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Evaluating the Determinants of Irish Inflation

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Evaluating the Determinants of Irish Inflation

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During the period from 1970 to the early 2000s, there was a consensus that Irish inflation was primarily determined by external factors. In this letter, we evaluate the relative importance of domestic factors, external factors, and inflation expectations and specify how these have changed over time. We find that since the crisis, external factors remain the most important determinants of inflation. However, domestic factors such as labour slack have been increasingly important in recent years. Evaluating published forecasts against a benchmark statistical model, the Central Bank performs best at shorter horizons, i.e. less than one year. This validates an approach that combines model-evidence with expert judgement.[3]

Introduction

Real activity in the economy has expanded at a robust pace over the past number of years. At the same time, the unemployment rate has fallen from 16 per cent at the peak of the financial crisis in the beginning of 2012 to just under 5 per cent at the beginning of 2020. According to the Phillips curve, there exists a negative relationship between inflation and unemployment. However, despite the economy experiencing such a robust period of expansion over recent years, the rate of change in consumer prices has been more subdued than expected.[4]

Accurate and credible forecasts of inflation are important. Staff economists projections of inflation are used in the formulation of monetary policy by central banks. This is because the transmission lag of monetary policy means that the central bank is targeting future inflation in its decisions rather than contemporaneous inflation. In the case of countries in the Eurosystem, whose monetary policy is conducted centrally by the ECB, the forecasts produced by the national central bank form part of the overall Eurosystem staff projection exercises which inform Governing Council decisions at the European Central Bank (ECB). On a national level, projections of future inflation are used by a variety of agents in the economy to set prices, to bargain for wages and to plan for future budgetary requirements. As such, producing credible inflation forecasts using the most up to date methodologies is an important part of the work of a central bank.

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[4] As measured by the Harmonised index of consumer prices (HICP)

Finding a model which improves upon a simple benchmark forecast has been shown by various studies to be difficult. The standard Phillips curve model has come in for criticism in recent years, with evidence that it does not improve upon univariate models (Stock and Watson, 2007). Atkeson and Ohanian (2001) showed that, of the standard Phillips curve forecasts that they considered, none improved upon a four quarter random walk benchmark over a 15 year period. Stock and Watson (2007) show that the unobserved components model with stochastic volatility (UCSV) model outperforms the backwards looking Phillips curve.

Our paper adds to the long literature on forecasting Irish inflation and on the relative importance of domestic and external factors. It has long been contended in the literature on forecasting Irish inflation that external forces predomininantly determine dynamics in consumer prices. This view originates from a series of papers in the mid 1970s by Geary and coauthors (Geary (1976), Geary and McCarthy (1976) and Geary and Jones (1975)). The work of Honohan and Flynn (1986) and Callan and Fitzgerald (1989) also concluded that, at that time, Irish price inflation was essentially determined by UK inflation.

Honohan and Lane (2003, 2004) conducted further analysis on the effect of external factors on Irish inflation. In the 2003 paper, the strength of the US dollar during 1999-2001 was argued to be the cause of the surge in Irish inflation to 7 per cent. The hypothesis was further confirmed when the subsquent dollar weakness led to a fall in Irish inflation.

Recently, some studies have challenged the view that domestic factors do not play a role in the determination of Irish inflation. Gerlach *et al.* (2016) argued that the studies which had been relied upon to make this assertion were too short. Using a long time series (back to 1926), they found that the difference between unemployment and the non-accelerating inflation rate of unemployment (NAIRU) was a significant determinant of inflation in Ireland. Bermingham *et al.* (2012) also found that there is a significant role for a Phillips curve model in explaining Irish inflation and in particular during the financial crisis. In terms of forecasting Irish inflation, there have been a series of papers which have looked at forecasting overall consumer prices as well as the components of the CPI. Bermingham (2007) looks at forecasting headline HICP using core inflation, while Bermingham (2008) quantifies the effects of oil price shocks on Irish inflation. Meyler, Kenny and Quinn (1998a) were the first to use Bayesian methods to forecast Irish inflation. The authors found a significant improvement in forecast performance resulting from the use of Bayesian techniques. However, they found that these forecasts suffered from a high degree of uncertainty as evidenced by wide error bands. In further work, Meyler, Kenny and Quinn (1998b) forecast HICP using autoregressive integrated moving average (ARIMA) models. The authors find that ARIMA models compare favourably to those from the BVAR analysis with the exception of forecasting turning points.

