000

Test regression including residuals from auxiliary regression (dependent variable: inflation) \ Displacement s=0

Variable	Coefficient	Std. Error	t-statistic	p-value
Constant	0.1392	0.0420	3.3112	0.0001
Inflation Expectations	0.0821	0.0323	2.5403	0.0012
Inflation (-1)	0.8640	0.0392	22.0498	0.0000
Output Gap	0.0287	0.0065	4.3933	0.0000
Residuals_Auxiliary	0.3025	0.0712	4.2504	0.0000

R-squared	0.9553	DW-statistic	1.5572
R-squared adjusted	0.9545	F-statistic	1.20E+03
Log-likelihood	57.7586	p-value (F-stat)	0.0000

Test regression including residuals from auxiliary regression (dependent variable: inflation) \ Displacement s=1

Variable	Coefficient	Std. Error	t-statistic	p-value
Constant	0.1245	0.0454	2.7397	0.0007
Inflation Expectations (-1)	0.0470	0.0329	1.4293	0.1540
Inflation (-1)	0.9005	0.0406	22.1633	0.0000
Output Gap	0.0304	0.0071	4.2604	0.0000
Residuals_Auxiliary (-1)	0.1095	0.0713	1.5359	0.1260

R-squared	0.9470	DW-statistic	1.6293
R-squared adjusted	0.9461	F-statistic	9.96E+02
Log-likelihood	39.8856	p-value (F-stat)	0.0000

TABLE 4

DURBIN-WU-HAUSMANN TEST FOR ENDOGENEITY IN THE OUTPUT GAP

Sample (adjusted): 1990:03 – 2008:12 (226 observations)

Auxiliary regression (dependent variable: output gap)

Variable	**Coefficient**	**Std. Error**	**t-statistic**	**p-value**
Constant	0.0322	0.1977	0.1629	0.8707
Inflation (-1)	0.7677	0.3209	2.3924	0.0176
Inflation (-2)	-0.8957	0.2902	-3.0860	0.0023
Inflation Expectations	0.1150	0.1380	0.8328	0.4059
Output Gap (-1)	0.9351	0.0343	27.2626	0.0000
R-squared	0.7899	DW-statistic	2.3990	
R-squared adjusted	0.7861	F-statistic	210.5302	
Log-likelihood	-300.1150	p-value (F-stat)	0.0000	

Test regression including residuals from auxiliary regression (dependent variable: inflation) \ Displacement s=0

Variable	**Coefficient**	**Std. Error**	**t-statistic**	**p-value**
Constant	0.1825	0.0427	4.2780	0.0000
Inflation Expectations	0.1442	0.0298	4.8388	0.0000
Inflation (-1)	0.7918	0.0368	21.5335	0.0000
Output Gap	0.0336	0.0077	4.3904	0.0000
Residuals_Auxiliary	-0.0233	0.0164	-1.4234	0.1560
R-squared	0.9521	DW-statistic	1.4455	
R-squared adjusted	0.9513	F-statistic	1.11E+03	
Log-likelihood	49.9085	p-value (F-stat)	0.0000	

Test regression including residuals from auxiliary regression (dependent variable: inflation) \ Displacement s=1

Variable	**Coefficient**	**Std. Error**	**t-statistic**	**p-value**
Constant	0.1329	0.0449	2.9611	0.0034
Inflation Expectations (-1)	0.0607	0.0315	1.9264	0.0553
Inflation (-1)	0.8851	0.0392	22.5947	0.0000
Output Gap	0.0357	0.0080	4.4535	0.0000
Residuals_Auxiliary	-0.0248	0.0171	-1.4495	0.1486
R-squared	0.9480	DW-statistic	1.5173	
R-squared adjusted	0.9470	F-statistic	1020.9750	
Log-likelihood	40.4064	p-value (F-stat)	0.0000	

TABLE 5

GENERALIZED METHOD OF MOMENTS ESTIMATION RESULTS

Sample (adjusted): 1990:03 – 2008:12 (226 observations)				
Dependent variable: Inflation (Year-on-year)				
Instrument List: Constant, Inflation Expectations (-1), Inflation Expectations (-2), Inflation (-2), Output Gap (-1), Output Gap (-2)				
Variable	**Coefficient**	**Std. Error**	**t-statistic**	**p-value**
Constant	0.1504	0.0647	2.3267	0.0209
Inflation Expectations	0.0885	0.0476	1.8578	0.0645
Inflation (-1)	0.8575	0.0654	13.1166	0.0000
Output Gap	0.0248	0.0086	2.8757	0.0044
R-squared	0.9508	DW-statistic	1.5377	
R-squared adjusted	0.9501	J-statistic	0.0175	

Notes: Inflation Expectations are quantified from the EC Business and Consumer Survey (see Section 3.1 for details). A Bartlett kernel with fixed bandwidth has been used for estimation.

TABLE 6

GENERALIZED EMPIRICAL LIKELIHOOD ESTIMATION RESULTS

Sample (adjusted): 1990:03 – 2008:12 (226 observations)				
Dependent variable: Inflation (Year-on-year)				
Instrument List: Constant, Inflation Expectations (-1), Inflation Expectations (-2), Inflation (-2), Output Gap (-1), Output Gap (-2)				
Variable	**Coefficient**	**Std. Error**	**t-statistic**	**p-value**
Constant	0.1466	0.0589	2.4891	0.0128
Inflation Expectations	0.0857	0.0418	2.0499	0.0404
Inflation (-1)	0.8615	0.0576	14.9549	0.0000
Output Gap	0.0242	0.0090	2.6930	0.0071
R-squared	0.9506	DW-statistic	1.5286	
R-squared adjusted	0.9500	J-statistic	0.0161	

Notes: Inflation Expectations are quantified from the EC Business and Consumer Survey (see Section 3.1 for details). A Bartlett kernel with fixed bandwidth has been used for estimation.

