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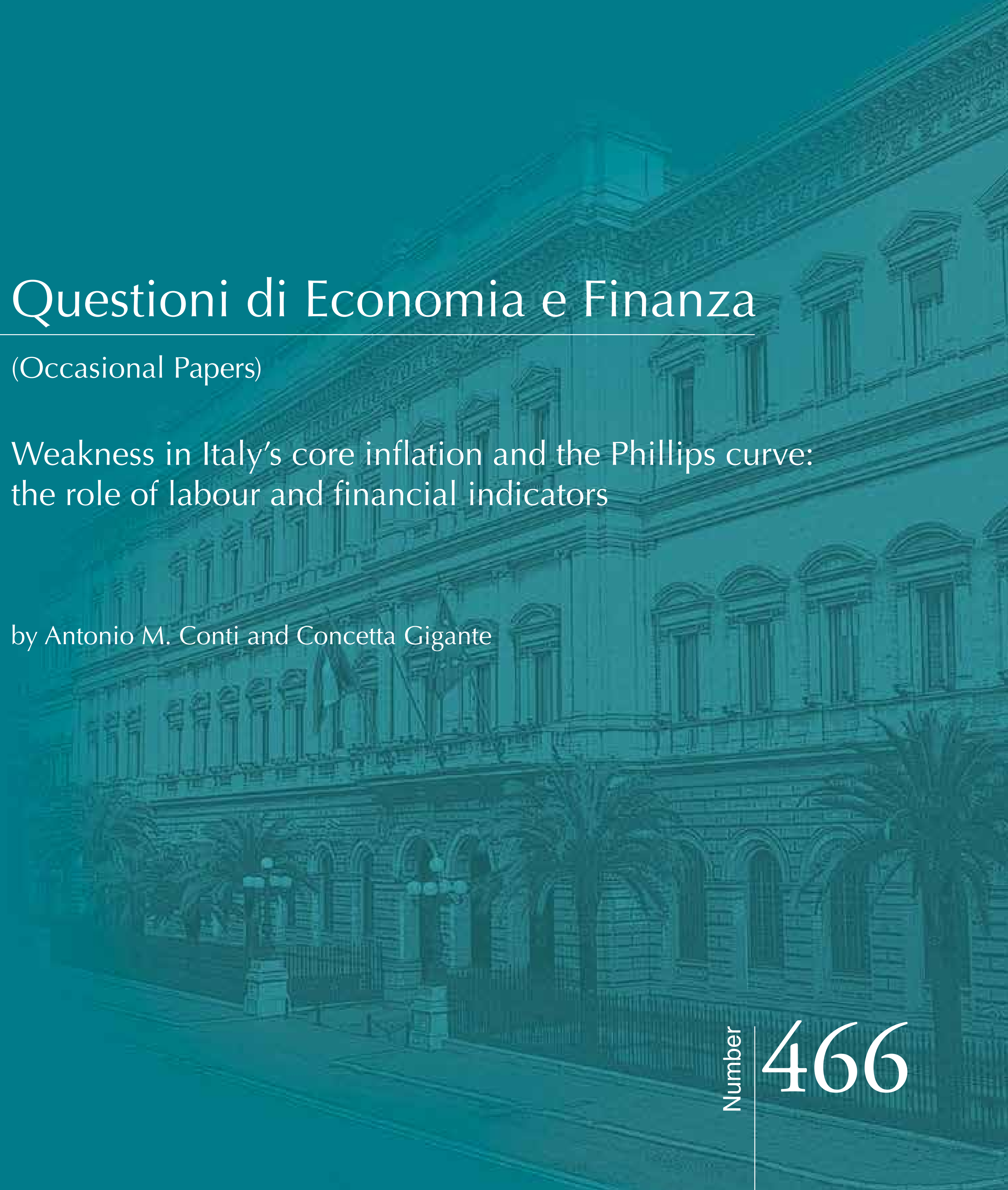

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WEAKNESS IN ITALY'S CORE INFLATION AND THE PHILLIPS CURVE: THE ROLE OF LABOUR AND FINANCIAL MARKET INDICATORS

by Antonio M. Conti[♦] and Concetta Gigante**

Abstract

We investigate the dynamics of core inflation in Italy, with a special focus on the period of low inflation after 2014, and through the lens of a Phillips curve framework. Composite indicators for the Italian labour and financial markets are constructed and included in a Phillips curve. Several results emerge from the empirical analysis. First, a statistically significant trade-off between core inflation and economic activity is observed, especially when measures of slack are derived from labour market variables. Second, financial indicators can help to better characterize the dynamics of core inflation. Third, when controlling for financial indicators, the slope of the Phillips curve turns out to be flatter, except for when it is measured by the amount of slack based on broad labour market conditions. Fourth, a steepening in the Phillips curve emerges in the aftermath of the Global Financial Crisis, while a stabilization is evident at the end of the sample. Fifth, non-linear techniques suggest that the weakness in core inflation may be especially dependent both on the level of labour market tightness and on that of trend inflation. These findings have non-negligible implications for modelling and forecasting inflation dynamics in Italy.

JEL Classification: C32, E32, E50.
Keywords: low inflation, Phillips curve, labour markets, financial stress, time variation.

Contents

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1 Introduction[1]

Inflation developments in advanced economies have puzzled economists and policymakers since 2008–09: deflation was milder than implied by the degree of the slack in the economy caused by the Global Financial Crisis, before falling persistently below central banks and professional forecasters expectations since 2012. The first puzzle, labeled as *missing deflation*, and the second one, *missing inflation*, have been thoroughly investigated using a wide set of theoretical and empirical tools (see, for example Watson, 2014; Del Negro *et al.*, 2015 and the references in Siviero and Neri, 2015 and Ciccarelli and Osbat, 2017). The literature has pointed at global and financial factors as the main explanation for the missing deflation, while de-anchoring in expectations and domestic factors have prevailed in explaining missing inflation (Gilchrist *et al.*, 2017; Coibion and Gorodnichenko, 2015).[2]

This strand of literature has been accompanied by a more specific debate, also pre–existing the low inflation period, on the usefulness of the Phillips curve for describing and forecasting inflation. In particular, a flattening of the Phillips curve since the early 60s has been documented (Blanchard *et al.*, 2015). However, evidence of a more recent steepening after the recent crises has been provided by Riggi and Venditti (2015). Such non–trivial shifts in the relation between inflation and economic activity, coupled with disappointing inflation dynamics in spite of the economic recovery, triggered the investigation of whether the Phillips curve was "dead" (Ball and Mazumder, 2014; Coibion and Gorodnichenko, 2015; Laseen and Sanjani, 2016; Bobeica and Jarocinski, 2017; Szafranek, 2017). While these authors conclude that the Philips curve is alive, a higher inflation has still failed to materialize notwithstanding strong improvement in economic dynamics and labour market outlook in the main areas of the World economy, also owing to a period of extraordinary monetary stimulus[3].

In this paper we investigate the determinants of the weakness in core inflation in Italy devoting a particular attention to the developments in labour and financial markets variables, hence adding to the aforementioned growing literature. The Italian economy looks particularly suitable to studying this question, as since 2008–09 it experienced a series of financial shocks which triggered a severe deterioration in economic activity and the labour market. Only since 2014 the latter trend in labour markets has been reverted, and more favorable conditions emerged, both in terms of employment and unemployment rates; by contrast, wage dynamics has remained subdued, contributing to a disappointing performance of core inflation, which still hovered below 1% on average in 2017. Interestingly, a recent analysis conducted by the staff of the Eurosystem has casted doubts on the usefulness of the Phillips curve for describing core inflation in Italy, as a range of different specifications based on this macroeconometric tool is not able to capture a relevant trade–off between prices dynamics and economic activity: in

[1]We are particularly indebted with Roberta Zizza for her guidance during this project and with Raffaella Nizzi, Anna Maria Stellati, and Silvia Tamburrano for helping us in assembling the dataset. We would also like to thank Chiara Osbat for her discussion at the Workshop on "Assessing the performance of the Italian economy: Demand and supply factors" and Simone Auer, Gaetano Basso, Francesco D'Amuri, Alberto Locarno, Stefano Neri, Sergio Santoro, Federico M. Signoretti, Stefano Siviero and Francesco Zollino for useful comments and insights. Part of this work was conducted while Concetta Gigante was intern at the Economic Outlook Division under the Bonaldo Stringher program. All remaining errors are the authors' own responsibility.

[2]Conti *et al.* (2015) provide a thorough investigation of the structural shocks driving core inflation downwards in the euro area as a whole as well as in its major countries.

[3]Yellen (2015) discusses the role of monetary policy in a low inflation environment; Conti (2017) uses a Bayesian VAR model to study the conduct of the FED monetary policy and its implications for the dynamics of US core inflation and wage growth.

fact, the dynamic predictions of core inflation lie systematically above the actual values since 2012:Q1, until 2016:Q2, the last available period in the report (see Figure 1; Ciccarelli and Osbat, 2017).

To simultaneously address our research questions on the role of labour and financial factors for weakness of core inflation and the soundness of the Italian Phillips curve, we use a factor-augmented Phillips curve framework, similar in spirit to Eickmeier and Pijnenburg (2013) and Albuquerque and Baumann (2017). We first build labour market and financial conditions indices for the Italian economy and we then use them to assess their contribution to the dynamics of core inflation in Italy. We start by a simple fixed–coefficients Phillips curve, and then we allow for time–varying coefficients and state–dependent slope, in order to test some possible conjectures proposed in the literature.

The main results are the following. As for the composite indicators, the first two common factors, labeled *level of activity* and *momentum* explain around 60% of the variance in the Italian labour market, 20 percentage points less than the analogous Kansas City Index for the US economy (Hakkio and Willis, 2013, 2014), hence signalling a bigger idiosyncratic component. These two indicators are correlated with the unemployment rate and the growth rate in hours worked, respectively. Moving to financial conditions, the first two factors explain around 80% of the variance, and they are basically correlated with the monetary policy rate and measures of financial stress, such as credit spreads and the CISS. Moving to the Phillips curve, we show that this relation is alive for the Italian economy, as it holds in a fixed coefficients framework according to a number of measures of slack. However, when controlling for financial indicators, only the specifications based on composite indicators extracted from the labour market keep holding. This reveals (i) a strong correlation between the size of the slack in economic activity and financial conditions and (ii) the importance of looking at a broad number of labour variables instead of relying on the unemployment rate only. Moreover, a conditional forecasting exercise shows that the labour market composite indicator (LMCI) explains core inflation dynamics better than either the unemployment gap or output-gap. When allowing for time–varying coefficients, a steepening in the slope of the Phillips curve is observed after 2008. However, when including financial variables the slope tends to flatten, especially at the end of the sample. Non linear estimation suggest that weakness in core inflation may be dependent on the level of labour market tightness, proxied by the level of the unemployment rate and of trend inflation especially. These specifications, however, only partially improve with respect to linear models.

Overall, we retain these broad messages: when trying to explain core inflation in Italy since 2012 it is important to account for a broad set of labour and financial indicators, possibly combining them to derive a vast grid of conditional forecasts.