The remainder of the paper is structured as follows. First, we conduct an exercise to identify which factors are important when forecasting Irish inflation. We attempt to uncover the main drivers of inflation and how these have changed post crisis. Since this model forms part of the toolkit used to generate the Bank's inflation forecasts. We then compare the

Bank's published forecasts with the standard univariate benchmark mode, the unobserved components model with stochastic volatility. Our results suggest that there has been a role for domestic measures of economic slack in determining inflation, in particular since the end of the financial crisis. Put another way, the Phillips curve is indeed a useful model when thinking about developments in Irish inflation. However, during all periods it remains imperative to condition on external variables when forecasting inflation. This goes some way in explaining the recent weakness in Irish inflation despite robust output growth. External shocks, brought on by Sterling depreciation after the UK vote to leave the European Union, as well as weakness in oil prices, have weighed on Irish inflation.

What Variables Drive Irish Inflation?

While generating the Central Bank's inflation projections, the forecaster must evaluate multiple sources of information in order to decide on the likely path of consumer prices. As outlined above, the variables that drive inflation change over time, and certain drivers not possible to capture in a single modelling framework. Expert judgement also plays an important role in this regard. For example, taking account of announced changes in administered prices such as VAT changes; public transport prices, etc.

One of the primary challenges is to determine which factors are most important at a given juncture. Our solution is to utilise Bayesian Model Averaging (BMA), which allows the forecaster to be agnostic on the specification and to estimate a large battery of models and to average them based on their forecast accuracy. BMA has the further advantage of using simple models that yield more stable estimates (because it uses fewer degrees of freedom) to identify important regressors, yielding results which are more informative and easier to interpret. The relevant model for forecasting might change over time. Moreover, the coefficients on the predictors may also change between periods (see Bobeica and Jarocinski, 2017).

With this in mind, we use Dynamic Model Averaging (DMA), which allows the weights on each forecasting model to change over time, thus dealing with this time variation. Changes in DMA were first proposed by Raftery et al. (2010) and they allow the weights used in the model averaging to change overtime. This methodolgy was first applied to examine the forecasting performance of Phillips curves in the euro area by Koop and Onorante (2012) and by Moretti, Onarante and Zakipour-Saber (2019).

Methodology

DMA is developed in Raftery, Karny and Ettler (2010) and used in Koop and Korobilis (2012) and the reader is referred to these papers for complete details. The dynamic aspect of DMA arises since it allows for a different model to hold at each time period. We assume a population p_k of K models

$$p_k\left(y_t|y^{t-1}\right), k = 1..K \tag{1}$$

where $y^s = (y_1, .., y_s)'$ is the past information up to time s and $p_k(y_t|y^{t-1})$ is the predictive density for model k at time t. We estimate our battery of models and evaluate them on the basis of their forecasting performance (on predictive density). Let $q_{t|s,j} = \Pr(k = j|y^s)$ be the probability that model j holds at time t given information through time s. DMA is a recursive algorithm which allows for the calculation of $q_{t|t,j}$ and $q_{t|t-1,j}$ for $j = 1, .., K$. Once calculated, weights $q_{t|t-1,j}$ can be used when forecasting y_t given information through time $t-1$. They can also be used to compute the "inclusion probability" of a variable or a set of models, that is the probability (and the importance) of these models relative to the complete set of K models. When estimating coefficients or impulse responses $q_{t|t,j}$ can be used to carry out model averaging in a time varying fashion.

