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# Variations of the New Keynesian Phillips Curve based on USA data

Bachelor Thesis

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Abstract

Using different frequency filters in a quantile regression framework we uncover some considerable asymmetries across quantiles for the backward and the forward-looking components of the New Keynesian Phillips Curve (NKPC) variations for the USA but no considerable differences among coefficients because of the different filter use. Additionally, we use a rolling regression with the Hodrick-Prescott filter and we find that the NKPC slope has changed during the 2008 financial crisis. We also document a further decline in inflation persistence during the crisis and an increase in the extent to which expected inflation matters in the NKPC.

## 1. Introduction

The New Keynesian Phillips Curve (NKPC) constitutes a key element of the modern macroeconomic analysis used for policy implications by central banks, ministries of finance and international organizations. The Phillips curve was firstly introduced by A. W. Phillips (1958) stating that inflation and unemployment have a stable and inverse relationship. However, the traditional Phillips curve, based on a backward-looking component, has been over the last decades challenged by the so-called NKPC.

Unlike its predecessor, the NKPC states that inflation has also forward-looking dynamics. As has been widely acknowledged, the precise specification of the Phillips curve may have dramatic implications from a central bank perspective. More specifically, a central bank can impose a disinflation policy at no cost in terms of output if inflation is a forward-looking phenomenon, whereas lowering steady-state inflation requires a recession in the context of the traditional, backward-looking Phillips curve.

Most of the empirical literature usually estimates the NKPC coefficients that are evaluated when the level of inflation is at the mean of the distribution conditional on its backward and forward-looking components and the marginal cost or the output gap. In this paper, using a quantile regression framework, we will examine the asymmetry of the responses of inflation across quantiles by using different frequency filters so as to investigate some variations of the NKPC and the extent to which the coefficients of the output gap and the lagged and expected inflation may vary depending on different filters. Additionally, we use a rolling regression with the Hodrick-Prescott filter to assess the stability of the NKPC parameters and see whether its estimates have severely changed because of the financial crisis of 2008.

The paper is organized as follows. In section 2 we will refer to the literature that has been developed regarding filters and the NKPC. Section 3 is devoted to the analysis of the methodology that we will follow in order to obtain our results and section 4 to a brief description of the data we have used. The quantile regression results are presented in section 5 and the rolling regression ones in section 6. Finally, section 7 will summarize our main findings.

## 2. Literature review

The empirical research of the New Keynesian Phillips Curve (NKPC) has received increasing attention among researchers for its implications on inflation dynamics and monetary policy. An intriguing characteristic of the NKPC is that it can be derived from optimal price-setting by firms. The standard New Keynesian Phillips Curve specification is based on Calvo's (1983) model of staggered price setting and it expresses current inflation as a function of expected inflation and real economic activity. In Calvo's model, firms set their price optimally, subject to a constraint on the frequency of price adjustment. However, a number of authors including Fuhrer and Moore (1995) criticize this version of the Phillips curve due to its inability to explain the inflation persistence in the postwar U.S. inflation data.

In this way, many economists have attempted to explain the observed inflation persistence by adding additional inflation lags in the NKPC, calling it a hybrid NKPC (Ball, 2000; Fuhrer and Moore, 1995; Gali and Gertler, 1999; Kozicki and Tinsley, 2001, 2002). The existence of the backward-looking component in the NKPC bears an important policy implication: if the backward-looking component is unimportant, a central bank can costlessly reduce inflation by decreasing the next period's inflation expectation one-for-one without depressing real economic activity. However, based on empirical evidence, the standard view is that the backward-looking component is considerable even though there is no consensus on the relative importance between the forward- and the backward-looking component.

The possibility of different results in the coefficients of the NKPC depending on the frequency filter has not been thoroughly investigated. Christiano and Fitzgerald (2003) in their relevant work for the band pass filter find that shifting power towards a particular frequency range causes the optimal filter to become more accurate in that range, and imposing symmetry in the omitted observations (Optimal Symmetric) results in a relatively small loss of efficiency in the center of the data set, but that loss grows in the tails. Christiano and Fitzgerald (1999) show that their band pass filter dominated the Baxter-King filter (BK) and the improvement when using their filter is not large enough compared to Hodrick-Prescott filter.

Hamilton (2018) infers that the HP filter intends to produce a stationary component, but in practice it can fail to do so, and can impose a great cost since it introduces spurious dynamic relations that have no basis in the true data-generating process. He alternatively proposes his method according to which it preserves the underlying dynamic relations and consistently estimates well-defined population characteristics for a broad class of possible data-generating processes.

Table 1. Frequency filters

| Frequency filters | Abbreviation |
|---|---|
| Baxter-King fixed length symmetric filter | BK |
| Christiano-Fitzgerald fixed length symmetric filter | CF fixed length symmetric |
| Christiano-Fitzgerald full sample asymmetric filter | CF full sample asymmetric |
| Hamilton filter | Hamilton |
| Hodrick-Prescott filter | HP |

As far as the response of inflation is concerned, it has been observed that it reacts differently depending on the part of the distribution being analyzed. Chortareas, Magonis and Panagiotidis (2012) imposed a two-stage quantile regression framework uncovering significant asymmetries across quantiles for all coefficients in an otherwise standard New Keynesian Phillips Curve (NKPC) for the euro area. They find that the coefficient of expected inflation is positive and statistically significant throughout the conditional distribution of inflation. The lagged inflation coefficient is insignificant in the right tail of the distribution of inflation and even when it is significant, it is dominated by the forward-looking component in the middle and the right of the distribution. At low inflation, the backward-looking component appears to dominate the forward-looking one at the first few quantiles.

In another similar work for the euro area it has been shown that the relationship between unemployment and inflation is negative and significant and that the slope has not changed significantly since the Global Financial Crisis (Hindrayanto, Samarina, Stanga, 2018). By using disaggregated data, Luengo-Prado, Rao and Sheremirov (2017) documented a significant decrease in the Phillips curve slope and an increase in the relative weight of forward-looking expectations around 2009–2010.

Literature can be divided as to the dominance of the backward-looking component against the forward looking one (The results are also summarized in Tables 1,2,3). Klein (1978) and Barsky (1987) were among the first to call attention to the dramatic changes in inflation persistence in long-run U.S. data. Fuhrer and Moore (1995) emphasized on the empirical inability of forward-looking specifications to capture inflation persistence and the fact that inflation persistence derives almost exclusively from the persistence in the driving output process. Additionally, Fuhrer (1997), Roberts (1997), Rudebusch (2002) and Linde (2005) find the backward-looking component in the NKPC to be more important. O'Reilly and Whelan (2005) Estrella and Fuhrer (2002) express the inability of the forward-looking component to capture inflation persistence for the euro-area and the USA respectively and Roberts (2005) compares several Phillips curve specifications and obtains a large backward-looking component on US data.

On the other hand, Gali and Gertler (1999), Sbordone (2002,2005) argue for a predominant role of the forward-looking component and Chang-Jin Kim and Yunmi Kim (2008) challenge the significant role of the backward-looking component. Gali, Gertler and Lopez-Salido (2001), find that inflation dynamics in the euro-area are more forward looking compared to USA. As Fuhrer (2010) mentions, with everything else being equal, a change in the relative weights of forward-looking and backward-looking inflation expectation components should be tightly linked to a change in inflation persistence.

Table 2. Summary of backward and forward-looking dominance in the literature

| Paper Title | Authors | Data | Results |
|---|---|---|---|
| The asymmetry of the New Keynesian Phillips Curve in the euro-area. | Chortareas, Magonis and Panagiotidis (2012) | Euro area | Forward-looking component dominance in the middle and the right of the distribution. |
| Sectoral inflation and the Phillips curve: What has changed since the Great Recession? | Luengo-Prado, Rao and Sheremirov (2017) | USA | Increase in the relative weight of forward-looking expectations around 2009–2010. |
| The (un) importance of forward-looking behavior in price specifications. | Fuhrer (1997) | USA | The backward-looking component in the NKPC is more important. |
| Is inflation sticky? | Roberts (1997) | USA | The backward-looking component in the NKPC is more important. |
| Inflation persistence | Fuhrer and Moore (1995) | USA | Inability of forward-looking specifications to capture inflation persistence. |

Table 3. Summary of backward and forward-looking dominance in the literature

| Paper Title | Authors | Data | Results |
|---|---|---|---|
| Assessing nominal income rules for monetary policy with model and data uncertainty. | Rudebusch (2002) | Euro area, USA | The backward-looking component in the NKPC is more important. |
| Estimating New-Keynesian Phillips curves: A full information maximum likelihood approach. | Linde (2005) | USA | The backward-looking component in the NKPC is more important. |
| Has Euro-area inflation persistence changed over time? | O'Reilly and Whelan (2005) | Euro area | Inability of the forward-looking component to capture inflation persistence. |
| Dynamic inconsistencies: Counterfactual implications of a class of rational-expectations models. | Estrella and Fuhrer (2002) | USA | Inability of the forward-looking component to capture inflation persistence.. |
| How well does the New Keynesian sticky-price model fit the data? | Roberts (2005) | USA | Large backward-looking component obtained. |

Table 4. Summary of backward and forward-looking dominance in the literature

| Paper Title | Authors | Data | Results |
|---|---|---|---|
| Inflation dynamics: A structural econometric analysis. | Gali and Gertler (1999) | USA | Predominant role of the forward-looking component. |
| Prices and unit labor costs: a new test of price stickiness. | Sbordone (2002) | USA | Predominant role of the forward-looking component. |
| Do expected future marginal costs drive inflation dynamics? | Sbordone (2005) | USA | Predominant role of the forward-looking component. |
| Is the backward-looking component important in a New Keynesian Phillips curve? | Chang-Jin Kim and Yunmi Kim (2008) | USA | The role of the backward-looking component is seriously challenged. |
| European inflation dynamics | Gali, Gertler and Lopez-Salido (2001) | Euro area, USA | Inflation dynamics in the euro-area are more forward looking compared to USA. |

## 3. Methodology

While the core NKPC is one that does not include a backward-looking component, the NKPC typically estimated is a hybrid one which also includes a backward-looking component as follows:

$$\pi_t = \gamma_b \pi_{t-1} + \lambda y_t + \gamma_f E_t \pi_{t+1}$$

where $\pi_t$ is the inflation rate, $\pi_{t-1}$ is past inflation, $E_t \pi_{t+1}$ is expected inflation and $y_t$ is a variable that captures economic activity which can either be represented by the output gap or the marginal cost. In our case, we use the output gap as a proxy for economic activity.