The remainder of the paper is as follows. In Section 2 we build the labour and financial conditions composite indicators, while in Section 3 we move to estimate linear fixed coefficients Phillips curves. Section 4 presents the non–linear extensions, while in Section 5 we conclude and discuss some possible directions for future research.

2 Building Composite Indicators

In this Section we construct labour Market Conditions Indicators (LMCI) for the Italian economy, borrowing from what has been recently done for the US economy by the Kansas City Fed

(Hakkio and Willis, 2013, 2014)[4]. This indicators are meant to summarize the health of the US labour market as depicted by a broad set of variables. We then apply the same methodology to the financial dataset in order to derive Financial Conditions Indicators (Hakkio and Keeton, 2009).

2.1 Methodology

The labour market conditions indicator is built by means of principal components analysis (PCA), applied to a bunch of possibly relevant labour market variables. Our strategy follows the approach pursued by Hakkio and Willis (2013, 2014), which look at by 24 US monthly variables to derive two synthetic measures of US labour market, one gauging the *level* – i.e. the *stance* – and the other the *change* – i.e. the *speed of improvement* – of labour activity. The PCA models the variance structure of the dataset by obtaining synthetic indicators which can be interpreted as a common signal. The derivation is pretty standard, and it is briefly sketched in the following lines. In particular, we assume that each stationary time series x_{it}, $i = 1, \ldots, n$ and $t = 1, \ldots, T$, where n is the number of variables and T is the sample length, is written as the sum of two mutually orthogonal unobservable components which account for the two sources of fluctuations: (i) the common component χ_{it} and (ii) the idiosyncratic component ξ_{it}. The common component χ_{it} is a linear combination of $r \leq n$ common factors f_{kt}, $k = 1, \ldots, r$.[5] Formally:

$$x_{it} = \chi_{it} + \xi_{it}, \tag{1}$$

$$\chi_{it} = \sum_{k=1}^{r} \lambda_{ik} f_{kt} = \boldsymbol{\lambda}_i' \mathbf{f}_t \tag{2}$$

where $\boldsymbol{\lambda}_i$ is an r-dimensional vector of factor loadings. The idiosyncratic components can be mildly cross sectionally correlated, while, provided that stationarity is ensured, no assumption is made on their serial correlation properties.[6]

2.2 Labour market data

Our labour dataset covers both hard and soft indicators: while the former represent the bulk of the relevant information for building a LMCI, the latter are important as the convey forward–looking content, focusing on firms' and households' expectations. In particular, our labour market dataset is composed by 44 variable at both monthly and quarterly frequencies belonging to the following categories:

[4]The NY FED as well has launched a labour market dashboard, entitled "Eight different faces of the labour market", see `http://libertystreeteconomics.newyorkfed.org/2014/03/just-released-beyond-the-unemployment-rate-eight-different-faces-of-the-labour-market.html`.

[5]The r common factors are in turn driven by $q \leq r$ common shocks u_{jt}, $j = 1, \ldots, q$. The literature has often referred to f_{kt} as the *static factors*, while to u_{jt} as *dynamic factors*. We do not pursue here a dynamic factor analysis, although it could be an interesting avenue for future research. For a formal treatment of the model presented in this Section see Forni *et al.* (2009).

[6]The literature refers to this model as the *approximate factor model* to be distinguish from the *exact factor model* which is characterized by cross-sectionally-dynamically uncorrelated idiosyncratic component, i.e. $\xi_{it} \sim iid(0, 1)$.

- **Employment rates**, for the aggregate economy and broken down by gender and age (labour Force Survey);
- **Unemployment rates**, for the aggregate economy and broken down by gender and age (labour Force Survey);
- **Participation rates** (labour Force Survey);
- **Employment–to–Population ratio** (labour Force Survey);
- **Hours worked per capita**, for total economy, manufacturing sector, construction and services (National Accounts);
- **Hourly earnings per capita**, for total economy, manufacturing sector, construction and services (National Accounts);[7]
- **Firms' expectations** over employment and their assessment over labour shortage (ISTAT);
- **Households' expectations** over unemployment (ISTAT);
- **Cassa Integrazione Guadagni**, i.e. temporary lay–off schemes for employed (INPS).

For a more specific description, refer to Appendix A.

The employment rates and hours worked provide information on the state of the cycle in the labour market from a *quantity* perspective, whereas unemployment rates complements this information but has a more persistent and slower adjustment to the dynamics of economic activity. Hourly earnings provide information on the state of the labour markets from a *price* perspective. It is important to include population data and participation rates, as the literature has recently stressed the role of labour force participation for inflation dynamics during recessions generated by a large and persistent drop in aggregate demand (Erceg and Levin, 2014; Nucci and Riggi, 2018). Finally, we also include survey data on firms' and households expectations over employment and unemployment, respectively. Crucially, these data provide information on firms' labour demand and obstacles to production, among which labour shortages is mentioned. The latter are increasingly monitored when interested in addressing labour market slack in the euro area (ECB, 2017; Bulligan *et al.*, 2017).

All data are seasonally adjusted by using TRAMO–SEATS when necessary. After converting monthly to quarterly frequency by taking averages, we end up with a balanced panel

[7]Contrary to the other variables, which refer to the "volume-side" of the labour market, the earnings convey information on the "price-side". This variable warrants some special care, because one may speculate that its inclusion in the construction of the LMCI may significantly affect the predictive content of the latter for core inflation. However, in the robustness checks we repeat the empirical analysis excluding earnings from the labour dataset before computing the LMCI and it turns down that the results are virtually unchanged. We then conclude that it is not the inclusion of wages that produces the superior forecasting performance of the LMCI.

spanning the sample 1998:Q1 – 2017:Q1, as we are constrained by soft data on firms' assessment of labour shortage, which start in 1998.[8]

In Figure 2 we show the results of applying PCA to the labour market dataset. The first factor is highly correlated with the unemployment rate (0.95), while second is closely related to employment rates and hours worked (0.76). The third factor is more weakly linked to hourly earnings, whereas the fourth factor resembles firms' expectations. The share of variance explained by the first factor is roughly equal to 35% of the overall variance, and it rises to 58% when adding the second factor. Compared to the Kansas City Index, in which the first two factors account for 82% of the overall variance, the Italian labour market displays weaker co-movements. In other words, it looks more characterised by a more relevant role of idiosyncratic forces.

The resulting Italian labour Market Conditions Indicators are displayed in Figure 4 together with shaded areas representing the Global Financial Crisis and the Sovereign Debt Crisis. The *momentum* experienced a deep contraction during the former, then it rebounded a bit before starting to fall again, turning negative in 2011:Q1. It is only in 2014:Q1 that the indicator reverts back to positive values, pointing to an improvement in the labour market. However, the picture looks different when examining the *level of activity.* Indeed, the decline started before the Global Financial Crisis did not stop until 2015, when the trend was inverted and the indicator started to gradually rise. In 2017:Q1 it was still 5 percentage points below its historical average, signalling ample margins of spare capacity in the labour market. Finally, it is useful to compute a measure of slack based on the LMCI (hereafter LMCI–GAP), in which the gap is defined with respect to the (time–varying) NAIRU (Non-Accelerating Inflation Rate of Unemployment). This allows us to compare this measure to alternative indicators of slack, such as several definitions of the output-gap, the unemployment gap, the participation gap and the long–term unemployment gap. We use the same methodology proposed by Albuquerque and Baumann (2017) to build the LMCI-GAP. Indeed, before deriving this measure of slack one has to purge the factors extracted from the labour markets from the most correlaTed variable. In detail, the new gap is given by the difference between the fitted value of regressing the unemployment rate on LMCI plus a constant, and the NAIRU. Formally, we have:

$$\widehat{ur}_t = \psi_0 + \psi_1 * LMCI1_t \tag{3}$$

$$LMCIGAP_t = \widehat{ur}_t - NAIRU_t \tag{4}$$

An alternative way of building the gap would be defining the LMCI–GAP with respect the long–term average of the first factor (i.e., zero). This would have however lost the information

[8]As for monthly data, result are basically unaffected when converting them to quarterly frequency by taking last month values.

conveyed by the evolution of the NAIRU over time. The LMCI–GAP lies in the bottom region of the range constructed: this means that it helps in capturing a higher degree of slackness than the analogous one printed by competing measures (see Figure 6).

2.3 Financial markets data

We now repeat the procedure based on principal components to derive financial conditions indicators. We mimic the financial sector block of the model by Laseen and Sanjani (2016), as we include a number of indicators related to financial stance and stress, particularly relevant for the Italian economy in the period under consideration. The dataset is as follows:

- **Loans to households and non–financial corporations**;
- **Loan rates to households and non–financial corporations**;
- **Credit risk indicators** by Gilchrist and Mojon (2014), for the banking sector and the real sector;
- **CISS**, for the euro area economy[9];
- **House prices**;
- **Stock prices**;
- **BTP10 years** government bond yield;
- **BUND10 years** government bond yield;
- **Monetary policy rate**, including the shadow rate by Krippner (2013) to capture the unconventional measures;
- **Financial uncertainty**, measured as the volatility on equity returns for euro area and US economy;
- **Economic policy uncertainty**, for Italy, euro area, US economy (Baker *et al.*, 2016);

We end up with 20 indicators and a balanced panel covering the sample 1999:Q1–2017:Q1,as we are constrained by the CISS and the spread indicators by Gilchrist and Mojon (2014), which are only available after the launch of the euro. In Figure 3 we display the results of the principal component analysis. The first two factors explain the 72% of the overall variance, a value which rises to the 88% when considering the third and the fourth factor as well. Interestingly, the first factor is strongly correlated with the monetary policy rate (0.9), whereas the second one is

[9]One may be concerned about the inclusion of the CISS in the financial dataset, as it is already a synthetic indicator. The results are however robust to the exclusion of the CISS from the financial dataset.

mostly related to the indicators of financial stress, in particular the CISS (0.77). This suggests that both factors could provide additional information content to the Phillips curve framework, and we are going to verify whether they help in explaining weakness in core inflation.

3 Phillips curve

In this Section we evaluate the dynamics of core inflation in Italy through the lens of a Phillips curve framework. We are especially interested in focusing on the most recent years, associated to large disinflationary shocks, both of global and domestic nature, which produced a prolonged period of low inflation, in Italy as well as in the other euro area countries (Ciccarelli and Osbat, 2017). In what follows, we are going to estimate equations across different specifications and then use them in a forecasting setting. Our aim is to exploit the LMCI to gain insights on low inflation in Italy, possibly establishing a clear link between labour slack and core inflation. We start with a fixed–coefficients specification, and then generalize to a time–varying framework.

3.1 Baseline model

Our empirical analysis is based on the following baseline specification of the Phillips curve, which includes both a forward–looking and a backward–looking structure related to firms' price–setting behaviour, in the spirit of the so–called hybrid specification proposed by Gali and Gertler (1999):

$$\pi_t = \mu + \alpha E_t \pi_{t+k} + \sum_{j=1}^{p} \beta_j \pi_{t-j} + \delta \hat{y}_t + \Gamma' Z_t + \eta_t, \quad k = 1, 2, ..., 6 \tag{5}$$

where μ is a constant term, π_t denotes the current core inflation rate as measured by the annual change in the HICP excluding energy, food and tobacco, $E_t \pi_{t+k}$ represents survey–based Consensus inflation expectations k– periods ahead, $\hat{y}_t$ is an estimated measure of the amount of slack in the economy, Z_t is a set of control variables such as global or financial indicators and, finally, η_t is a white noise with zero mean and variance equal to σ_η^2.