To see how the weights are calculated, note that the predictive density appears in the model updating equation of:

$$q_{t|t,s} = \frac{q_{t|t-1,s}p_k(y_t|y^{t-1})}{\sum_{l=1}^{K} q_{t|t-1,l}p_l(y_t|y^{t-1})}. \tag{2}$$

If we knew $q_{t|t-1,s}$ then, starting with $q_{0|0,s}$ we could recursively calculate the key elements of DMA: $q_{t|t,j}$ and $q_{t|t-1,j}$ for $j = 1, .., K$. Raftery et al. (2010) provide this missing link by using the approximation:

$$q_{t|t-1,s} = \frac{q^{\alpha}_{t-1|t-1,s}}{\sum_{l=1}^{K} q^{\alpha}_{t-1|t-1,l}}. \tag{3}$$

A detailed justification for why this is a sensible approximation is given in Raftery et al. (2010). Suffice it to note here that it implies:

$$q_{t|t-1,s} \propto \left[q_{t-1|t-2,s}p_s\left(y_{t-1}|y^{t-2}\right)\right]^{\alpha} \tag{4}$$

$$= \prod_{i=1}^{t-1}[p_s(y_{t-i}|y^{t-i-1})]^{\alpha^i} \tag{5}$$

The previous result clarifies that a model j will receive more weight at time t if it has fit well in the recent past (fit is measured by the predictive likelihood, $p_j(y_{t-i}|y^{t-i-1})$). The interpretation of “recent past” is controlled by the forgetting factor, α. Thus, if $\alpha = 0.99$ (our benchmark value and also the value used by Raftery et al., 2010), forecast performance five years ago receives 80 per cent as much weight as forecast performance last period (when using quarterly data). If $\alpha = 0.95$, then forecast performance five years ago receives only about 35 per cent as much weight. These considerations suggest that we focus on the interval $\alpha \in (0.95, 0.99)$.

In our short data set, the potential advantages of DMA are clear. We can include models featuring a large number of explanatory variables, but if these are overfitted their predictive density will be low and DMA will attach more weight to more parsimonious models, thus lessening the problems caused by the curse of dimensionality while keeping all candidate models.[5] Furthermore, DMA allows for model change. It can capture cases where certain explanatory variables or model frameworks are important in certain periods, but not in others. Given our application, which covers the time from the introduction of the euro and through to the recent financial crisis, allowing for such chance may be important.

Results

Most of the debate around whether domestic factors play a role in determining Irish inflation notes that the Phillips curve can take many specifications or functional forms. As noted in Moretti et al. (2019), a model capturing all of the potential regressors would suffer from multicollinearity, among other problems. In order to account for this uncertainty about the model, we follow the example of Moretti et al. (2019) and estimate a large number of Phillips curve specifications. In each case, the dependent variable is core inflation, defined as the year on year percentage change in HICP excluding food and energy. The regressors are divided into four groups: real activity, expectations, labour market indicators (measuring domestic developments) and external indicators. Since there is no specific measure of inflation expectations for Ireland, euro area wide measures are used.[6] Each Phillips curve model contains an autoregressive component, one lagged real activity variable and at most one variable from each of the remaining groups. In total, we recursively estimate 845 Phillips curve models over a sample period from 1999 to 2007.

The inclusion probabilities obtained using DMA are informative on the subject of the relative importance of domestic and external factors. Figure 1 shows the probability of inclusion for each of the different groups of variables. Labour variables capture the importance of domestic factors. It is clear from Figure 1 that indeed external variables are the most important determinants of inflation dynamics in Ireland. They have a high inclusion probability throughout the entire sample period. Domestic factors appear to have been less important during in the period immediately before the crisis. However, since the beginning of the crisis, domestic factors have increased in importance as measured by their inclusion probability. This supports the finding of Bobeica and Jarocinski (2017). Since the beginning of the recovery domestic factors appear to have a similar inclusion probability to external factors. This is in line with the findings of Bermingham et al. (2012).