The weights on lagged inflation and expected future inflation do not necessarily sum up to one as in the model developed by Gali and Gertler (1999). It is worth mentioning that this assumption is not restrictive. In some Generalized Method of Moments (GMM) estimations, it has been estimated that in many cases, $\gamma_b$ and $\gamma_f$ summed up to a value larger than 1, a value that is precluded in theoretical models (Jondeau, Le Bihan, 2005).

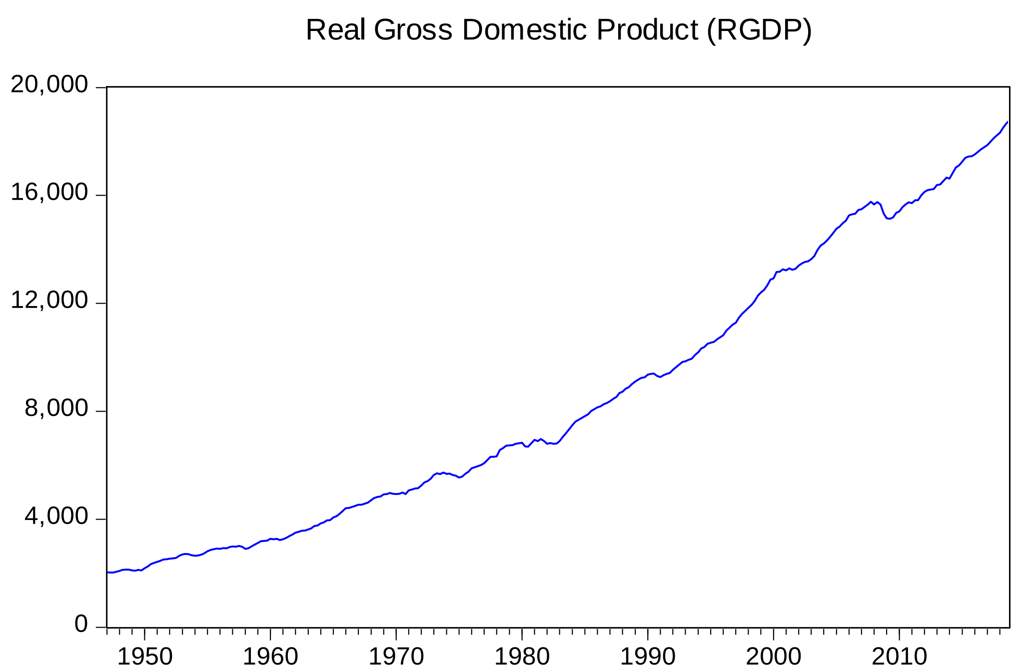


Figure 1. USA Real Gross Domestic Product (RGDP)

As it can be seen in Figure 1, economic activity clearly displays an upward trend during the years with only some minor temporary decreases with the most notable one being in the financial crisis of 2008. What has to be mentioned is the fact that the American RGDP has increased by approximately nine times since 1947.

Moreover, we occasionally use a dummy variable that takes a value equal to one for the fourth quarter of 2008 (2008Q4). The reason we do this is because we want to exclude the outlier that appears at that quarter due to the recent financial crisis that took place in 2007-2009 which can be considered as an extreme event. In this way, we knock out this observation from the sample by forcing the residual for that observation to zero. As it can be seen from Figure 2, the observation corresponding to 2008Q4 for inflation is way of the rest of the data[1]. If we had included the outlier in our sample it is possible that it would have some severe effects on our estimators due to the big penalty they would receive by the increased Residual Sum of Squares (RSS).

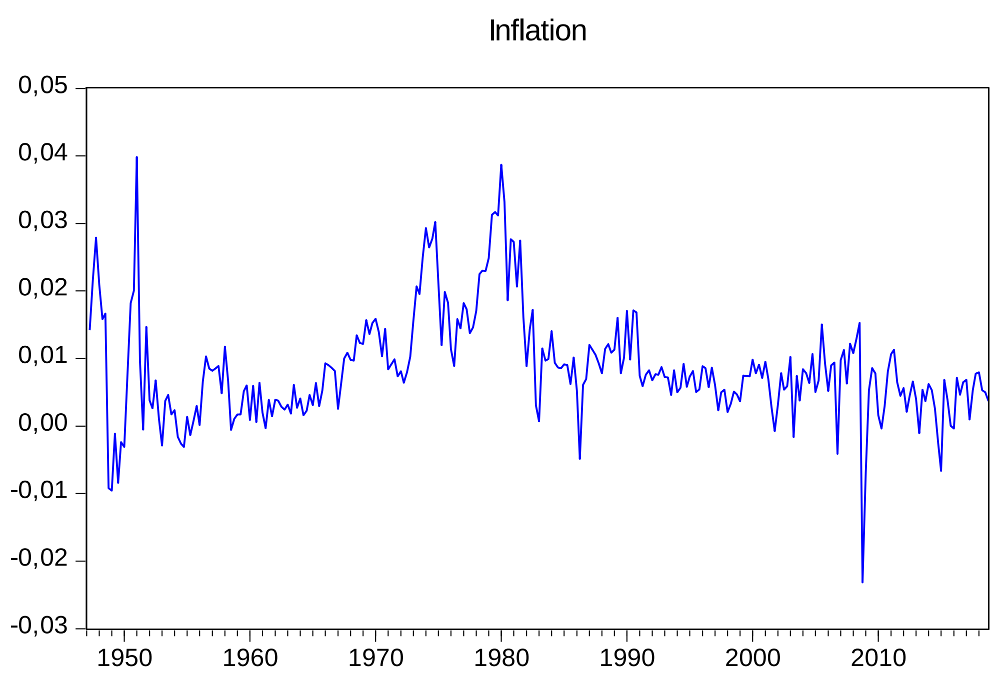


Figure 2. USA inflation 1947-2018

[1] All Figures and parameter estimations have been made via EViews.

However, if we use an OLS regression for our NKPC models with different frequency filters, we will notice that the inclusion of a dummy variable will not give back any improved results compared with the ones without a dummy. In table 5, we can see that the p-values of our estimates are not decreased in their majority, thus not improving our NKPC models. Furthermore, for the quantile regression results, the inclusion of the dummy variable produces significantly better results and estimates of the NKPC only in the case of the output gap with the Baxter-King frequency filter. As it can be seen in Table 6, the p-value of $\gamma_b$ decreases and so does the p-value of $\lambda$, thus leading to a better NKPC model. In every other case, the p-values of the NKPC models are not strongly ameliorated and even in cases of slightly decreased p-values, the rest of them are increased, making the inclusion of the dummy variable harmful and unnecessary for our estimates and models.

Table 5. Estimated results with and without the inclusion of the dummy variable at 2008Q4 with OLS

| | No dummy included | | Dummy included | |
|---|---|---|---|---|
| | Coefficients | p-values | Coefficients | p-values |
| Lagged inflation ($\gamma_b$) | -0.118008 | 0.5429 | -0.096580 | 0.5831 |
| Output gap BK ($\lambda$) | 0.000561 | 0.0125 | 0.000497 | 0.0148 |
| Expected inflation ($\gamma_f$) | 1.133451 | 0.0000 | 1.127321 | 0.0000 |
| Lagged inflation ($\gamma_b$) | -0.106133 | 0.5831 | -0.085239 | 0.6272 |
| Output gap CF fixed length symmetric ($\lambda$) | 0.000606 | 0.0147 | 0.000530 | 0.0188 |
| Expected inflation ($\gamma_f$) | 1.119578 | 0.0000 | 1.114168 | 0.0000 |
| Lagged inflation ($\gamma_b$) | -0.079196 | 0.6715 | -0.057121 | 0.7396 |
| Output gap CF full sample asymmetric ($\lambda$) | 0.000499 | 0.0217 | 0.000419 | 0.0364 |
| Expected inflation ($\gamma_f$) | 1.080516 | 0.0000 | 1.073042 | 0.0000 |
| Lagged inflation ($\gamma_b$) | 0.074034 | 0.7649 | -0.050229 | 0.8221 |
| Output gap Hamilton ($\lambda$) | 0.000005 | 0.5071 | -0.000001 | 0.8609 |
| Expected inflation ($\gamma_f$) | 0.873661 | 0.0049 | 1.064638 | 0.0002 |
| Lagged inflation ($\gamma_b$) | -0.102920 | 0.5813 | -0.080084 | 0.6409 |
| Output gap HP ($\lambda$ | 0.000571 | 0.0062 | 0.000496 | 0.0098 |
| Expected inflation ($\gamma_f$) | 1.104994 | 0.0000 | 1.096650 | 0.0000 |

Table 6. Estimated results with and without the inclusion of the dummy variable at 2008Q4 with quantile regression for θ=0.5

| | No dummy included | | Dummy included | |
|---|---|---|---|---|
| | Coefficients | p-values | Coefficients | p-values |
| Lagged inflation ($\gamma_b$) | 0.107201 | 0.6544 | 0.258892 | 0.2775 |
| Output gap BK (λ) | 0.000697 | 0.0047 | 0.000613 | 0.0198 |
| Expected inflation ($\gamma_f$) | 0.911411 | 0.0003 | 0.759752 | 0.0026 |
| Lagged inflation ($\gamma_b$) | 0.244647 | 0.2966 | 0.297116 | 0.2235 |
| Output gap CF fixed length symmetric (λ) | 0.000766 | 0.0045 | 0.000622 | 0.0327 |
| Expected inflation ($\gamma_f$) | 0.772009 | 0.0019 | 0.716026 | 0.0054 |
| Lagged inflation ($\gamma_b$) | 0.253158 | 0.3264 | 0.268327 | 0.2986 |
| Output gap CF full length asymmetric (λ) | 0.000426 | 0.0945 | 0.000334 | 0.1891 |
| Expected inflation ($\gamma_f$) | 0.762137 | 0.0047 | 0.749596 | 0.0056 |
| Lagged inflation ($\gamma_b$) | 0.299363 | 0.4573 | 0.291187 | 0.4637 |
| Output gap Hamilton (λ) | 0.000001 | 0.9026 | 0.000001 | 0.9902 |
| Expected inflation ($\gamma_f$) | 0.686566 | 0.1540 | 0.709214 | 0.1356 |
| Lagged inflation ($\gamma_b$) | 0.131689 | 0.5922 | 0.156570 | 0.5221 |
| Output gap HP (λ) | 0.000628 | 0.0198 | 0.000597 | 0.0288 |
| Expected inflation ($\gamma_f$) | 0.874239 | 0.0007 | 0.849135 | 0.0009 |