Table 1 reports the estimation output of model (5). The coefficients are OLS estimates with robust Newey–West standard errors. Holding constant the lag structure of the equation, which has been found performing well when considering $p = 4$, we estimate 9 specifications by combining three different measures of inflation expectations (1, 4, 6 quarters ahead) with three different measures of slack of particular interest (the unemployment gap, the output gap computed by the IMF by using a production function approach and the LMCI–GAP)[10]. Impor-

[10]We choose to focus on these three different measures of slack in the Table because the unemployment gap is found to have a very good performance in the estimates and forecasts of Italy core inflation, while the IMF estimates of the output gap have been used by Riggi and Venditti (2015), which provide a similar framework. Estimates obtained using different measures of output gap, such those provided by the OECD, the European

tantly, in this first set of estimates $Z_t = 0$, namely we do not consider other factors (such, for example, global and financial indicators), and concentrate on the role of inflation expectations and on the slack in the economy. Some preliminary remarks are in order. First, we observe a high persistence of Italian core inflation, as witnessed by $\hat{\alpha}_1, \hat{\alpha}_2, \hat{\alpha}_4$[11]. This finding is consistent with the literature on the Phillips curve (see, for example, Stock and Watson, 2007; Watson, 2014) and it reports that once inflation moves from the inflation target, it may take some time to monetary policy to bring it back to the desired value. Second, medium–term inflation expectations (6 quarters–ahead) are found to be not significant in all considered specifications (columns 1–3).[12] This is also the case when considering 4 quarters–ahead inflation expectations (columns 4–6). By contrast, short–term inflation expectations, measured at 1 quarter–ahead, are statistically significant at 1% level for all measures of slack here considered. These findings are similar to those obtained by Mazumder (2018) when looking at the euro area as a whole: he shows a weakening of the ECB anchor of 2% for eurozone core inflation after the Global Financial Crisis. Furthermore, Bartiloro *et al.* (2017) document a considerable weakening in the empirical link between the dispersion of Italian firms' inflation expectations and the distance between current inflation and the ECB inflation target, showing that firms have put an increased weight on prior beliefs related to low inflation because of an increased perception of uncertainty. Pieced together, this evidence should ring a bell in terms of possible de-anchoring of inflation expectations. Third, the slack measures have strongly statistically significant coefficients, irrespective of the inflation expectations definition. They posit a meaningful trade–off between core inflation and slack. However, it has to be stressed that measuring slack by the LMCI–GAP suggests a stronger trade–off, as its estimated coefficient is almost twice as large that the one obtained when looking at the simple unemployment gap. This means that for 1 percentage point of LMCI–GAP, core inflation is reduced by almost 0.14%. Also, this suggests that a broader consideration of the role of labour markets convey more information than the simple unemployment gap and that monitoring them well beyond unemployment could be importantl for the appropriate calibration of the monetary stance: absent that link, one could think of a flatter (less steep) Phillips curve.

3.2 Including global variables

A non-trivial role in driving inflation downward after 2012 may have been played by global factors, both supply and demand. We have then accordingly extended our baseline model to include variables such as the most likely candidate to affect the dynamics of core inflation, either via the cost of the input either *via* the expectations channel (namely, second round effects

Commission or the Projection Database of the ECB do not alter the results. They are available upon request from the authors.

[11] $\hat{\alpha}_3$ is never found to be statistically different from zero, hence it is not reported across the 9 specifications.

[12] This finding holds when using other possible measures of slack, such as those considered in Figure 6.

of large increases or decreases in commodity prices). In particular, we have estimated different versions of equation (5) by including among the Z_t changes in relative import prices, changes in oil price and the exchange rate, both $vis - \grave{a} - vis$ with the US dollar and in nominal effective terms, facing a larger basket of divisia. The coefficient of the global variable is only marginally different from zero in some cases, hence not pointing to a large role of foreign pressures for Italy core inflation, possibly also because of the correlation with the inflation expectations measure, which ranges between 0.30 and 0.50, depending on the considered global variable.

The bulk of the findings summarized in Section 4.1 are confirmed: in particular, the results related to different measures of slack are broadly unaffected, as domestic factors have been more relevant for explaining Italian core inflation.[13]

3.3 Including financial indicators

We then move on to examine how the results of the Phillips curve estimates change when including financial variables among the controls. We mainly focus on the first factor extracted from the financial dataset, and plotted in Figure 5; however, we also evaluate the possible role of the second one. Also, we compare the findings obtained when including those indicators that are closely correlated to the FCI, namely the policy rate, which includes the shadow interest rate for the period of the ZLB, and the CISS, as a proxy of financial stress (see Table 2).

The estimated parameters for the policy rate and the first factor have the expected sign, i.e. for both variable we get a negative coefficient, as a monetary tightening lowers core inflation. However, the estimates are only slightly significant (at the 10% level at best) when estimating the Phillips curve in some specific subsamples of interest, but not over the full sample[14]. As for the CISS and the second factor, macroeconomic theory does not suggest a clear–cut a priori on the expected sign of the estimated coefficient. Indeed, on the one hand one could expect that an increase in financial stress could reduce inflation *via* a contraction in economic activity (demand effects dominate in the transmission mechanism through more convenient financing costs; Curdia and Woodford (2010); Gertler and Karadi (2011)), whereas a different strand of literature has documented an increase in inflation following tighter financial conditions, mainly due to the pass–through of higher financing costs for firms (the so called cost channel; Gaiotti and Secchi, 2006; Ravenna and Walsh, 2006 or the hedging behaviour of firms against the risk of future higher external finance conditions Gilchrist *et al.*, 2017 or the presence of persistent low demand for financially constrained firms Duca *et al.*, 2017)[15]. Our results suggest that the latter effect has prevailed for Italian core inflation, although the estimated coefficients for

[13]In this regard, see also Conti and Santoro (2018), who conduct a decomposition of the Italian core inflation in cyclical and transitory factors, relying on a Phillips curve framework similar to the contribution by de Charsonville et al., 2017. Tables with the full set of estimates are available on request from the authors.

[14]For example, when estimating until 2011:Q4 and using the LMCI–GAP as a measure of slack, the estimated coefficient of the fourth lag of the FCI1 is equal to -0.053, with a p-value around 0.13.

[15]For a more detailed discussion on the impact of financial shocks on inflation see Abbate *et al.* (2016)

both the CISS and the second financial factor are weakly significant over some samples (in particular, until 2012:Q4), as well as observed for the first financial factor. This finding helps for explaining the relatively high levels of inflation observed during the sovereign debt crisis, in spite of GDP contraction, and it is consistent with evidence provided on the impact of financial shocks on Italian inflation using alternative empirical strategies, such as multivariate time series models (Neri and Ropele, 2015) and firm–level data (Duca *et al.*, 2017).

As for the impact of including financial variables in the Phillips curve on the results presented in Section 3.1, the bulk of the findings reported for the baseline specification are confirmed, but some remarks are in order. In particular, an interesting result is that when including the first FCI, the significance of slack measures is very weakened, basically vanishing except for LMCI. This is less evident when including the second FCI (columns (3) and (4)). Overall, this evidence seems to suggest that the degree of slack associated to output gap measures is mainly correlated to financial shocks, not surprisingly, as Italy was severely and persistently hit by the Sovereign Debt crisis of 2011.

Equipped with our estimates, we are going to use them to conduct some conditional forecasting exercises, which we explain in the following subsection.

3.4 Conditional forecasting

After having estimated our baseline model, we use it for a conditional forecasting exercise useful to understand the role of different slack measures in explaining the missing inflation in the period 2012:Q1–2014:Q4 and the subsequent low inflation period. In practice, we conduct two experiments. First, we re-estimate the model on the sample 1999:Q1–2011:Q4, and then use the estimated coefficients and the actual values of the explanatory variables to verify the predictive power of our equation. Second we repeat the same experiment, but estimating until 2014:Q4. We start by commenting on the results of the conditional forecasting exercise for the baseline Phillips curve, where only inflation expectations and alternative measures of slack are considered. In particular, Figure 7 displays the results and compares the conditional forecast obtained when using the LMCI–GAP to a range of forecasts based on different measures of output–gap and unemployment gap, estimated by a production function approach, statistical filters or recovered in deviation from potential output and the NAIRU as estimated in the ECB Projection Database. It can be noticed that for the period 2012:Q1 – 2017:Q1 (see panel a) the best description of core inflation is by far obtained when measuring slack by means of the LMCI–GAP. Indeed, not only the actual values of the series lie within the 90% confidence interval of the conditional forecast based on LMCI–GAP, but the remaining set of forecasts based on measures of unemployment gap and output gap tend to systematically overestimate core inflation. As for the second horizon, when looking at the period 2015:Q1 – 2017:Q1, the comparison looks less unfavorable to the other measures of slack, as LMCI would contribute to underestimate the dynamics of core inflation in the first half of 2015. This could be likely related to the delayed impact of monetary policy measures on labour markets, in contrast to a more immediate reaction of economic activity to the expansionary stance by the ECB. Again, it should be stressed that towards the end of the sample core inflation lies in the lower region of the traditional slack measures – based conditional forecasts, closer to the one obtained by using the LMCI.

We then repeat the two exercises by adding financial factors to the baseline specification (alternatively single and composite indicators, see Figure 8), and forecasting on their future path as well. It is apparent that considering financial factors helps in capturing the increase of Italian core inflation observed in early 2015, confirming a role of the ECB monetary easing in sustaining prices dynamics. Also, it is worth mentioning that the conditional forecasts range between 0.1 and 1.3, depending on the considered financial indicator. One could have then expected a deep drop like the one effectively observed, should the information provided by inflation expectations, slack and financial conditions have been available in early 2012. This strengthen the overall message of this experiments, i.e. the usefulness of Phillips curves to assess core inflation in Italy, possibly relying on a wide set of labour and financial indicators. The conditional forecasts obtained on the period 2015:Q1 – 2017:Q1 broadly confirm the evidence discussed above.

Finally, we proceed to estimate again several models akin to (5) in which, beyond adding the other measures of slack and financial factors, we also consider a set of controls Z_t for global indicators, such as changes in import prices, oil prices, nominal effective exchange rates to verify the performance of the LMCI–GAP in forecasting core inflation. The results are shown in Figure 9 and confirm the important role of exploiting a wide set of labour market indicators to properly understand the dynamics of core inflation in Italy. Indeed, the darker grey area indicates the conditional forecasts obtained when measuring the degree of slack in the economy by using the LMCI–GAP: it is immediate to see that the actual y-o-y changes in the HICP excluding food, energy and tobacco lie in that range, or very close to that, since 2013, hence suggesting a superior information content to the simple unemployment gap or the output gap. As for the period subsequent to the launch of the APP, something is not captured again especially in the earlier part of 2015, in spite of the inclusion of the policy rate or the exchange rate among the considered models (see Figure 9.b). This is likely signalling some forward guidance effect not captured by neither of our explanatory variables. Financial variables are supposed to be related to this aspect, and they indeed in help capturing the 2015 period. However, after 2015:Q3, they produce an overshooting of the forecast, suggesting that something is not captured by the model. This may be related to some structural break, such as a flattening in the Phillips curve, i.e. a weakening in the link between core inflation and economic activity, or to some transitory factors, such as idiosyncratic dynamics in some particular sector. A likely candidate for this is the dynamics of accomodation services and package holidays, which experimented favorable developments in 2015 because of the organization of the Expo in Milan, before dropping in 2016 due to the base effect[16].