Figures 2, 3 and 4 break down the inclusion probabilities of the variables contained within the broad groups. In the real activity group, the unemployment gap has the highest inclusion probability on average over the sample period. This confirms the work of Bermingham et al. 2012. During the early years of the crisis, when unemployment in Ireland rose from 5 per cent to 15 per cent, the inclusion probability increased significantly. This is in line with the prediction of the standard Phillips curve, as the increase in unemployment occured at the same time as a significant decline in inflation. In 2012/2013, as the recovery began, there was an increase in the inclusion probability of the non-employment index (Byrne and

[5] See Koop and Korobilis (2009a) for evidence that DMA can effectively find very parsimonious models.
[6] A full description of the variables used is outlined in the data appendix

Figure 1: Inclusion Probabilities of Grouped Variables

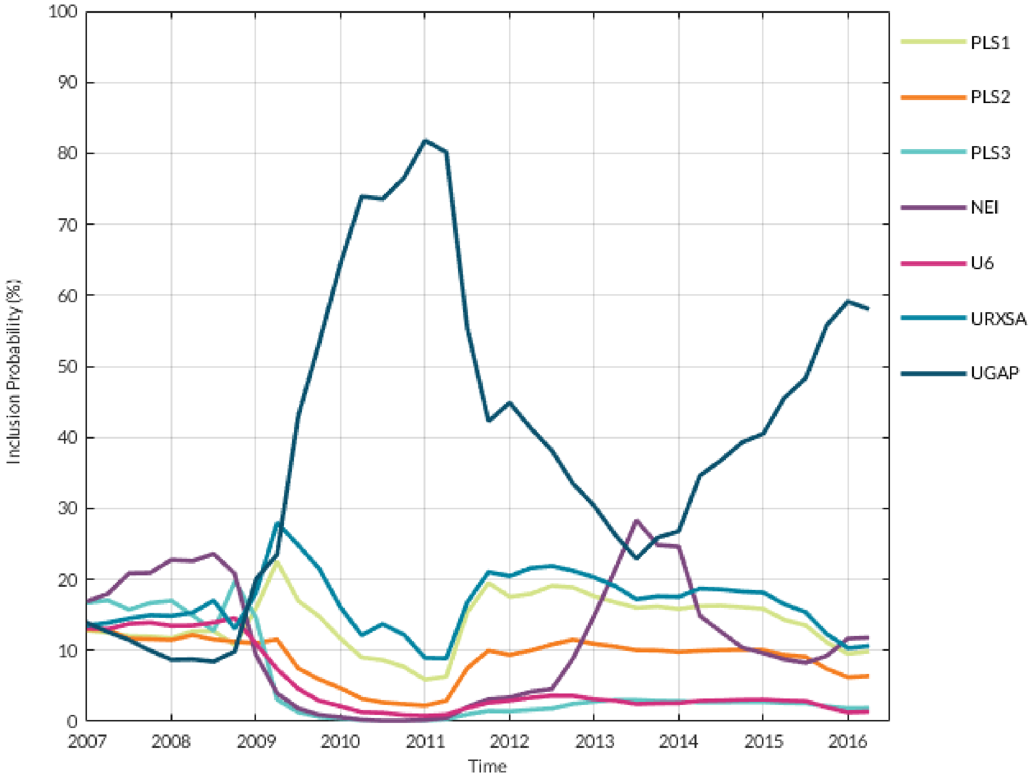
Conefrey, 2017). This could reflect the fact that, although the unemployment rate was beginning to fall, there was a significant jump in discouraged workers who were classified as being outside of the labour force but who still exerted downward pressure on wages and thus consumer prices.

The inclusion probabilities of the inflation expectations variables are illustrated in figure 3. During all periods, short term expectations appear be the most important; one year ahead euro area inflation linked swaps being the most important during the early onset of the financial crisis and one year ahead inflation swap spot rates had the highest inclusion probability in the years 2012 to 2017.

Consistent with the literature on forecasting Irish inflation, external variables have the highest inclusion probabilities over most of the sample period. Of the external variables included in our analysis, the real effective exchange rate (REER) has the highest inclusion probability over much of the period.[7] This reflects the importance of developments in the pound sterling and the US dollar for Irish inflation. At the same time, the price of oil is important throughout the full sample period. Oil is both an input into many consumption goods and affects their prices indirectly through transport costs. World industrial produc-

[7] This confirms the result of Reddan and Rice, 2017)