In order to estimate the backward and forward-looking components across the whole distribution, we impose a quantile regression framework which allows us to estimate the marginal effect on inflation across its distribution. Quantile regression was firstly introduced by Koenker and Bassett (1978) and it is based on the minimization of the asymmetrically weighted sum of absolute errors. Let β be a vector with the corresponding coefficients. If we suppose that $y_t$ $\{y_t: t = 1, \dots, T\}$ is a random sample on a random variable Y, then the θth sample quantile, $0 < \theta < 1$, may be defined as any solution to the following minimization problem:

$$\min_{\beta \in \mathbb{R}} = \theta \sum_{t \in \{t: y_t \geq \beta\}} |y_t - \beta| + (1 - \theta) \sum_{t \in \{t: y_t < \beta\}} |y_t - \beta|$$

A generalization of the minimization problem posed above can be shown as follows: By replacing $y_t$ with inflation $\pi_t$ and with $X_t$ being a matrix with all the independent variables we have:

$$\min_{\beta \in \mathbb{R}} = \theta \sum_{t \in \{t: y_t \geq X_t' \beta\}} |\pi_t - X_t'\beta| + (1-\theta) \sum_{t \in \{t: y_t < X_t'\beta\}} |\pi_t - X_t'\beta|$$

For low quantiles, i.e. for $\theta = 0.05, \ldots, 0.45$ of the dependent variable, the observations below the specific quantile are more heavily weighted. The opposite is true for higher quantiles ($\theta = 0.55, \ldots, 0.95$). Minimizing the above equation with respect to $\beta$ is equivalent to a linear programming problem. In this context, the parameter, for example $\lambda$, estimated at the specific quantile $\theta_1$ is interpreted as the change of inflation at this specific quantile (and not at the conditional mean as it happens in OLS) caused by one percent change in the output gap. Similarly, the parameters $\gamma_b$ and $\gamma_f$ are interpreted as the change of inflation caused by one percent change in the forward and backward-looking components. The greater the number of quantiles the researcher estimates the more accurate and precise is the description of the conditional distribution of inflation.

A key issue when it comes to estimate the Phillips curve relates to inflation expectations which are by nature unobservable and not readily measurable. Most studies employ survey-based measures of inflation expectations which may even not be representative (Coibon, Gorodnichenko, Kumar, Pedemonte, 2018) or other methods such as the Generalized Method of Moments (GMM) and the Maximum Likelihood (ML) technique ( Jondeau, Le Bihan, 2005) or the method of the Unobservable Components (UC) (Hindrayanto, Samarina, Stanga, 2018). However, the analysis of the different expectations methods that exist is beyond the scope of this paper and we will not go deeper into the description of each method. In our research we utilize a relatively simpler way to approach expectations' estimates.

Firstly, we use an OLS regression framework where we set inflation as our dependent variable and we use an intercept (α) and past inflation ($\pi_{t-1}$) as our independent variables. The above description can be summarized as follows:

$$\pi_t = \alpha + \delta\pi_{t-1} + e_t$$

From this regression, we take the residuals $e_t$ and subtract them from current inflation observations $\pi_t$. As a result, we are enabled to acquire easily some expectations estimates that we will use for the estimation of the NKPC.

Furthermore, we will use a rolling regression to assess the parameter stability of the NKPC throughout the years and emphasize on the extent to which the parameters have changed since the recent financial crisis. Rolling regressions are often used in time series analysis to assess the stability of the model parameters with respect to time. One way to assess the stability of the model parameters is to compute the parameter estimates over a rolling window with a fixed sample size over the entire sample.

If the parameters are truly constant over the entire sample, then the rolling estimates over the rolling windows will not change much. If the parameters change at some point in the sample, then the rolling estimates will show the extent to which the estimates have changed over time. We use a fixed window size of 40 (10 years) and a step size of 8 (2 years). For the examination of the parameter stability we will use the NKPC estimated with the HP filter output gap.

## 4. Data

In order to estimate the NKPC for the USA it is necessary to collect statistical data of the variables we are interested in. The sample period runs from 1948:Q1 to 2018:Q4 at quarterly frequency. Our data are drawn from the FRED (Federal Reserve Economic Data) database and are all seasonally adjusted.

Inflation is generated by using the logarithmic first differences of Consumer Price Index data (CPI). As a proxy for real economic activity, we use output gap. Output is simply defined as Real Gross Domestic Product (RGDP). A different output gap is estimated for each frequency filter used to estimate the NKPC: The Hodrick-Prescott filter, the Hamilton filter, the Christiano-Fitzgerald fixed length symmetric filter, the Christiano-Fitzgerald full sample asymmetric filter and the Baxter-King fixed length symmetric filter. Theoretically, potential output is the output level that would prevail under fully flexible prices (maximum-efficiency output).

The reason we use frequency filters is because they will enable us to create trend lines that will capture potential RGDP and this will lead to the estimation of the output gap. A positive output gap indicates a high demand for goods and services in an economy and it means that actual output is more than full-capacity output, causing inflation to rise. On the other hand, a negative output gap indicates a lack of demand for goods and services in an economy and that actual output is less than what an economy can produce at full capacity, implying a declining GDP growth rate and potential recession.

To estimate the NKPC we use one inflation lag to capture the backward-looking component or, in other words, lagged inflation, and one inflation lead to capture the forward-looking component or, in other words, the expected inflation.

5. Quantile regression results with different frequency filters

Figure 3 shows the estimation of the output gaps with different frequency filters. As it can be readily observed, the estimations of the output gap with BK filter, the CF fixed length symmetric and full sample asymmetric and HP filter are very close to one another. Only in a few cases does the CF full sample asymmetric output gap slightly deviates from the other three. However, the filter that gives some rather divergent estimates compared to the others is the Hamilton filter. The Hamilton filter estimates are usually a lot higher than the other ones and rarely do they meet the estimates of the other filters. This only occurs in 1973 and at the end of 1979, periods that are well-known for the oil crises that took place back then and 2008 which again coincides with the recent financial crisis.

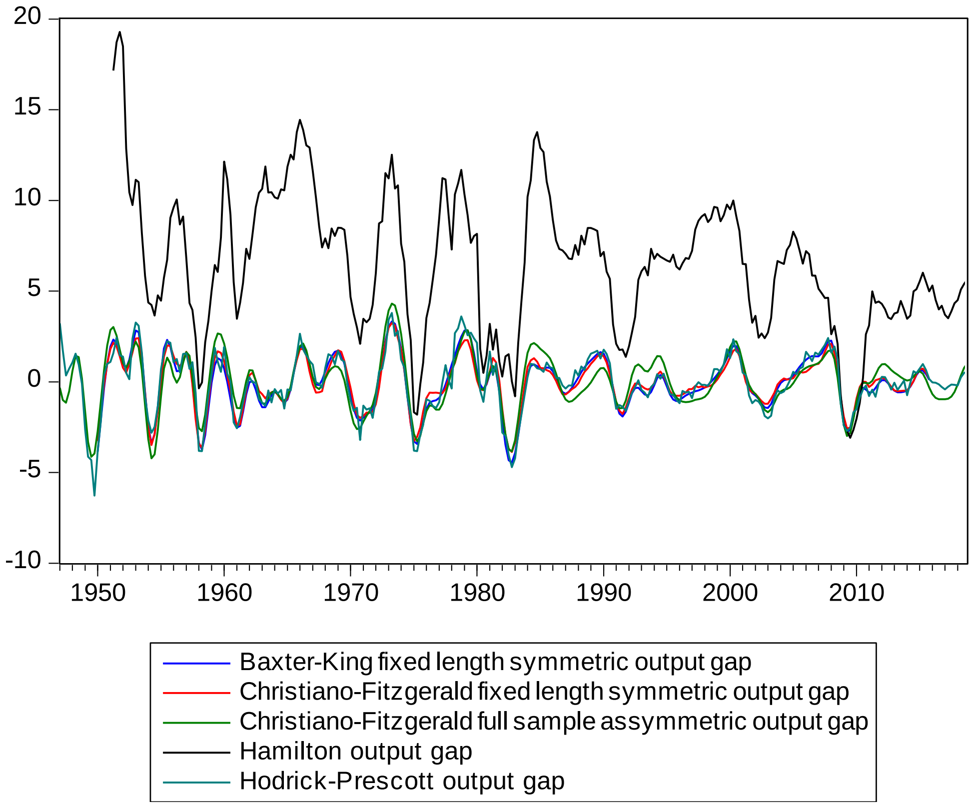


Figure 3. Estimation of output gaps with different filters

We shall now analyze the results of every NKPC, each one with the use of a different filter so as to examine the possible consequences of the different filter usage in NKPC estimates. We specify nineteen quantiles, i.e. for θ = 0.05, 0.1, 0.15, 0.2, ..., 0.9, 0.95.

The results[2] reported in Table 7, referring to the case of BK filter, reveal evidence of asymmetries for the backward and forward-looking components in the NKPC, but not for the output gap. The backward-looking coefficient is statistically significant in the left and the right tail of the distribution and decreases when moving towards the upper tail of the distribution of inflation. At higher quantiles the backward-looking coefficient $\gamma_b$, takes negative values. On the other hand, the forward-looking component is statistically significant at the first two quantiles and for θ = 0.4 and higher. Although in the left tail of

[2] All coefficient variances and covariances are computed using the Huber Sandwich method. The sparsity function is estimated through Kernel residual method using the bandwidth method of Hall–Sheather.

the distribution $\gamma_f$ takes negative values, it takes values greater than one from the middle of the distribution and higher. The output gap ($\lambda$) takes very small values throughout the distribution. While $\lambda$ approaches the median, it becomes statistically significant and when it departs from the median it becomes insignificant. The OLS estimators have some differences compared with the estimators for $\theta = 0.5$. The values of $\gamma_b$ and $\gamma_f$ are lower and higher respectively and the values of the dummy and $\lambda$ are very close to one another.