Overall, it is important to retain two key messages from this analysis. First, the Italian Phillips curve is still alive, when appropriately specified. Second, and consequently, our set of specifications represent a serious improvement in forecasting Italian core inflation with respect to those summarised in the report by Ciccarelli and Osbat (2017).

3.5 The role of wages for the LMCI–GAP

Presenting the labour dataset we have stressed that the large part concerns measures of activity, both of hard and soft nature, with the only exceptions of wages, which provide a prices perspective on labour markets conditions. One may then ask what is the benefit (if any) of including hourly earnings in the construction of the composite indicators. To address this issue we repeat our analysis by excluding wages from labour data when running the principal components analysis. In Figure 10 we first show the comparison between the LMCI obtained from the full labour dataset and those extracted when excluding wages. There are no differences. In particular, the second LMCI is broadly unaffected, while some slight discrepancies emerge for the first one, that is the level of activity (which is the most helpful in predicting core inflation). Indeed, when including wages the level of activity signals a higher distance from its long–term average, signaling that weak wage dynamics plays a role in a more precise assessment of labour slack. Consistently, when running the conditional forecast exercise for core inflation by using a LMCI–GAP which relies on the "no–wages" level of activity one achieves higher forecasts (yellow line) than the analogous obtained with the baseline LMCI–GAP (red line, see Figure 10, bottom panel), although there is no statistically significant difference. We conclude that, while monitoring and including wages into LMCI may provide important information for assessing the labour market stance, this analysis does not reveal an incremental predictive content of hourly earnings for core inflation.

4 Relaxing the assumption of fixed coefficients

Since we have seen that the linear models provide a good description of core inflation of core inflation especially during some time spans, and in order to investigate the possibility of structural breaks in the slope of the Phillips curve above all, we now move to a more general framework, relaxing the assumption of fixed coefficients.

[16]A complementary analysis by Conti and Santoro (2018) reveals that the dynamics of core inflation in Italy is largely affected by accomodation services–based transitory factors in 2015 and 2016.

4.1 Time variation

The estimates reported in Table 1 for the slope of the Phillips curve range between 0.05 and 0.14 and represent averages over a period which includes two deep crises. Furthermore, the jury is still out in the debate over the steepening vs. flattening of this relation, with relevant policy implications for monetary policy. Hence, we investigate the possibility that the slope of the Italian Phillips curve changes over time following two different approaches: (i) a rolling–regression estimate and (ii) a state–dependence estimate. The first approach involves the adoption of simple rolling regressions, using model (5) with short–term inflation expectations and the different measures of slack, considered one at a time. We then estimate equation (5) on rolling windows of 28 quarters each, and we show the results in Figure 11. The evidence informs about the time–varying nature of the trade–off between inflation and economic slack: in particular, it shows a steepening of the Phillips curve around 2013Q1, also found by Riggi and Venditti (2015), and then documents a stabilization (or flattening) at the end of the sample, starting around 2016:Q1. This evidence holds for all the considered measures of slack and could provide an explanation to the recent lack of sustained path in core inflation, in spite of a much improved outlook in terms of GDP growth.

A remarkable feature of these estimates is an important difference which emerges between the three measures of slack: indeed, when adopting the LMCI–GAP the slope of the Phillips curve is almost always statistically different from zero, with the exception of the period 2010:Q3 – 2012:Q2, whereas, by contrast, the slope estimated using the uneployment gap or the output gap becomes different from zero in the last part of the sample. This intuitively explains why the conditional forecasts obtained using the LMCI–GAP beat the other ones, as a more stable relation between core inflation and economic slack is observed when looking at a broad set of labour variables.

It is then interesting examining how this evidence changes when including financial factors among the regressors, especially focusing on the composite indicators FCI1 and FCI2. In Figure 12 we confirm that the inclusion on financial factors weaken the statistical relevance of the trade–off, which remains different from zero for the LMCI–GAP only[17]. As for time variation in financial factors, the rolling regressions how that the impact of FCI1 becomes strongly significant towards the beginning of 2015, hence likely reflecting the restored benefits of the monetary easing by the ECB on Italian core inflation.[18] The relevance of FCI2 for core inflation rises after 2011, then staying statistically significant. This signals a supply nature of financial stress, since an increase in FCI2 raises core inflation and provides a non–trivial implication consistent with the one suggested by Abbate *et al.* (2016): since unconventional

[17]The graphs obtained when using unemployment gap and output gap are available upon request from the authors

[18]The financial factors have been purged by the effects of the business cycle, namely the unemployment rate. However, results with the unpurged financial factors are broadly in line with those presented in Figure 12.

monetary policies have reduced the level of credit spreads and in general improved credit markets conditions, it is possible that they are unintendedly keeping inflation low. It should be however noted that this phenomenon would be better evaluated in a multivariate setting, which allow for spillovers between financial variables, slack and inflation, with the possibility of switching across regimes of financial stress (high vs. low). This goes beyond the scope of this paper, and therefore we confine ourselves in hinting at this possibility, leaving this topic high on our future research agenda. In the following subsection we concentrate instead on two possible nonlinearities related to labour market conditions.

4.2 Threshold regressions

We consider here two possible forms of non–linearities [19]. First, we test whether the slack of the Phillips curve is dependent by the degree of labour market tightness, by allowing the slope to have a stronger (weaker) impact when unemployment is low (high). In order to do so, we divide the unemployment gap (or the LMCI–GAP) by the level of unemployment (or the level of unemployment purged from the first LMCI), following the approach by Debelle and Laxton (1997).

$$\pi_t = \mu + \alpha E_t \pi_{t+k} + \sum_{j=1}^{p} \beta_j \pi_{t-j} + \delta_1 \hat{y}_t + \delta_2 \hat{y*}_t + \Gamma' Z_t + \eta_t, \quad k = 1, 2, ..., 6 \tag{6}$$

where $\hat{y*}_t$ denotes the tightness–corrected measure of slack.

Second, following Veirman (2009) and Albuquerque and Baumann (2017), we explore the possibility that the slope of the Phillips curve depends on the level of trend inflation, as follows:

$$\pi_t = \mu + \alpha E_t \pi_{t+k} + \sum_{j=1}^{p} \beta_j \pi_{t-j} + (\delta_1 + \delta_2 \bar{\pi}) \hat{y}_t + \Gamma' Z_t + \eta_t, \quad k = 1, 2, ..., 6 \tag{7}$$

where $\bar{\pi}$ denotes trend inflation, defined as the average y-o-y core inflation over the previous ten years [20].

The estimation results provide tentative evidence that threshold effects may indeed play a role in explaining the weakness of core inflation in Italy. First of all, the estimate of δ_1 is higher when dividing the slack by the level of unemployment rate, suggesting that the trade–off between inflation and slack is really influenced by the degree of the labour market tightness. Second, the level of trend inflation is statistically significant, i.e. the slope varies with the level

[19] This subsection presents preliminary evidence which is going to be deepened in further following steps. We have also tried to map into the assessment of core inflation the non–linearity documented by Bulligan *et al.* (2017), who prove on euro area data a decreasing impact of unemployment on wage dynamics when hours worked are far from their cyclical peak. However, including this kind of threshold does not significantly improve the fit and the forecast of the Phillips curve.

[20] A similar analysis based on inflation expectations instead of trend inflation has been performed by Foroni and Porqueddu (2015) for the euro area.

of trend inflation, confirming that there could be some state–dependent pricing la De Veirman (2009). Importantly, in terms of forecasting, these two specifications seem to perform quite well over the most recent span (2007:Q1 – 2017:Q1), where they improve over the linear models at least to some extent from a point–forecast perspective only and not in terms of a formal test of predictive accuracy (see Figure 13).

The overall message of the analysis performed relaxing the assumption of fixed coefficients in the Phillips curve is that, in spite of a satisfactory performance of linear, fixed–coefficients models, especially those based on broad measures of labour slack and financial conditions, there are non–negligible sources of instabilities in the relation between Italian core inflation and economic activity, which could be worth of a deeper investigation in multivariate settings.

5 Concluding remarks

In this paper we studied the factors behind the weak dynamics of core inflation in Italy through the lenses of a Phillips curve framework augmented with factors–based measures of labour and financial markets. By doing so, we took a shortcut and exploited the information stemming from a large number of series in a univariate framewok. We showed that a statistically and economically significant trade–off between core inflation and economic slack does exist for the Italian economy, in particular when taking into account broad composite indicators on labour market data instead of simple univariate measures of gap.

Furthermore, we have documented a role for non–linearities in helping to forecast inflation. Finally, we also showed how labour and financial indicators crucially interact to correctly pin–down the slope of the Phillips curve.

Setting future research agenda, it seems worth investigating some possible extensions of our modelling framework, such as adding stochastic volatility, estimating bivariate models in which trend inflation and the NAIRU are jointly determined and, finally, using a multivariate dynamic framework which allows for the spillover mechanisms between goods, labour and financial markets. Since the economic debate on these issues, above all the existence of a NAIRU and, as a consequence, of a long–run trade–off for the central bank, has still been going on (Blanchard, 2017), further work is warranted.