TABLE 7

BENCHMARK PARAMETRIC PHILLIPS CURVE ESTIMATION RESULTS

Sample (adjusted): 1990:07 – 2008:12 (222 observations)				
Dependent variable: Inflation (Year-on-year)				
Variable	**Coefficient**	**Std. Error***	**t-statistic**	**p-value**
Constant	0.1304	0.0494	2.6399	0.0089
Inflation Expectations (-6)	0.0657	0.0268	2.4479	0.0152
Inflation (-1)	0.8810	0.0386	22.8393	0.0000
Output Gap	0.0313	0.0135	2.3149	0.0215
R-squared	0.9437	DW-statistic	1.4960	
R-squared adjusted	0.9429	F-statistic	1217.8940	
Log-likelihood	38.9988	p-value (F-stat)	0.0000	

* Newey-West HAC Standard Errors (lag truncation=4)

TABLE 8

SEMIPARAMETRIC ESTIMATION RESULTS WITH ALTERNATIVE OUTPUT GAP MEASURES

Sample (adjusted): 1990:07 – 2008:12 (222 observations)				
Dependent variable: Inflation (Year-on-year) adjusted by nonparametric regression (1st step)				
Output Gap: Log-difference between Actual and Potential Output [obtained via Hodrick-Prescott Filter (λ=14400)]				
Variable	**Coefficient**	**Std. Error***	**t-statistic**	**p-value**
Expected Inflation (-6) [adjusted]	0.0661	0.0272	2.4304	0.0159
Inflation (-1) [adjusted]	0.8820	0.0370	23.8059	0.0000
R-squared	0.9440	DW-statistic	1.6283	
R-squared adjusted	0.9437	Log-likelihood	52.6765	
Output Gap: Log-difference between Actual and Potential Output [Quadratic Time Trend]				
Variable	**Coefficient**	**Std. Error***	**t-statistic**	**p-value**
Expected Inflation (-6) [adjusted]	0.0516	0.0298	1.7286	0.0853
Inflation (-1) [adjusted]	0.8961	0.0378	23.7008	0.0000
R-squared	0.9366	DW-statistic	1.6499	
R-squared adjusted	0.9363	Log-likelihood	52.8061	

* Newey-West HAC Standard Errors (lag truncation=4)

Note: The effect of the output gap has been partialled out from the dependent and independent variables in this regression.

TABLE 9

SEMIPARAMETRIC ESTIMATION RESULTS FOR SUB-SAMPLES

Dependent variable: Inflation (Year-on-year) adjusted by nonparametric regression (1st step)

Sub-Sample 1: 1990:07 – 1999:07 (109 observations)

Variable	Coefficient	Std. Error*	t-statistic	p-value
Expected Inflation (-6) [adjusted]	0.1023	0.0488	2.0970	0.0383
Inflation (-1) [adjusted]	0.8613	0.0684	12.6005	0.0000
R-squared	0.9682	DW-statistic	1.6740	
R-squared adjusted	0.9679	Log-likelihood	33.5392	

Sub-Sample 2: 1999:08 – 2008:12 (111 observations)

Variable	Coefficient	Std. Error*	t-statistic	p-value
Expected Inflation (-6) [adjusted]	0.1073	0.0688	1.5591	0.1219
Inflation (-1) [adjusted]	0.8103	0.0431	18.7881	0.0000
R-squared	0.8245	DW-statistic	1.6234	
R-squared adjusted	0.8229	Log-likelihood	25.5625	

* Newey-West HAC Standard Errors (lag truncation=4)

Note: The effect of the output gap has been partialled out from the dependent and independent variables in this regression.

TABLE 10

PARAMETRIC ESTIMATION RESULTS INCLUDING INDUSTRIAL PRODUCTION VERSUS GDP BASED OUTPUT GAP – QUARTERLY MODEL

Sample (adjusted): 1990Q3 – 2008Q4 (74 observations)

Dependent variable: Inflation (Year-on-year)

Output gap based on quarterly euro area GDP

Variable	**Coefficient**	**Std. Error***	**t-statistic**	**p-value**
Constant	0.3802	0.1199	3.1704	0.0023
Inflation Expectations (-2)	0.1390	0.0873	1.5924	0.1158
Inflation (-1)	0.7076	0.1109	6.3813	0.0000
Output Gap (from GDP)	0.1276	0.0549	2.3236	0.0231
R-squared	0.8734	DW-statistic	1.8518	
R-squared adjusted	0.8678	F-statistic	160.7591	
Log-likelihood	-15.8524	p-value (F-stat)	0.0000	

Output gap based on quarterly euro area industrial output

Variable	**Coefficient**	**Std. Error***	**t-statistic**	**p-value**
Constant	0.3098	0.1260	2.4584	0.0164
Expected Inflation (-2)	0.1574	0.0832	1.8908	0.0628
Inflation (-1)	0.7225	0.1132	6.3802	0.0000
Output Gap (based on Ind. Prod.)	0.0621	0.0258	2.4039	0.0189
R-squared	0.8766	DW-statistic	1.8539	
R-squared adjusted	0.8713	F-statistic	165.6932	
Log-likelihood	-14.8739	p-value (F-stat)	0.0000	

* Newey-West HAC Standard Errors (lag truncation=4)

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