Table 7. Quantile regression and OLS estimates with the use of Baxter-King filter

| Quantile | $\gamma_b$ | $\gamma_f$ | $\lambda$ | Dummy |
|---|---|---|---|---|
| 0.05 | 1.085081* | -0.941914* | 0.000121 | -0.026995*** |
| 0.1 | 1.070543*** | -0.636939** | 0.000006 | -0.030921*** |
| 0.15 | 0.963237*** | -0.456380 | 0.000234 | -0.031570*** |
| 0.2 | 0.672444** | -0.049631 | 0.000620** | -0.032273*** |
| 0.25 | 0.566426 | 0.132664 | 0.000687*** | -0.033049*** |
| 0.3 | 0.437585 | 0.359661 | 0.000844*** | -0.034001*** |
| 0.35 | 0.484006 | 0.367636 | 0.000771*** | -0.034880*** |
| 0.4 | 0.297827 | 0.598734** | 0.000745*** | -0.035162*** |
| 0.45 | 0.149904 | 0.791996*** | 0.000818*** | -0.035440*** |
| 0.5 | 0.258892 | 0.759752*** | 0.000613** | -0.036843*** |
| 0.55 | 0.048583 | 1.027639*** | 0.000697*** | -0.037161*** |
| 0.6 | -0.099628 | 1.216668*** | 0.000785*** | -0.037363*** |
| 0.65 | -0.260628 | 1.441441*** | 0.000654** | -0.038034*** |
| 0.7 | -0.349496* | 1.595808*** | 0.000738** | -0.038682*** |
| 0.75 | -0.568503*** | 1.893302*** | 0.000647* | -0.039410*** |
| 0.8 | -0.808666*** | 2.213560*** | 0.000390 | -0.040259*** |
| 0.85 | -1.072996*** | 2.586622*** | 0.000008 | -0.041484*** |
| 0.9 | -1.528219*** | 3.230648*** | 0.000104 | -0.043174*** |
| 0.95 | -2.684855*** | 4.669683*** | 0.000265 | -0.044707*** |
| OLS estimators | -0.096580 | 1.127321*** | 0.000497** | -0.036447*** |

Note: * Indicate statistical significance at 10%, ** Indicate statistical significance at 5%, ***Indicate statistical significance at 1%

As it can be seen in Tables 8 and 9, the NKPC with the Christiano-Fitzgerald fixed length symmetric filter does not differ much compared to the Christiano-Fitzgerald full sample asymmetric filter. The backward-looking coefficient in the CF fixed length symmetric case is again statistically significant in the left and the right tail of the distribution and steadily decreases when moving towards higher levels of inflation. At lower quantiles, $\gamma_b$ takes high values close to 1 and decreases as it moves on to higher quantiles. For $\theta \geq 0.6$ $\gamma_b$ takes negative values. The same pattern is observed for the CF full sample asymmetric case. The forward-looking component of the two is significant at the first two quantiles and becomes insignificant as it approaches the median. Nevertheless, the pattern changes at the median and $\gamma_f$ becomes statistically significant for $\theta \geq 0.45$ while it also increases when moving from lower to higher quantiles. They initially take negative values and only for $\theta \geq 0.25$ do they take positive values. Some few differences are displayed in the output gaps. On the one hand, the usage of the CF fixed length symmetric filter leads to statistically significant $\lambda$ for $0.2 \leq \theta \leq 0.75$ while on the other hand $\lambda$ of the CF full sample asymmetric filter is significant for $0.15 \leq \theta \leq 0.5$. In both cases the values of $\lambda$ are quite small and they decrease while moving to the upper tail of the distribution. For $\gamma_b$ and $\gamma_f$ the OLS values are again lower and higher respectively for both filters when compared to the ones provided for $\theta = 0.5$ for the quantile regression. The estimators of $\lambda$ are very close.

Table 8. Quantile regression and OLS estimates with the use of Christiano-Fitzgerald fixed length symmetric filter

| Quantile | $\gamma_b$ | $\gamma_f$ | $\lambda$ |
|---|---|---|---|
| 0.05 | 0.982080*** | -0.893043*** | 0.000148 |
| 0.1 | 1.084830*** | -0.653061** | 0.000163 |
| 0.15 | 0.859589*** | -0.335969 | 0.000463 |
| 0.2 | 0.612941** | -0.003240 | 0.000663** |
| 0.25 | 0.538269 | 0.146103 | 0.000658** |
| 0.3 | 0.463662 | 0.306078 | 0.000901*** |
| 0.35 | 0.500954 | 0.349008 | 0.000771*** |
| 0.4 | 0.376151 | 0.511871 | 0.000831*** |
| 0.45 | 0.174646 | 0.763795** | 0.000846*** |
| 0.5 | 0.244647 | 0.772009*** | 0.000766*** |
| 0.55 | 0.085418 | 0.987590*** | 0.000749** |
| 0.6 | -0.057636 | 1.167938*** | 0.000695** |
| 0.65 | -0.226115 | 1.404425*** | 0.000705** |
| 0.7 | -0.441168** | 1.687532*** | 0.000799** |
| 0.75 | -0.541594** | 1.862606*** | 0.000786** |
| 0.8 | -0.770986*** | 2.172665*** | 0.000491 |
| 0.85 | -1.063314*** | 2.575698*** | 0.000105 |
| 0.9 | -1.398583*** | 3.061688*** | 0.000001 |
| 0.95 | -2.679868*** | 4.664026*** | 0.000269 |
| OLS estimators | -0.106133 | 1.119578*** | 0.000606** |

Note: * Indicate statistical significance at 10%, ** Indicate statistical significance at 5%, ***Indicate statistical significance at 1%

Table 9. Quantile regression and OLS estimates with the use of Christiano-Fitzgerald full sample asymmetric filter

| Quantile | $\gamma_b$ | $\gamma_f$ | $\lambda$ |
|---|---|---|---|
| 0.05 | 1.400476** | -1.319248*** | 0.000375 |
| 0.1 | 1.204884*** | -0.800937*** | 0.000296 |
| 0.15 | 0.907170*** | -0.384969 | 0.000523* |
| 0.2 | 0.790360*** | -0.211549 | 0.000552** |
| 0.25 | 0.660672** | 0.008366 | 0.000567** |
| 0.3 | 0.540075** | 0.222336 | 0.000729*** |
| 0.35 | 0.469041* | 0.345503 | 0.000720*** |
| 0.4 | 0.430762 | 0.447826 | 0.000599*** |
| 0.45 | 0.208469 | 0.725132** | 0.000617*** |
| 0.5 | 0.253158 | 0.762137*** | 0.000426* |
| 0.55 | 0.143516 | 0.908499*** | 0.000415 |
| 0.6 | -0.022590 | 1.119244*** | 0.000457* |
| 0.65 | -0.218927 | 1.398902*** | 0.000400 |
| 0.7 | -0.502992** | 1.750355*** | 0.000495* |
| 0.75 | -0.581145*** | 1.922521*** | 0.000210 |
| 0.8 | -0.753523*** | 2.162719*** | 0.000008 |
| 0.85 | -1.037898*** | 2.543093*** | 0.000009 |
| 0.9 | -1.502127*** | 3.195399*** | 0.000009 |
| 0.95 | -2.670239*** | 4.704152*** | 0.000001 |
| OLS estimators | -0.079196 | 1.080516*** | 0.000499** |

Note: * Indicate statistical significance at 10%, ** Indicate statistical significance at 5%, ***Indicate statistical significance at 1%

Table 10 depicts the results of the NKPC with the use of the Hamilton filter. The backward-looking component decreases as it moves on to higher levels of inflation and it is statistically significant at the lower and the upper tail of the distribution. At lower levels of inflation, and more specifically for $\theta \geq 0.3$, it takes values greater than one and for $\theta \geq 0.6$ it takes negative values. The forward-looking component is statistically significant only at the right tail of the distribution and at the same time it takes values greater than one at these high values of inflation which are even greater than two at very high quantiles such as $\theta = 0.85, 0.9, 0.95$. The output gap is statistically insignificant throughout the distribution and takes very small values which are occasionally negative. The fact that the output gap is insignificant can partly explain the comment that was made at the beginning of this section referring to the rather divergent estimates that are made with the Hamilton filter in comparison with the others. In contrast to the previous cases, the OLS estimators are all increased in comparison to the median values of the quantile regression.

Table 10. Quantile regression and OLS estimates with the use of Hamilton filter

| Quantile | $\gamma_b$ | $\gamma_f$ | $\lambda$ |
|---|---|---|---|
| 0.05 | 1.023402*** | -0.979361*** | -0.000001 |
| 0.1 | 1.047443** | -0.608010 | -0.000006 |
| 0.15 | 1.112342** | -0.647250 | 0.000003 |
| 0.2 | 1.035291** | -0.542293 | 0.000117 |
| 0.25 | 1.045295** | -0.529902 | 0.000166 |
| 0.3 | 1.126030** | -0.549170 | 0.000220** |
| 0.35 | 0.938956* | -0.264753 | 0.000179 |
| 0.4 | 0.580000 | 0.206526 | 0.000126 |
| 0.45 | 0.323789 | 0.601183 | 0.000003 |
| 0.5 | 0.299363 | 0.686566 | 0.000001 |
| 0.55 | 0.168644 | 0.870854* | 0.000001 |
| 0.6 | -0.009482 | 1.097035** | 0.000003 |
| 0.65 | -0.109068 | 1.248293*** | 0.000003 |
| 0.7 | -0.371958 | 1.597738*** | 0.000002 |
| 0.75 | -0.463568 | 1.784905*** | -0.000001 |
| 0.8 | -0.583124* | 1.967924*** | 0.000001 |
| 0.85 | -1.035435*** | 2.568564*** | -0.000006 |
| 0.9 | -1.701267*** | 3.441224*** | -0.000154 |
| 0.95 | -2.661221*** | 4.689693*** | -0.000122 |
| OLS estimators | 0.074034 | 0.873661*** | 0.000005 |

Note: * Indicate statistical significance at 10%, ** Indicate statistical significance at 5%, ***Indicate statistical significance at 1%

Finally, Table 11 shows that the use of the Hodrick-Prescott filter does not seem to differ much with the other filters. The backward-looking coefficient is statistically significant in the left and the right tail of the distribution and takes negative values when moving towards the upper tail. The median is insignificant as is the whole middle part of the distribution for $0.35 \leq \theta \leq 0.65$. Expected inflation is significant for most quantiles with the exception of $0.2 \leq \theta \leq 0.35$. Additionally, $\gamma_f$ rises when moving to higher levels of inflation and takes values greater than two at the highest quantiles. The output gap is statistically significant in the middle of the distribution and takes very small values that are close to 0.