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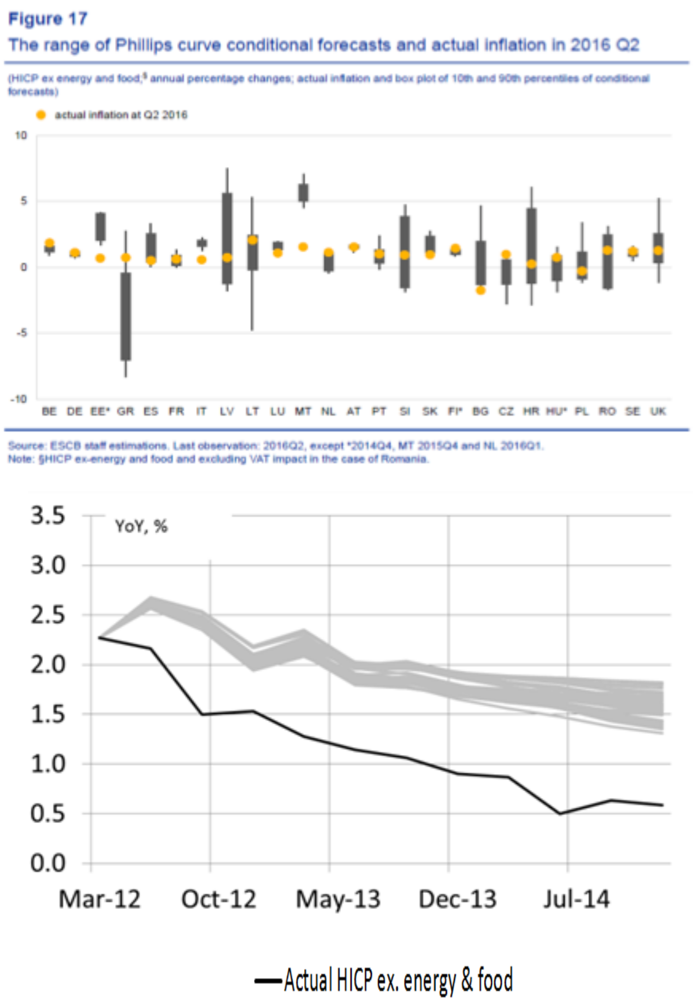
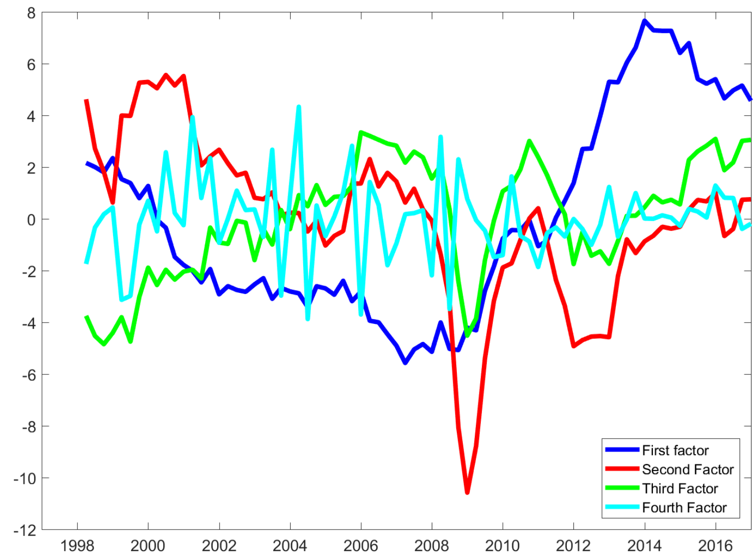
Figures and Tables

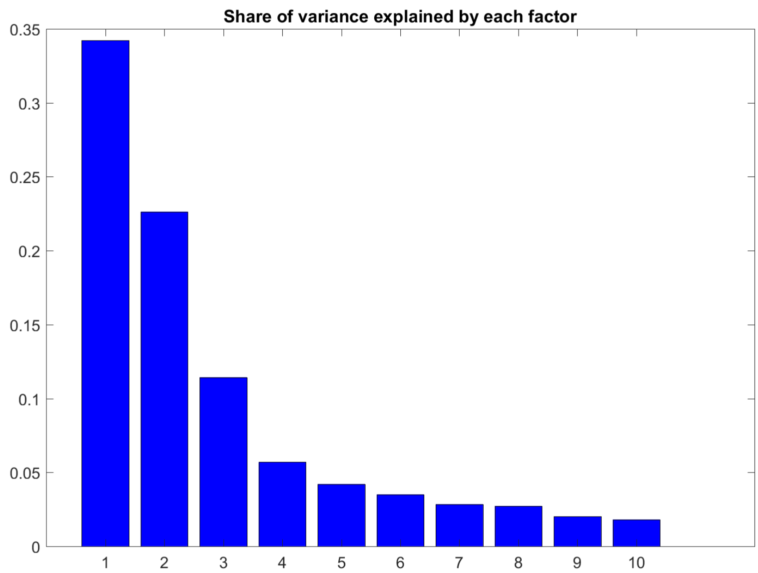
Figure 1: FORECASTING PERFORMANCE OF THE PHILLIPS CURVE FOR ITALY CORE INFLATION IN THE ECB LOW INFLATION TASK FORCE REPORT.



Notes: The top panel shows the range of Phillips curve-based conditional forecasts of core inflation for each euro area country. The bottom panel displays the range of Phillips curve-based conditional forecasts of core inflation for Italy. In both cases the conditional forecast is computed on the sample starting in 2012:Q1, after estimating the Phillips curve until 2011:Q4.

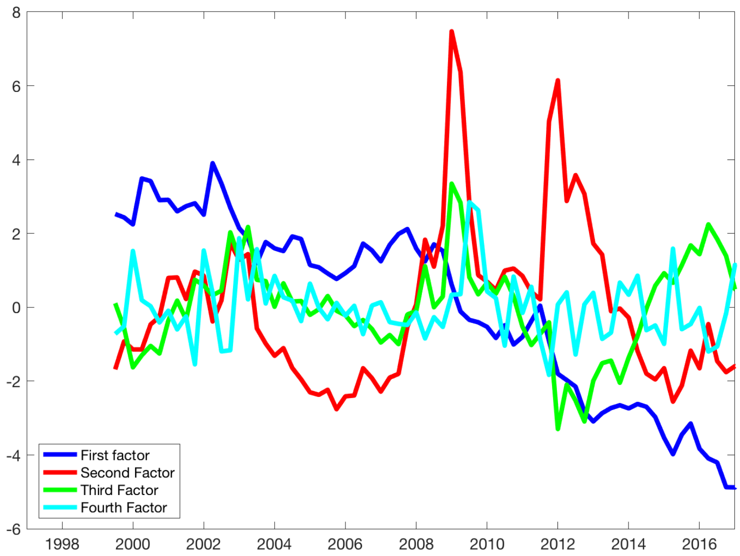
Figure 2: PRINCIPAL COMPONENT ANALYSIS (PCA) ON LABOUR MARKET DATA.

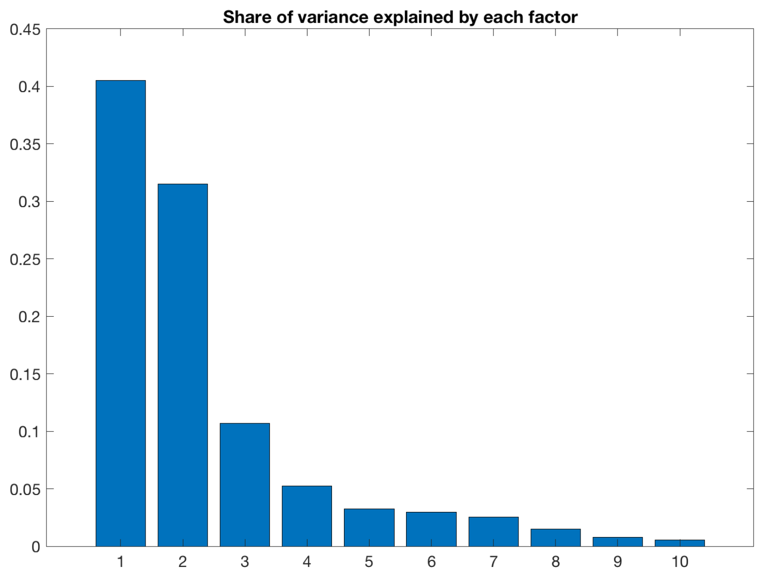




Notes: The top panel shows the share of variance explained by the each of the ten first principal components (static factors) extracted by the labour market dataset (blue bars) when taking first difference in order to achieve stationarity. The bottom panel displays the dynamics of the first four principal components (static factors; colored lines as described in the legend).

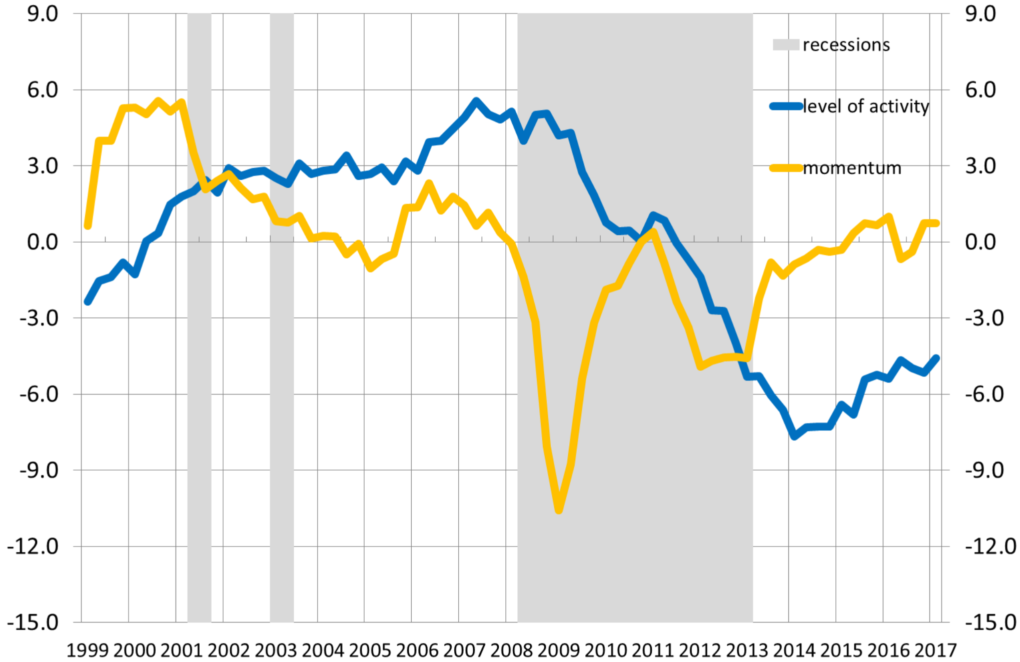
Figure 3: Principal Component Analysis (PCA) on financial markets data.





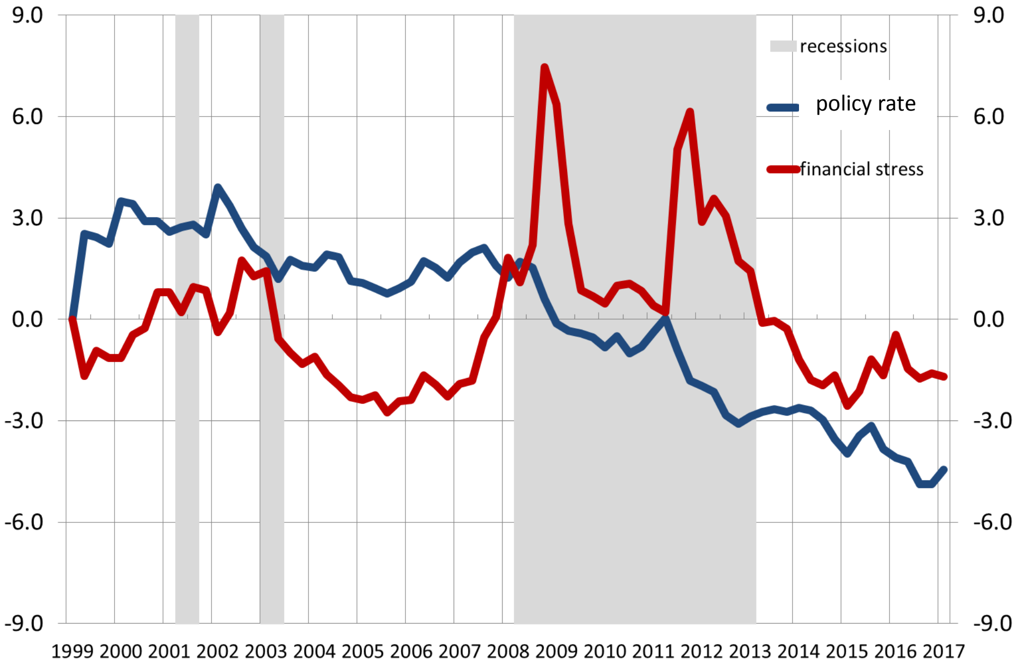
Notes: The top panel shows the share of variance explained by the each of the ten first principal components (static factors) extracted by the labour market dataset (blue bars) when taking first difference in order to achieve stationarity. The bottom panel displays the dynamics of the first four principal components (static factors; colored lines as described in the legend).