Table 11. Quantile regression and OLS estimates with the use of Hodrick-Prescott filter

| Quantile | $\gamma_b$ | $\gamma_f$ | $\lambda$ |
|---|---|---|---|
| 0.05 | 1.294164** | -1.178089*** | 0.000363 |
| 0.1 | 1.283276*** | -0.885113*** | 0.000454 |
| 0.15 | 0.958395*** | -0.444449* | 0.000402 |
| 0.2 | 0.833945*** | -0.228066 | 0.000633** |
| 0.25 | 0.767867*** | -0.085948 | 0.000799*** |
| 0.3 | 0.540208** | 0.218679 | 0.000871*** |
| 0.35 | 0.403488 | 0.423382 | 0.000694*** |
| 0.4 | 0.393236 | 0.478437* | 0.000635** |
| 0.45 | 0.191728 | 0.750848*** | 0.000780*** |
| 0.5 | 0.131689 | 0.874239*** | 0.000628** |
| 0.55 | 0.097603 | 0.964763*** | 0.000643** |
| 0.6 | -0.072163 | 1.185286*** | 0.000564* |
| 0.65 | -0.282466 | 1.452195*** | 0.000588* |
| 0.7 | -0.412233** | 1.638286*** | 0.000547* |
| 0.75 | -0.712945*** | 2.046498*** | 0.000437 |
| 0.8 | -0.785676*** | 2.199553*** | 0.000007 |
| 0.85 | -1.063404*** | 2.573579*** | 0.000008 |
| 0.9 | -1.583921*** | 3.299968*** | 0.000159 |
| 0.95 | -2.863022*** | 4.911939*** | 0.000590* |
| OLS estimators | -0.102920 | 1.104994*** | 0.000571*** |

Note: * Indicate statistical significance at 10%, ** Indicate statistical significance at 5%, ***Indicate statistical significance at 1%

The results discussed above can all be summarized in Figures 4,5,6,7,8 with each one including information for the BK fixed length symmetric filter, the CF fixed length symmetric filter, the CF full sample asymmetric filter, the Hamilton filter and the Hodrick-Prescott filter respectively.

The above findings suggest that when inflation is high, it is expectations that matter most, since $\gamma_f$ is statistically significant and takes high values at higher quantiles while the backward-looking component, although significant, takes negative values at higher quantiles. At low inflation the backward-looking component dominates the forward-looking one. Not only does $\gamma_b$ take high values that are close to 1 at lower quantiles but $\gamma_f$ is also negative at low inflation rates. Finally, the output gap coefficient ($\lambda$), does not really vary throughout the distribution, exhibiting an overall upward slope at lower quantiles, a zero slope at middle quantiles and a downward slope at higher quantiles.

In the BK filter case, it is worth to analyze the interpretation of the dummy variable values. As already mentioned in section 2, we have used a dummy variable on inflation for the observation corresponding to 2008Q4 which is an outlier as shown in Figure 2. What Figure 4 and Table 7 depict, is that the dummy variable takes negative values for all 20 quantiles included in the survey that are all statistically significant. The dummy values steadily decrease when moving from lower to higher quantiles. The interpretation of the dummy variable can be made as follows: Let us take the case of the median (θ =0.5) where the value is equal to -0.036843. This means that during the crisis, ceteris paribus, the mean value of inflation in the USA decreased by almost 3.7%.

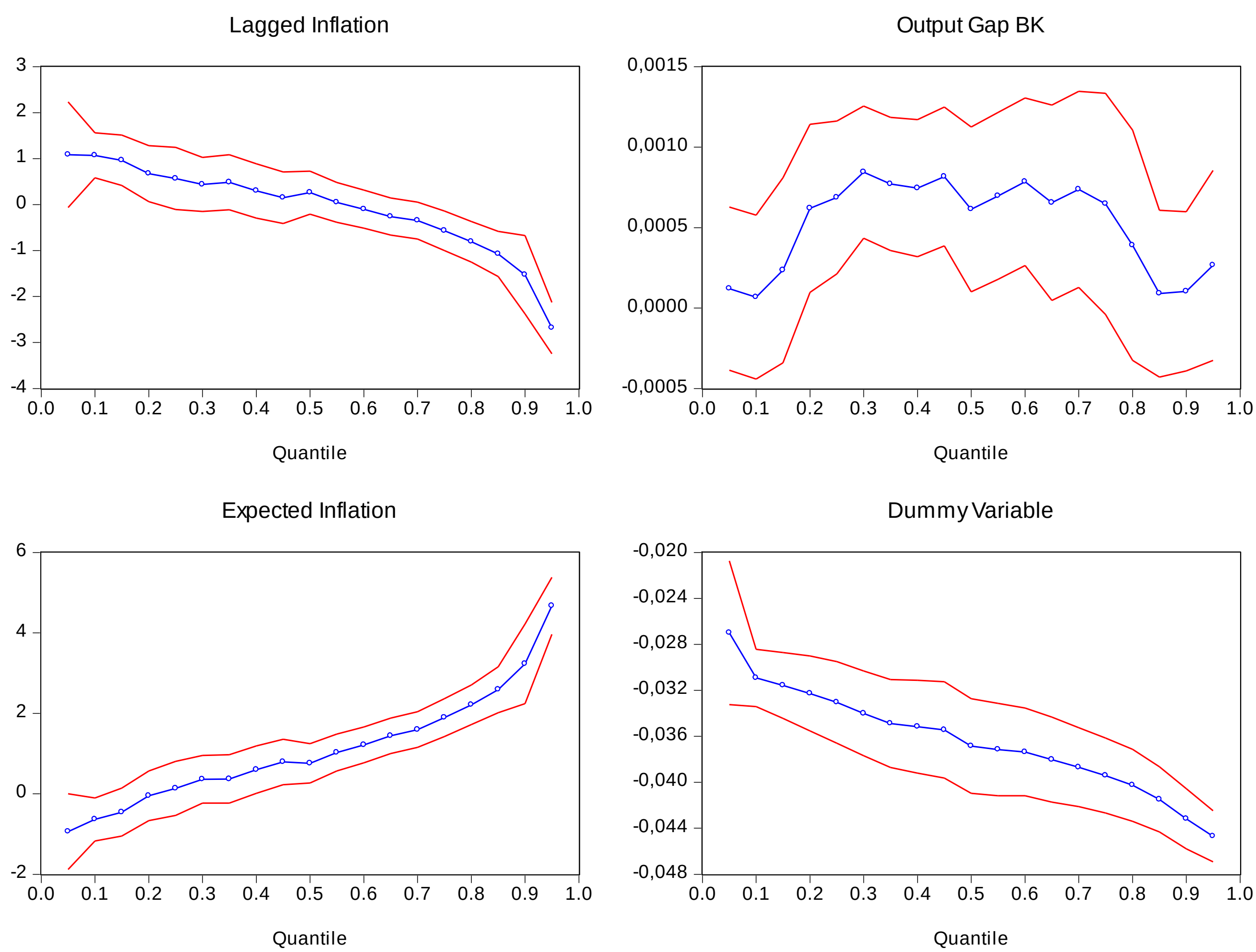


Figure 4. Quantile estimates across quantiles in a 95% confidence interval with the Baxter-King filter

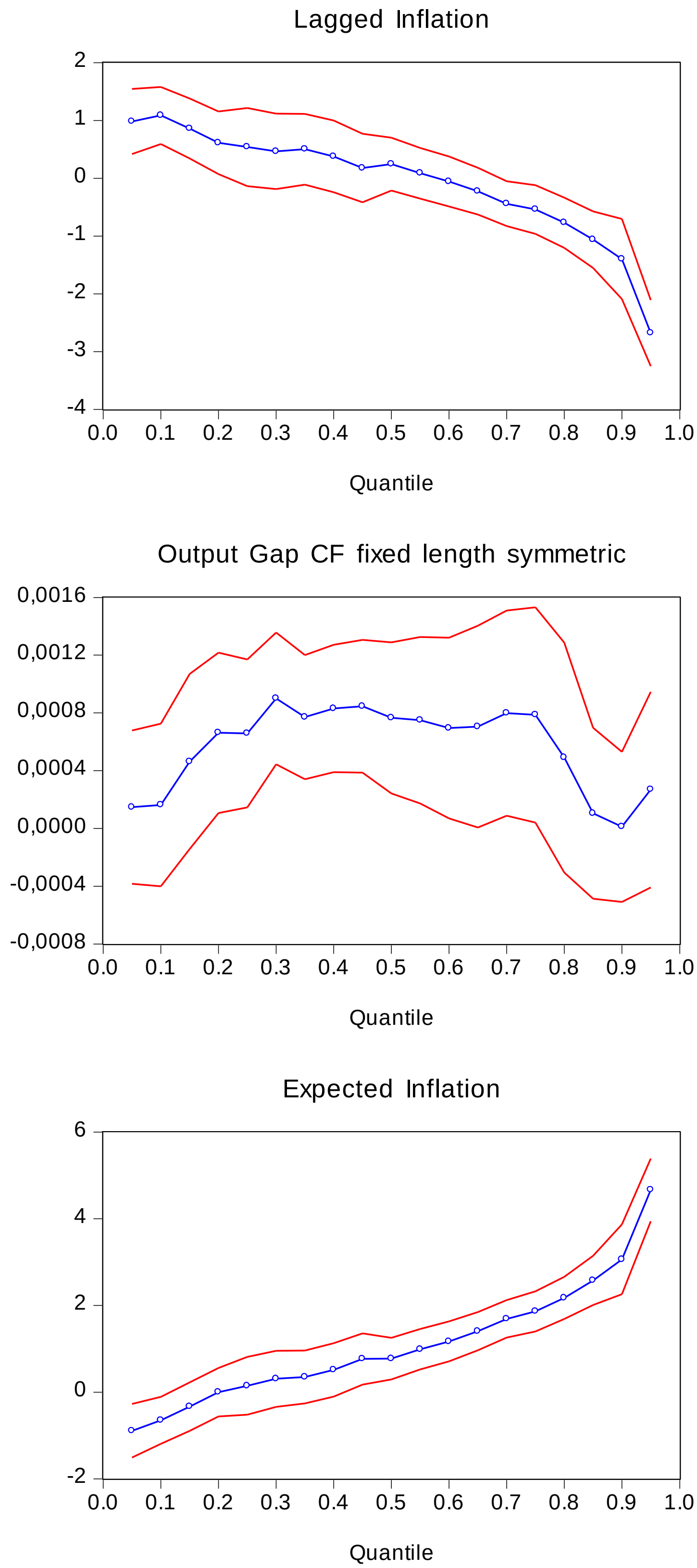


Figure 5. Quantile estimates across quantiles in a 95% confidence interval with Christiano-Fitzgerald fixed length symmetric filter

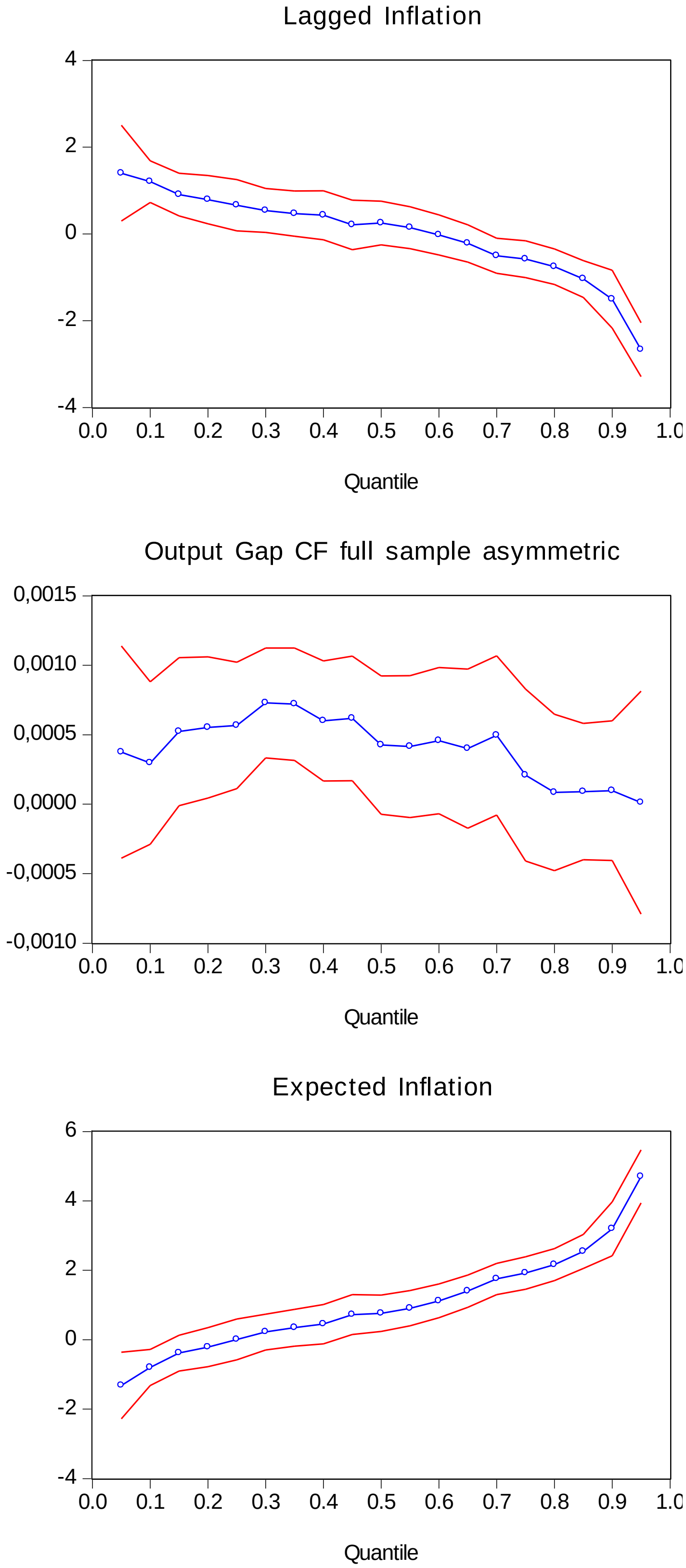


Figure 6. Quantile estimates across quantiles in a 95% confidence interval with Christiano Fitzgerald full sample asymmetric filter

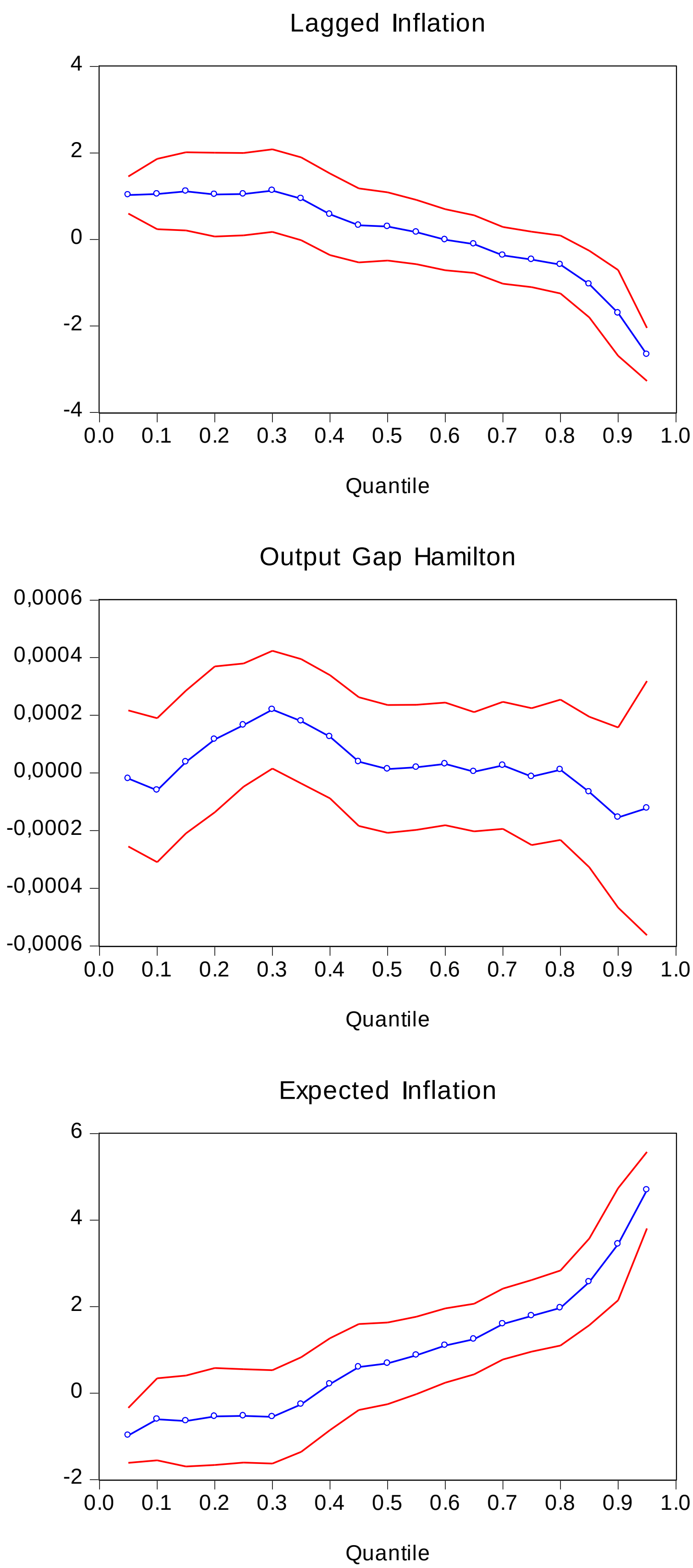


Figure 7. Quantile estimates across quantiles in a 95% confidence interval with Hamilton

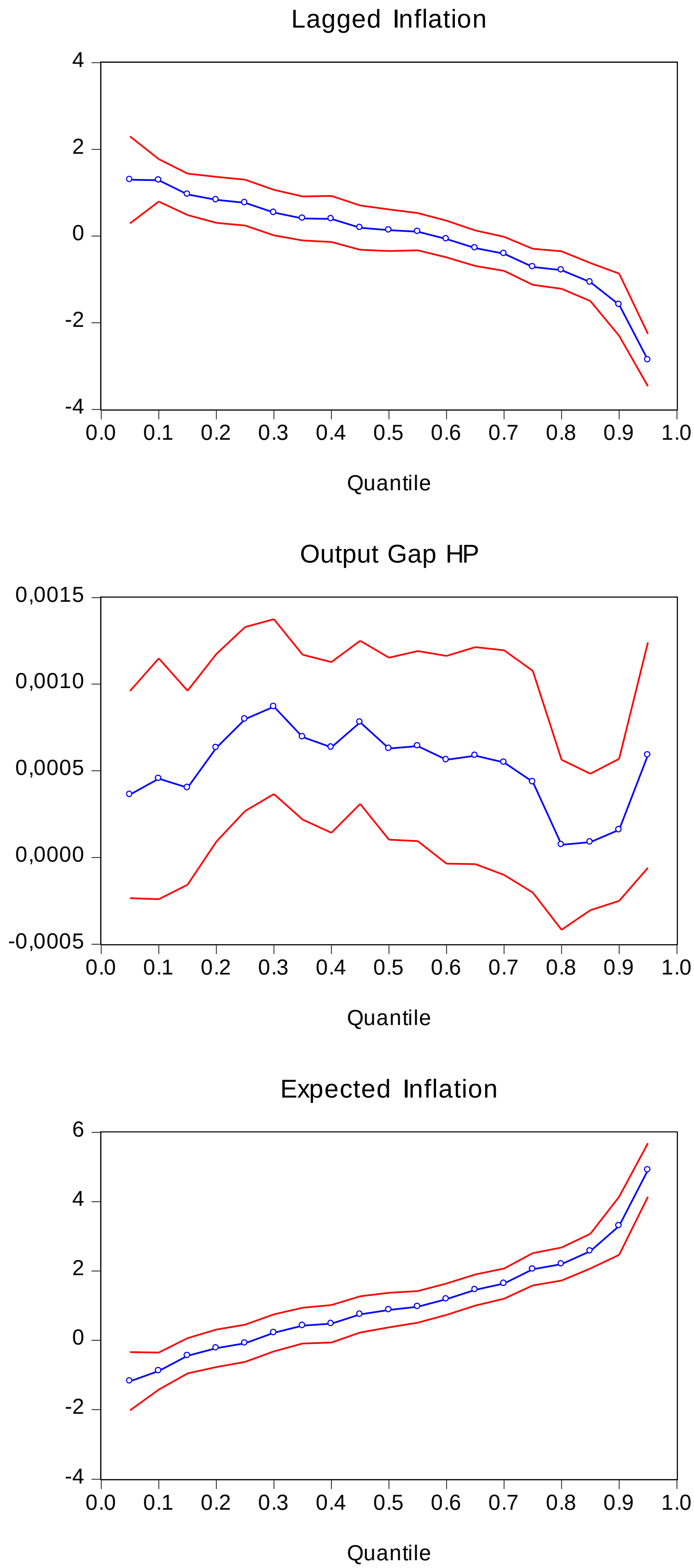


Figure 8. Quantile estimates across quantiles in a 95% confidence interval with Hodrick-Prescott filter