Figure 4: Italy Labour Market Conditions Indicators.



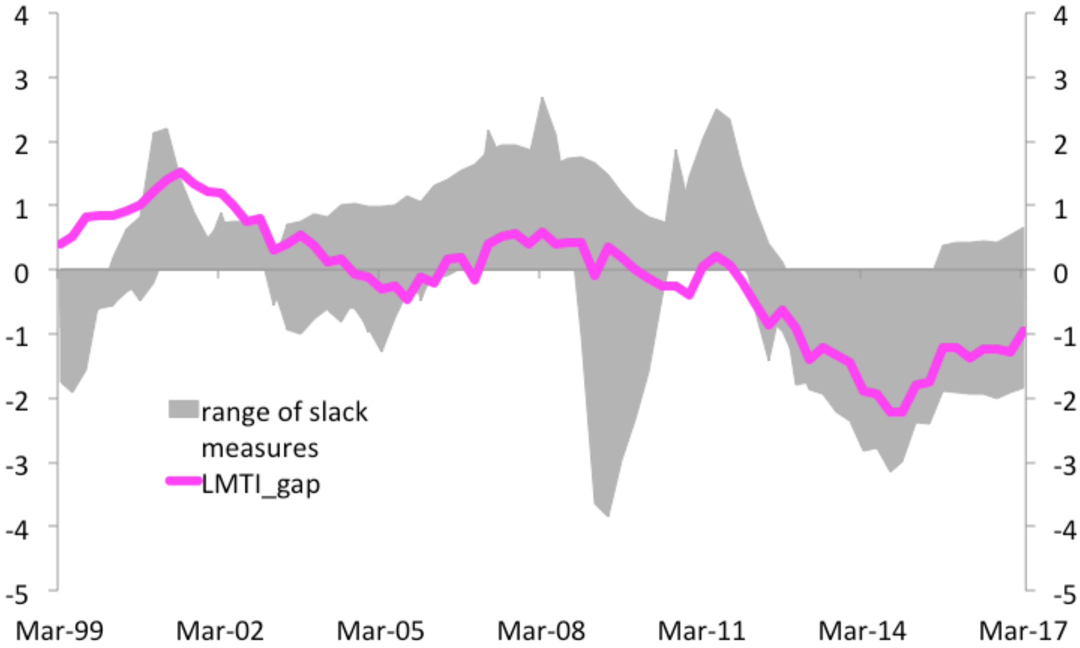
Notes: The graph shows the first (blue line) and the second (orange line) principal component extracted by the labour market dataset. The shaded grey area represent the recessions associated to the Global Financial Crisis of 2008–09 and the Sovereign Debt Crisis of 2011–13, which are considered as a double-dip recession (and hence painted as a continued period of negative growth in spite of some slight recovery of real GDP). With respect to the top panel of Figure 2, notice that the first principal component (i.e., the *level of activity*) is normalized to assume values greater than zero when labour markets are in an expansionary period.

Figure 5: Italy Financial Market Conditions Indicators.



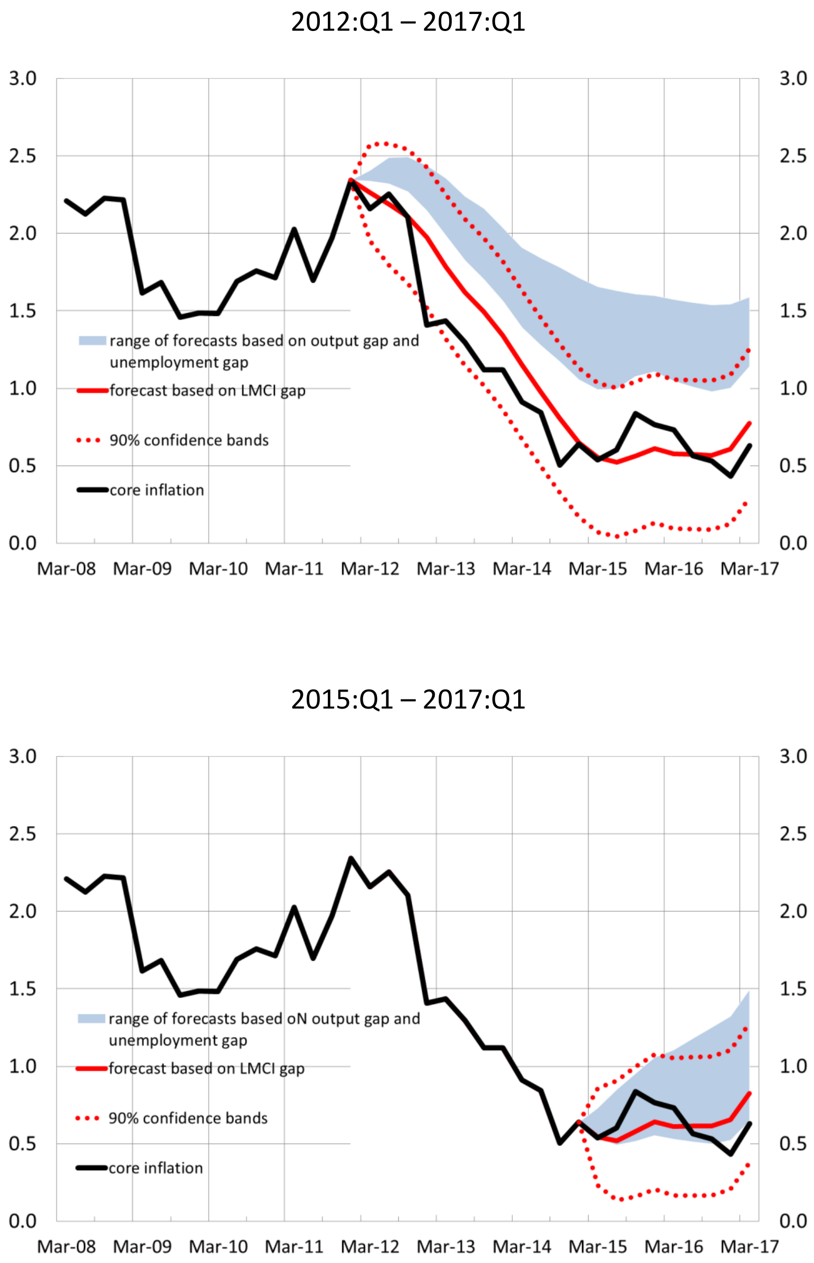
Notes: The graph shows the first (blue line) and the second (red line) principal component extracted by the labour market dataset. The shaded grey area represent the recessions associated to the Global Financial Crisis of 2008–09 and the Sovereign Debt Crisis of 2011–13, which are considered as a double-dip recession (and hence painted as a continued period of negative growth in spite of some slight recovery of real GDP).

Figure 6: Range of slack measures for Italian economy.



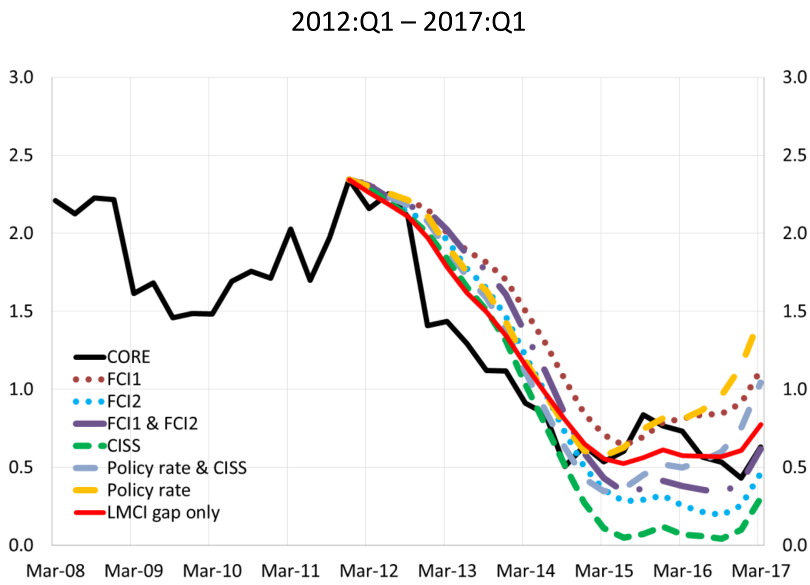
Notes: The graph shows the labour Market Conditions Index-based gap (LMCI, magenta line) and the range of other slack measures (shaded grey area). The latter includes the following slack measures: output–gap based on HP filter and on production function approach - both Bank of Italy and IMF estimates, the unemployment gap, the long–term unemployment gap and the participation gap.

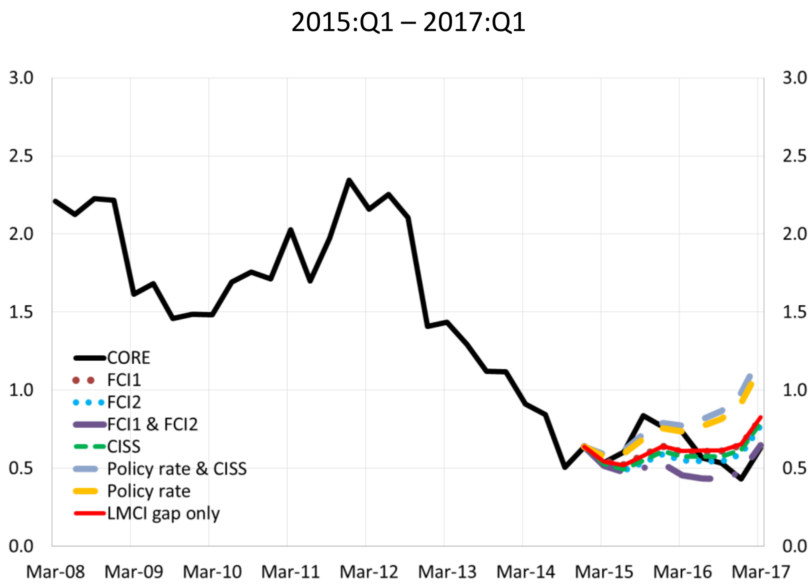
Figure 7: Conditional forecasts of Italy core inflation: baseline Phillips Curve model.