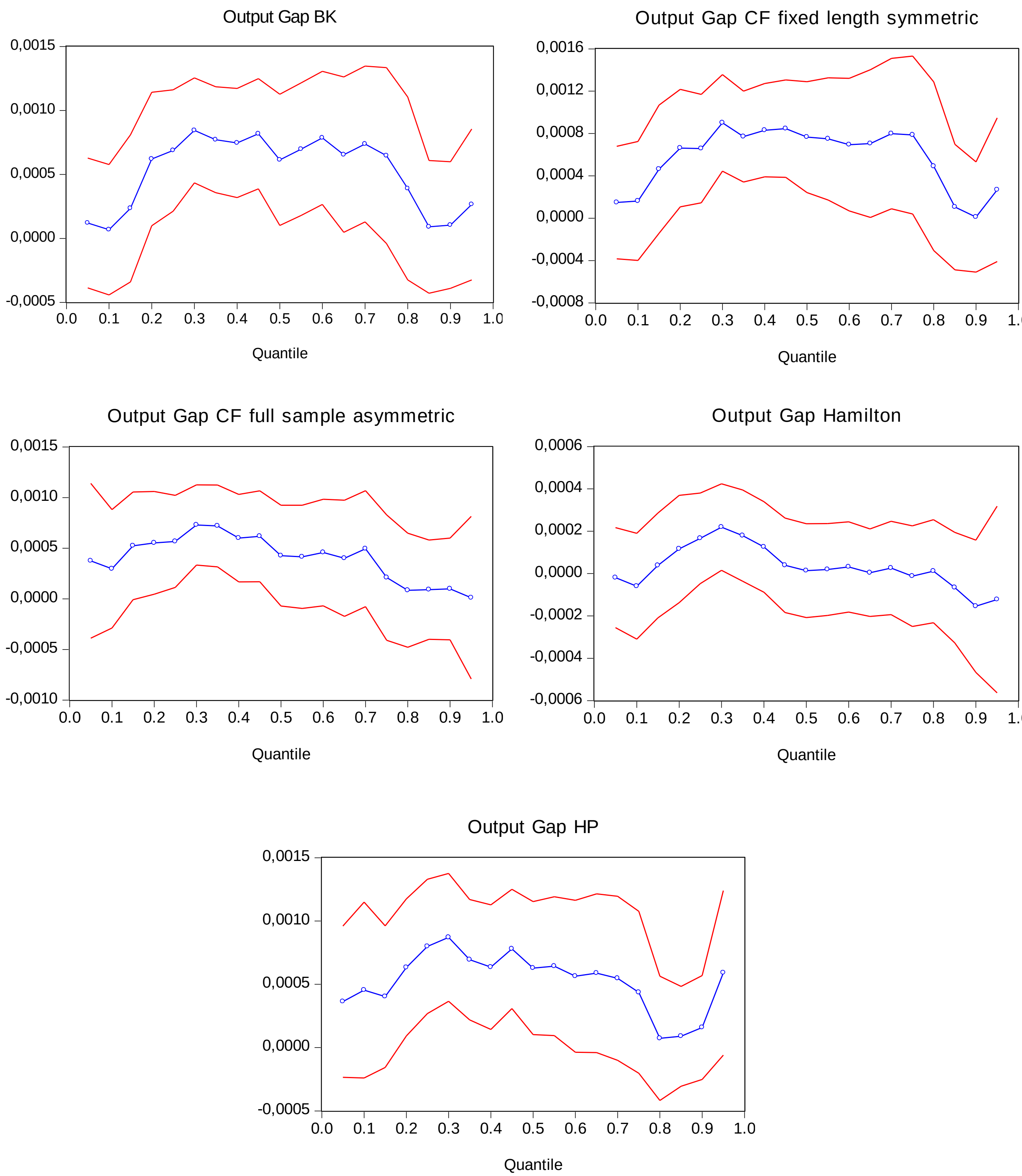


Figure 9. Output Gaps with different frequency filters

In Figure 9 we can have a closer look at all the output gaps that we estimated with different frequency filters. In general, our findings do not reveal important asymmetries for the five different output gaps. They all range to certain limited levels that are always close to 0, implying that the output gap does not really affect the NKPC even when these values are statistically significant which happens mostly at middle quantiles.

The filters that produce the highest output gap values are the BK filter, the CF fixed length symmetric filter and the Hodrick-Prescott filter with values close or even above 0.0008. On the other hand, the CF full sample asymmetric filter produces slightly lower values when we compare them with the ones of the filters already mentioned. Finally, the use of the Hamilton filter yields some very low values that do not exceed 0.0002 which is also the only statistically significant values given by this filter. Therefore, as has already been discussed earlier in this section, the Hamilton filter gives us some rather different results when compared to the other ones.

6. Rolling regression results

In Figure 10 we can see the rolling regression coefficients of lagged inflation ($\gamma_b$), output gap ($\lambda$) and expected inflation ($\gamma_f$). Table 12 summarizes the above results and includes the levels of statistical significance of these estimates. The fixed window size we have used is 40 (10 years) and the step size is 8 (2 years).

What can be observed is that at the beginning of our sample $\gamma_b$ takes values that are very close to zero. However, in the mid-1970s, a huge drop in the value of $\gamma_b$ occurs which is continued until 1984., coinciding with the era of the oil crisis. As far as the 2007-2009 financial crisis is concerned, again a large decline in the estimate of $\gamma_b$ is being found, implying that inflation persistence over that period severely declined.

The output gap dynamics indicate that the recent financial crisis was the reason for a radical change in the NKPC slope. In 2008, a huge increase in the estimate of the output gap ($\lambda$) occurs which shows that the crisis strongly affected inflation dynamics over that period. Apart from that, another interesting finding is that, although $\lambda$ was not statistically significant until 2008, it became significant at the time of the crisis demonstrating in this way the importance of the crisis event and its impact on inflation dynamics.

Finally, the forward-looking component $\gamma_f$ corroborates our previous findings regarding the backward-looking component $\gamma_b$. In the mid-1970s, $\gamma_f$ strongly increases from a value of 0.27 to 1.12 and takes even values that are greater than 3 in 1982 and 1984. After that period, $\gamma_f$ remained in high levels and in the era of the 2008 financial crisis it further increased from a value of 2.6 in 2006 to 3.9 in 2008. During the whole period, and especially after the mid-1970s, $\gamma_f$ was highly statistically significant.

The rolling R-squares exhibited in Figure 12 reveal some very unpredictable dynamics. Although the R-squares initially take very low values even below 0.2, they increase abruptly in 1970 and take values that are close to 0.7 until the end of 1980s. Subsequently however, they abruptly decline again to reach values even below 0.1 in 2007. The R-square of the NKPC was not seriously affected by the 2008 financial crisis.

All the above results can be summarized as follows: lagged inflation does not affect current inflation as much as it used to. As a result, inflation persistence has declined throughout the years and it further decreased when the 2008 financial crisis occurred. The output gap exhibited a radical change in 2008 implying that the NKPC slope was modified over that period and it also began to be statistically significant. Furthermore, expected inflation is becoming more and more crucial for the NKPC and became even more important during the crisis since $\gamma_f$ took its highest value in 2008. The crisis was not portrayed in the rolling NKPC R-square since it did not really change compared to values before 2008.