Notes: The graph shows actual values of Italy core inflation (black line) compared to a range of six conditional forecasts based on the baseline Phillips curve model (light blue area) obtained by using four different measures of the output gap (IMF, annual values interpolated by a quadratic trend; ECB Projection Database; band-pass filter) and two measures of the unemployment gap (ECB Projection Database; band-pass filter). The straight red line is the conditional forecast obtained by using the LMCI–GAP, while the dotted red lines represent the 90% confidence interval. In the top panel the estimation sample is 1999:Q1–2011:Q4, while in the bottom panel the estimation sample is 1999:Q1 - 2014:Q4.

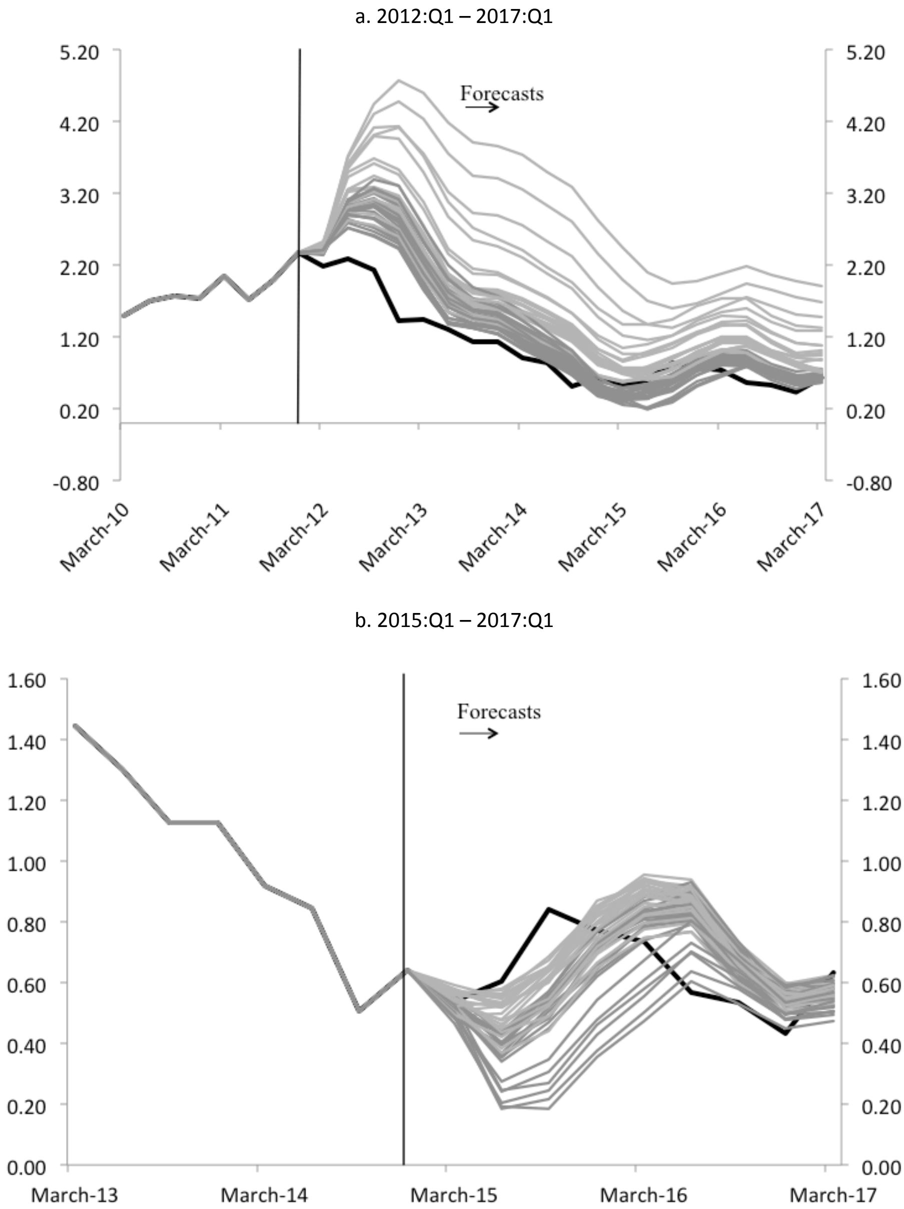
Figure 8: Conditional forecasts of Italy core inflation:the role of financial factors.





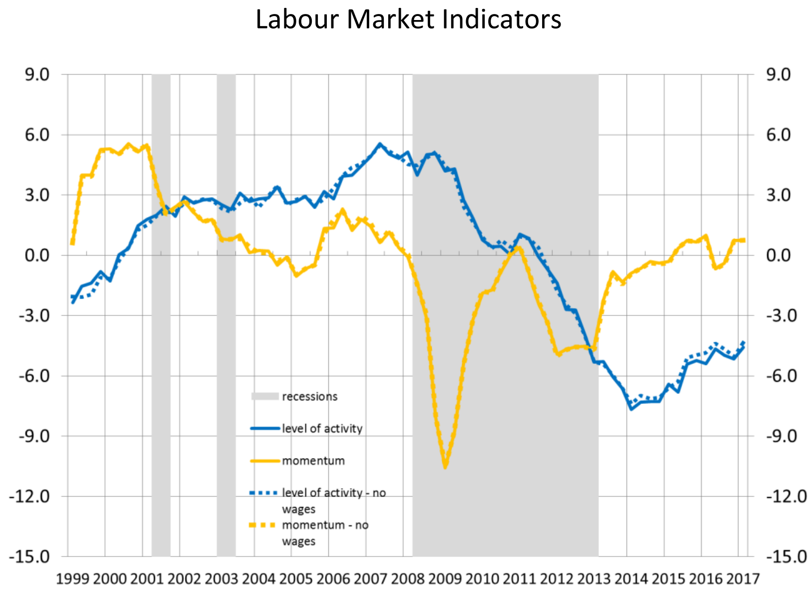
Notes: The graph shows actual values of Italy core inflation (black line) compared to three conditional forecasts based on the baseline Phillips curve mode augmented by different financial indicators: the first financial factor (FCI1, dotted brown line), the second financial factor (FCI2, cyan dotted line), the FCI1 and FCI2 jointly (violet dashed line), the CISS indicator (dashed green line), the policy rate and the CISS jointly (light blue dashed line), the policy rate (dashed orange line) and the baseline conditional forecast obtained by relying on the LMCI–GAP only (red straight line). In the top panel the estimation sample is 1999:Q1–2011:Q4, while in the bottom panel the estimation sample is 1999:Q1 - 2014:Q4.

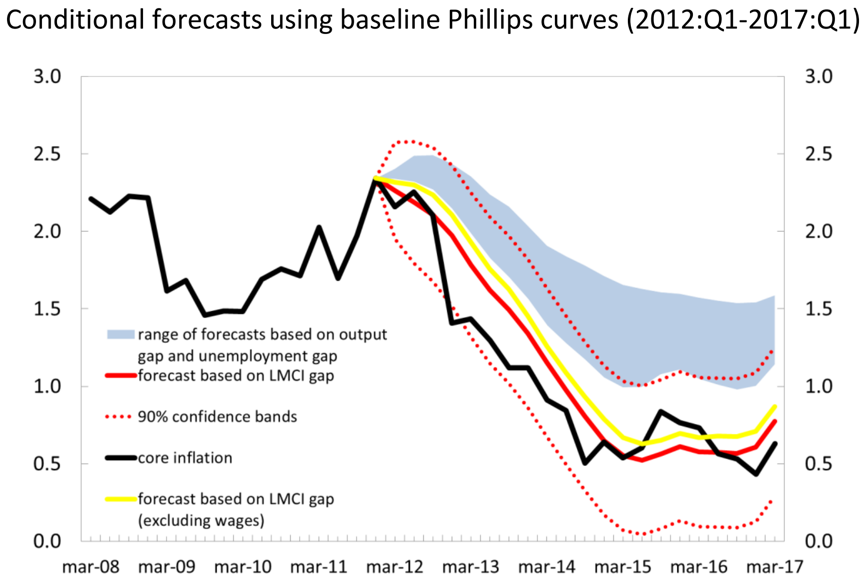
Figure 9: Conditional forecasts of Italy core inflation: different Phillips Curve models.



Notes: The graph shows actual values of Italy core inflation (black line) compared to a set of conditional forecasts based on different Phillips curve models, based on a range of slack measures, inflation expectations, global and financial variables. Dark grey lines are conditional forecasts obtained by using the LMCI–GAP, while light grey lines are conditional forecasts obtained by using other slack measures. In the top panel the estimation sample is 1999:Q1–2011:Q4, while in the bottom panel the estimation sample is 1999:Q1 - 2014:Q4.

Figure 10: Labour Markets Conditions and core inflation: the role of wages.

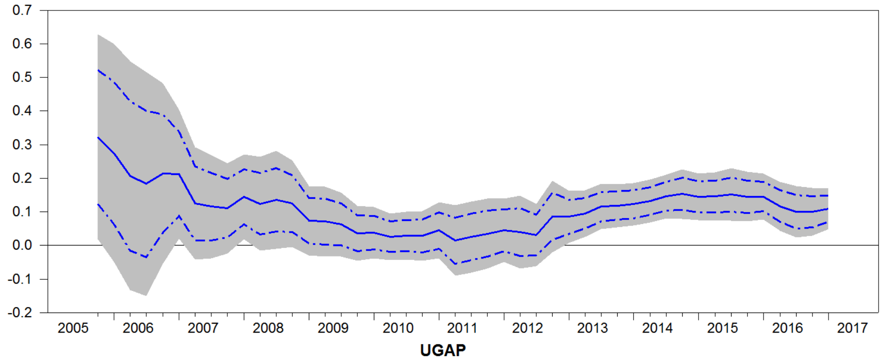




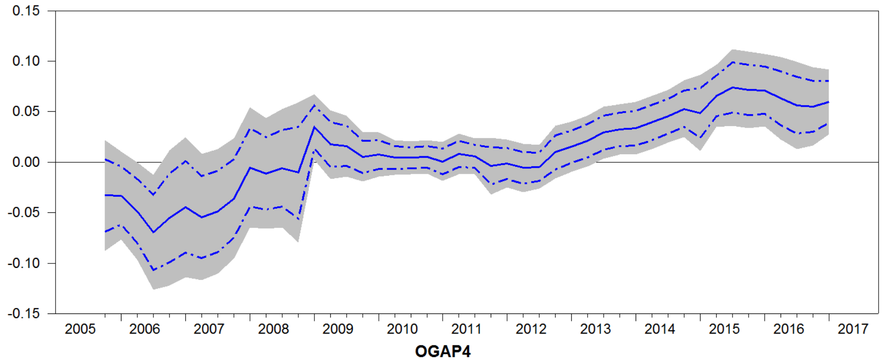
Notes: The top panel shows the first and second LMCI extracted from a dataset which excludes hourly wages (dotted lines) related tho those extracted from the full dataset (straight lines). The bottom panel shows the conditional forecast of core inflation obtained on the LMCI-gap computed from the first LMCI excluding wages (yellow line) compared to the baseline conditional forecast (red lines) together with its 90% confidence interval and the range of the forecasts conditional on other measures of output gap and unemployment gap. In the top panel the estimation sample is 1999:Q1–2017:Q1, while in the bottom panel the estimation sample is 1999:Q1 - 2011:Q4.