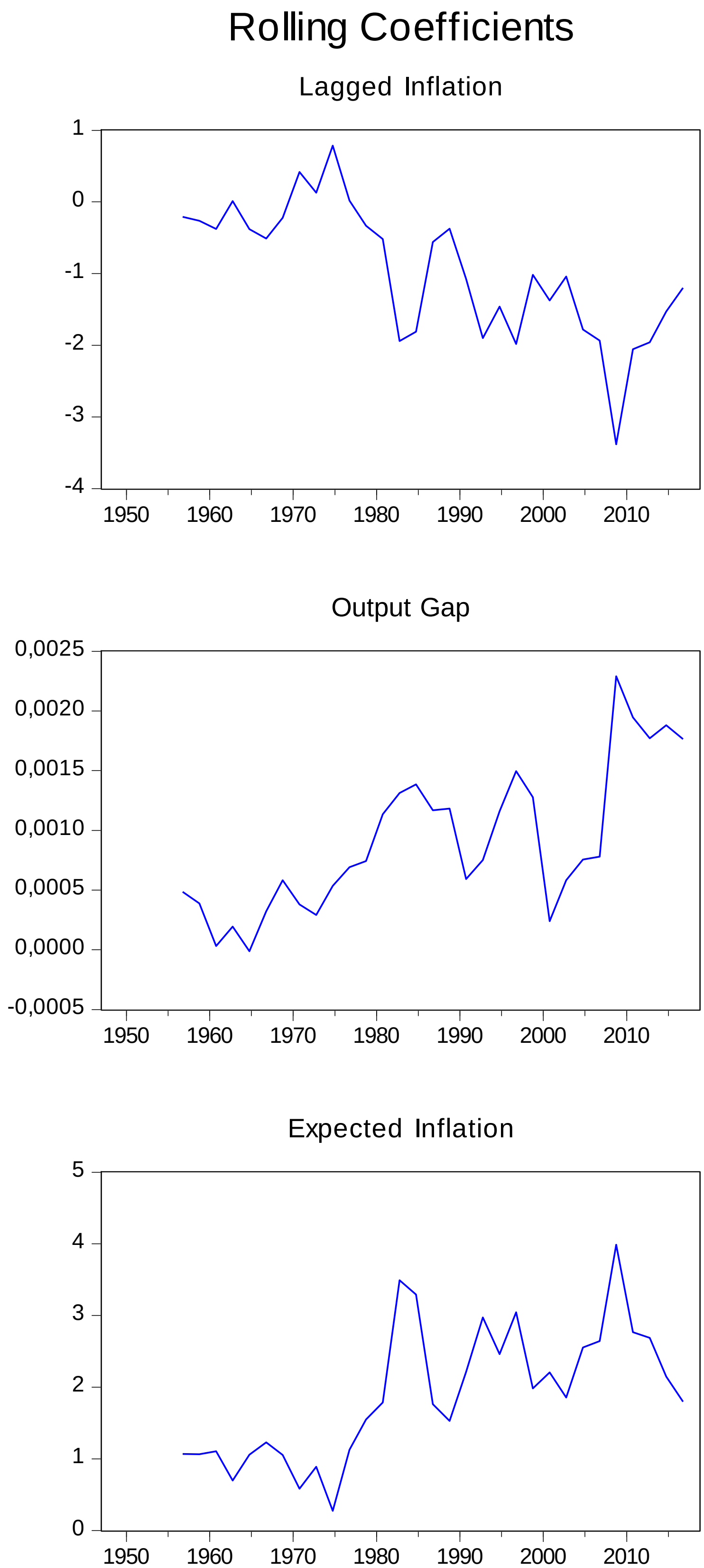


Figure 10. Rolling coefficients with the use of Hodrick-Prescott filter

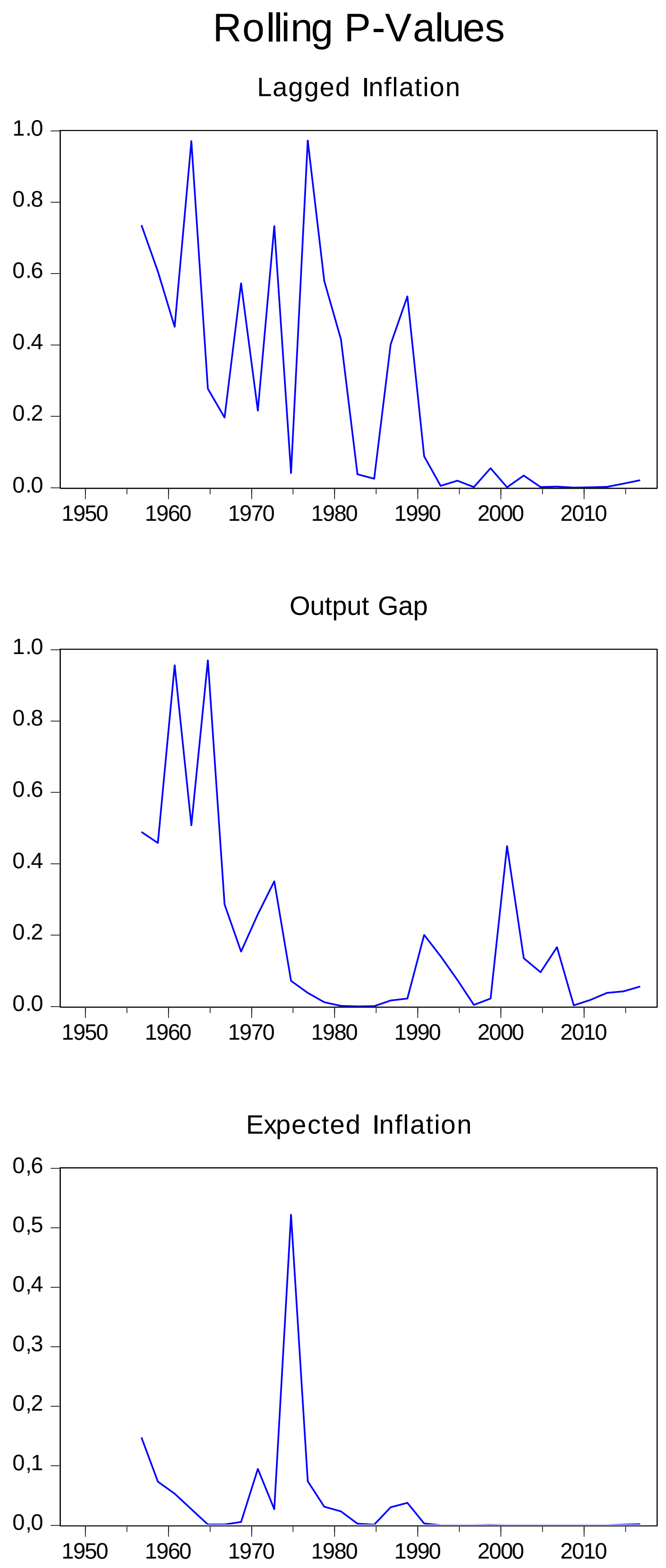


Figure 11. Rolling p-values of the coefficients

Table 12. Rolling coefficients for window size 40 (10 years) and step size 8 (2 years)

| Date | $\gamma_b$ | $\lambda$ | $\gamma_f$ |
|---|---|---|---|
| 1956 | -0.209671 | 0.000485 | 1.066366 |
| 1958 | -0.263136 | 0.000389 | 1.063410* |
| 1960 | -0.376306 | 0.000003 | 1.104413* |
| 1962 | 0.011889 | 0.000193 | 0.694703** |
| 1964 | -0.380083 | -0.000001 | 1.058517*** |
| 1966 | -0.512956 | 0.000323 | 1.230328*** |
| 1968 | -0.223632 | 0.000583 | 1.055295*** |
| 1970 | 0.416686 | 0.000381 | 0.583655* |
| 1972 | 0.127254 | 0.000292 | 0.889049** |
| 1974 | 0.783597** | 0.000536* | 0.272040 |
| 1976 | 0.018180 | 0.000691** | 1.124493* |
| 1978 | -0.330949 | 0.000743** | 1.547873** |
| 1980 | -0.517918 | 0.001134*** | 1.786279** |
| 1982 | -1.940605** | 0.001313*** | 3.491964*** |
| 1984 | -1.811602** | 0.001385*** | 3.292396*** |
| 1986 | -0.557790 | 0.001169** | 1.763896** |
| 1988 | -0.374277 | 0.001182** | 1.530185** |
| 1990 | -1.076738* | 0.000593 | 2.211421*** |
| 1992 | -1.900124*** | 0.000752 | 2.972593*** |
| 1994 | -1.461654** | 0.001161* | 2.460034*** |
| 1996 | -1.982006*** | 0.001496*** | 3.043884*** |
| 1998 | -1.017628* | 0.001277** | 1.984135*** |
| 2000 | -1.375504*** | 0.000241 | 2.206704*** |
| 2002 | -1.039226** | 0.000582 | 1.855483*** |
| 2004 | -1.781923*** | 0.000756* | 2.552149*** |
| 2006 | -1.934808*** | 0.000781 | 2.642912*** |
| 2008 | -3.383258*** | 0.002290*** | 3.986046*** |
| 2010 | -2.055288*** | 0.001946** | 2.764948*** |
| 2012 | -1.959226*** | 0.001771** | 2.687840*** |
| 2014 | -1.527716** | 0.001880** | 2.146484*** |
| 2016 | -1.197728** | 0.001765* | 1.795847*** |

Note: * Indicate statistical significance at 10%, ** Indicate statistical significance at 5%, ***Indicate statistical significance at 1%

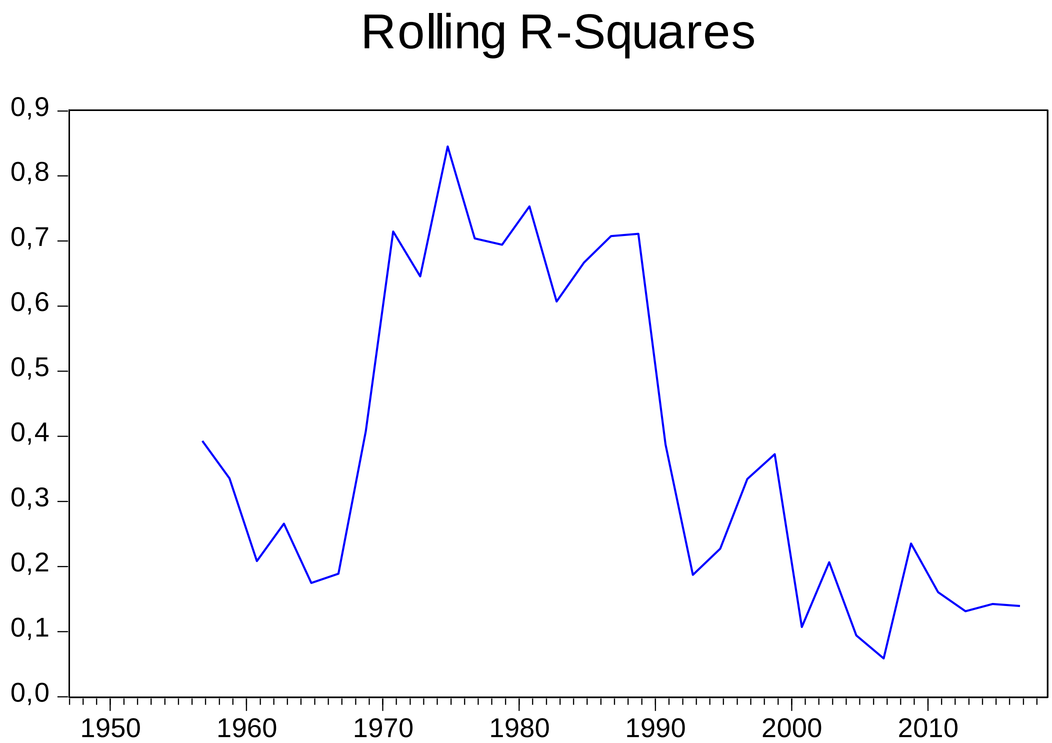


Figure 12. Rolling R-Squares of every period

7. Conclusions

We use different frequency filters in a quantile regression framework to estimate variations of the New Keynesian Phillips Curve (NKPC). We find that when inflation ranges at high levels, it is expectations that matter, since $\gamma_f$ is statistically significant and takes high values at higher quantiles while the backward-looking component is insignificant and negative at higher quantiles. At low inflation rates the backward-looking component dominates the forward-looking one. The coefficient $\gamma_b$ takes high values that are close to 1 at lower quantiles and $\gamma_f$ is negative at low inflation rates. Finally, the output gap coefficient, $\lambda$, does not really vary throughout the distribution, exhibiting an overall upward slope at lower quantiles, a zero slope at the middle quantiles and a downward slope at higher quantiles.

Despite the asymmetries indicated in lagged and expected inflation, the output gaps do not show any important asymmetries throughout the sample. Furthermore, the use of different filters does not particularly change the coefficients, the signs or the levels of statistical significancy across quantiles. The only noticeable difference comes when we use the Hamilton filter which produces the highest output gap but when it enters the NKPC the statistical significance of $\lambda$ is further diminished.

When it comes to rolling regression estimates, we come to the conclusion that inflation persistence has severely declined since $\gamma_b$ more negative as we approach 2008 when it decreased even more. The output gap showed a radical change in 2008 implying that the NKPC slope was modified over that period and it also began to be statistically significant while it was not previously. Finally, the forward-looking component of the NKPC is becoming more and more important for the NKPC estimation exhibiting a noticeable increase in 2008 by reaching its highest level.

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