Figure 11: Time variation in the slope of the Phillips curve.

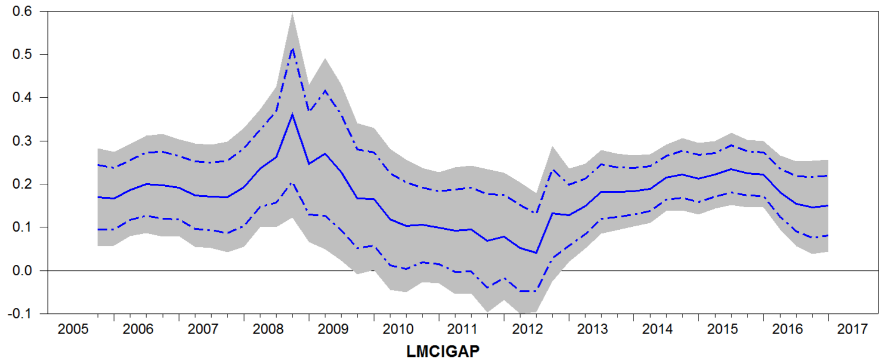
a. Unemployment gap



b. Output gap

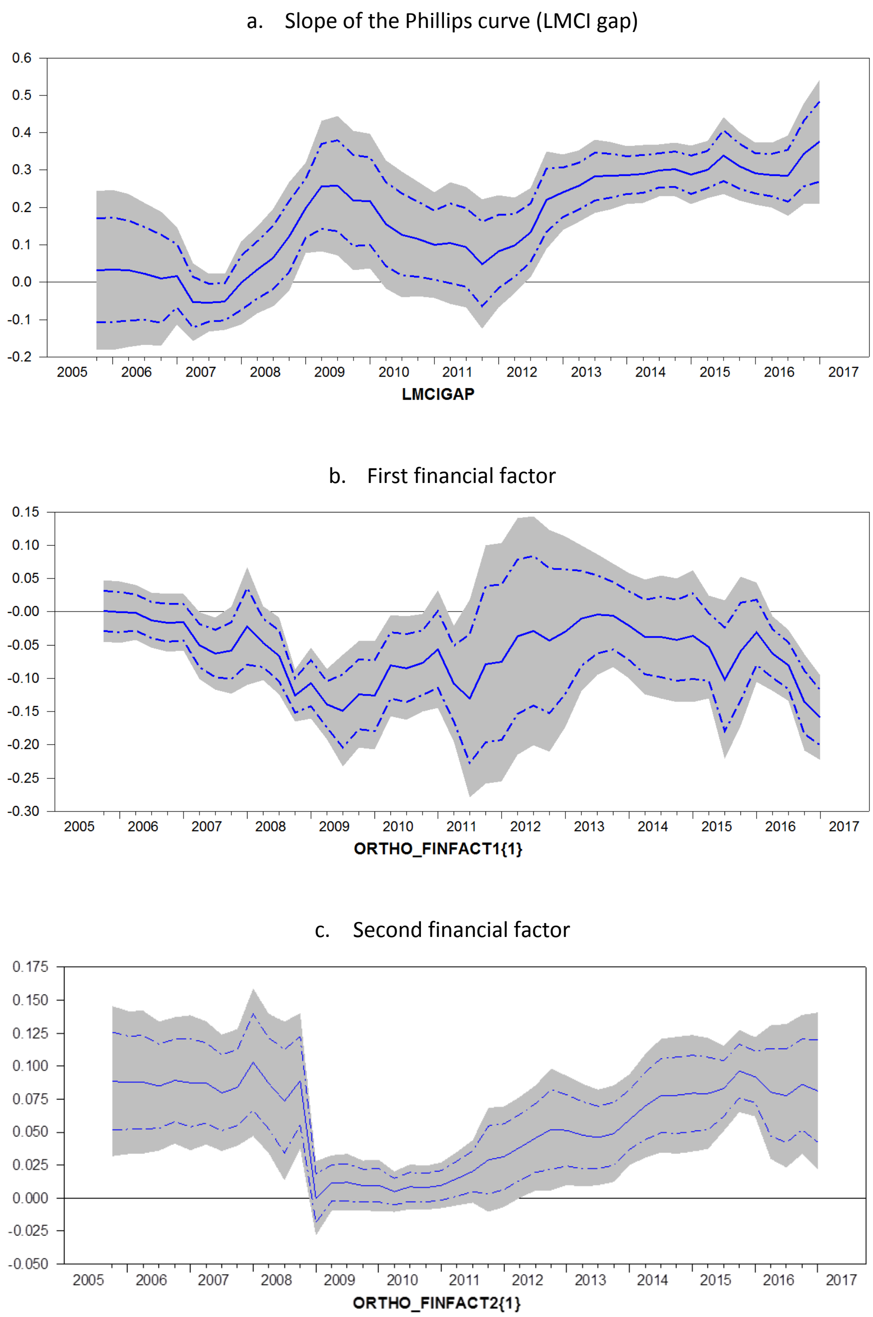


c. LMCI gap



Notes: The graph shows the estimates of the slope of the Phillips curve, based on a rolling window of 28 quarters and using the baseline model under three different measures of slack. The blue straight line is the point estimate, while the dashed blue line represents its 68% confidence interval and the shaded grey area its 95% confidence interval.

Figure 12: Time variation in the slope of the Phillips curve and financial factors.



Notes: The graph shows the estimates of the slope of the Phillips curve and of the impact of financial factors on core inflation, based on a rolling window of 28 quarters. The blue straight line is the point estimate, while the dashed blue line represents its 68% confidence interval and the shaded grey area its 95% confidence interval. The financial factors have been purged by the business cycle variables.

Figure 13: Conditional forecast of core inflation using threshold Phillips Curves: LMCI–GAP.

a. Slope dependent by the degree of labour market tightness

b. Slope dependent by the level of trend inflation

Notes: The graph shows the conditional forecasts (magenta lines) of core inflation based on the two non linear specifications presented in Section 4.2.

Table 1: Phillips curves estimates, baseline model.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Constant	0.180	0.026	0.306	0.180	0.082	0.320	0.202	0.115	0.374
	(0.211)	(0.146)	(0.157)**	(0.140)	(0.104)	(0.120)***	(0.120)***	(0.051)***	(0.095)***
π_{t-1}	0.760	0.731	0.663	0.756	0.752	0.648	0.681	0.721	0.607
	(9.376)***	(0.010)***	(0.078)***	(0.077)***	(0.090)***	(0.073)***	(0.099)***	(0.097)***	(0.085)***
π_{t-2}	0.276	0.317	0.308	0.274	0.311	0.304	0.272	0.288	0.295
	(2.749)	(0.106)***	(0.092)***	(0.095)***	(0.109)***	(0.090)***	(0.092)***	(0.104)***	(0.086)***
π_{t-4}	-0.182	-0.153	-0.236	-0.183	-0.140	-0.236	-0.167	-0.174	-0.205
	(-2.042)	(0.094)*	(0.072)*	(0.078)***	(0.083)***	(0.069)***	(0.083)***	(0.078)***	(0.074)***
$E_t\pi_{t+6}$	0.042	0.083	0.095						
	(0.249)	(0.596)	(0.095)						
$E_t\pi_{t+4}$				0.050	0.022	0.108			
				(0.042)	(0.108)	(0.069)			
$E_t\pi_{t+1}$							0.092	0.090	0.089
							(0.037)***	(0.042)***	(0.034)***
Ugap	0.083			0.081			0.066		
	(2.026)			(0.038)***			(0.027)***		
Ogap		0.048			0.051			0.020	
		(0.019)***			(0.022)			(0.022)	
LMCIgap			0.136			0.138			0.125
			(0.031)***			(0.031)***			(0.034)***
N	73	73	73	73	73	73	73	73	73
$\bar{R}^2$			0.92	0.90	0.90	0.92	0.91	0.91	0.92

Notes: OLS regressions estimates with robust standard errors in parentheses (Newey–West correction). The dependent variable is the y-o-y percentage point changes in the HICP excluding food, energy and tobacco. The estimation sample is 1999:Q1 - 2017:Q1. Asterisks ***, **, * denote statistical significance at - respectively - 1%, 5%, 10% confidence level, N is the number of available observations and $\bar{R}^2$ is the adjusted coefficient of determination.

Table 2: PHILLIPS CURVES ESTIMATES, FINANCIAL VARIABLES.

	FCI	Policy rate	FCI2	CISS
Slack coefficient				
Ugap	0.022	0.039	0.067	0.079
	(0.028)	(0.025)*	(0.025)***	(0.032)***
Ogap	-0.020	0.001	0.025	0.026
	(0.019)	(0.013)	(0.014)**	(0.013)**
LMCIgap	0.073	0.122	0.125	0.127
	(0.040)*	(0.040)***	(0.040)***	(0.034)***
N	72	72	72	72
$\bar{R}^2$	0.92	0.90	0.90	0.92

Notes: OLS regressions estimates with robust standard errors in parentheses (Newey–West correction). The dependent variable is the y-o-y percentage point changes in the HICP excluding food, energy and tobacco. The estimation sample is 1999:Q2 - 2017:Q1. Asterisks ***, **, * denote statistical significance at - respectively - 1%, 5%, 10% confidence level, N is the number of available observations and $\bar{R}^2$ is the adjusted coefficient of determination.

Appendix - Dataset

Table A-1: LABOUR MARKET DATA.

Category	Frequency	Source	Sample
Employment rates	Q	Istat	
Unemployment rates	Q	Istat	
Hours worked per capita	Q	Istat	
Hourly earnings per capita	Q	Istat	
Population	A	Istat	
Participation rates	Q	Istat	
Firms' expectations over Employment	M	Istat	
Households' expectations over Employment	M	Istat	
CIG	M	INPS	

Table A-2: MACROECONOMIC DATA.

Category	Frequency	Source	Sample
HICP, all items	M	Istat	
HICP, excluding energy, food and tobacco	M	Istat	
HICP, Services	M	Istat	
HICP, NEIGS	Q	Istat	
Inflation Expectations, 1-4 periods ahead	M	Consensus	
Oil prices	D	Bloomberg	
€/ $ exchange rate	D	ECB	
Nominal effective exchange rate (NEER19)	D	ECB	
Real GDP	Q	Istat	

Table A-3: FINANCIAL MARKET DATA.

Category	Frequency	Source	Sample
Loans to Households	Q	Bank of Italy	
Loans to Non–financial corporations	Q	Bank of Italy	
Loan rate to Households	Q	Bank of Italy	
Loan rate to Non–financial corporations	Q	Bank of Italy	
GM spreads (5)	M	Gilchrist and Mojon	
House prices	Q	Istat	
Stock prices (MIB)	D	Datastream	
CISS	D	ECB	
BTP10Y	D	Datastream	
BUND10Y	D	Datastream	
VIX US	D	FRED St. Louis	
VIX EA	D	ECB	
EPU Italy	M	FRED St. Louis	
EPU EA	M	FRED St. Louis	
EPU US	M	FRED St. Louis	