Figure 2: Real Activity, Inclusion Probabilities Over Time



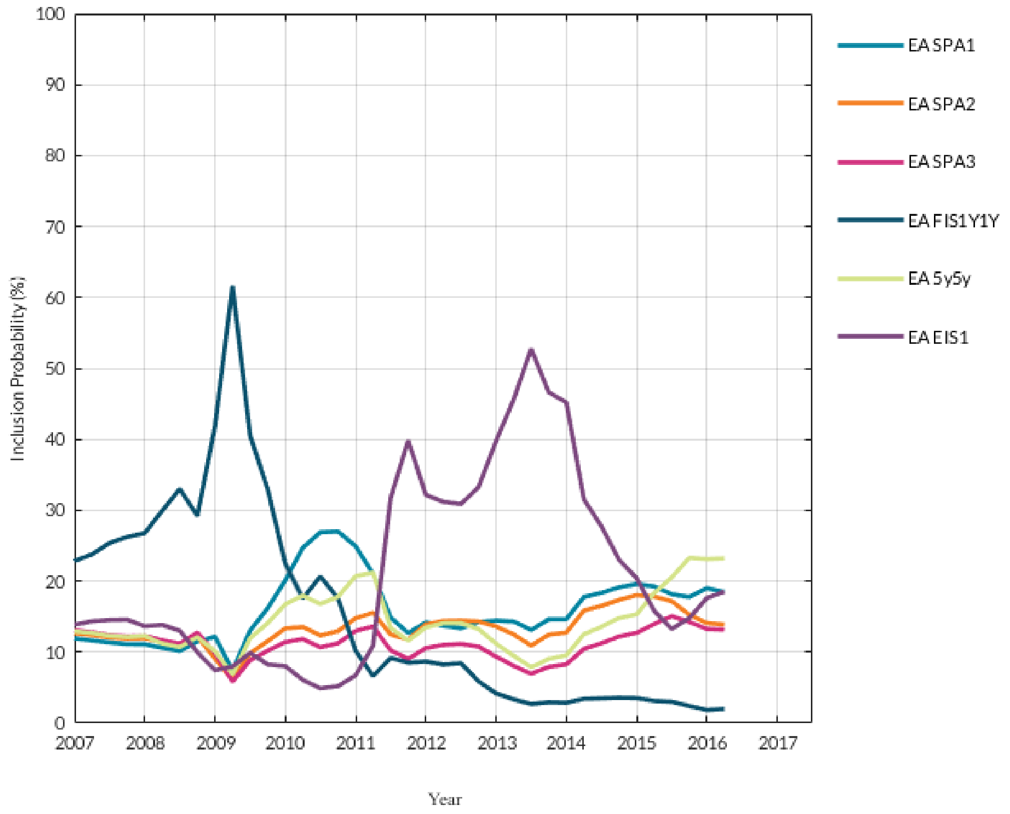
tion has a high inclusion probability during the period from 2007 to 2009 as the global recession impacted on price developments throughout most advanced economies.

Forecasting Inflation

The published forecasts of the Central Bank rely on information from models such as that described above, as well as a significant amount of expert judgement. Expert judgement takes account of factors which affect inflation dynamics, but which are not able to be captured in the formal models used. For example, if the econometrician knows about an imminent increase in public transport fares, or other so called "administered prices" .

Studies have suggested that simple univariate models often outperform more sophisticated forecasting approaches (Atkeson and Ohanian, 2001; Stock and Watson, 2002). With this in mind, we want to compare the Bank's official forecasts, which encompass model and judgement based elements, to a similar benchmark forecast. Recent innovations in the literature have augmented the integrated moving average benchmark with time varying parameters. Stock and Watson (2007) found that inflation in the US was well described by the univariate unobserved component model with stochastic volatility. The UCSV model postulates that inflation is the sum of stochastic trend τ_t and a serially uncorrelated disturbance

Figure 3: Inflation Expectations, Inclusion Probabilities Over Time



with stochastic volaility. Both components feature stochastic volatility captured by R_t and Q_t, with mutually independent error terms, v_t and e_t . The stochastic volatility R_t and Q_t follow independent random walk processes.

$$\pi_t = \tau_t + R_t^{1/2} v_t$$

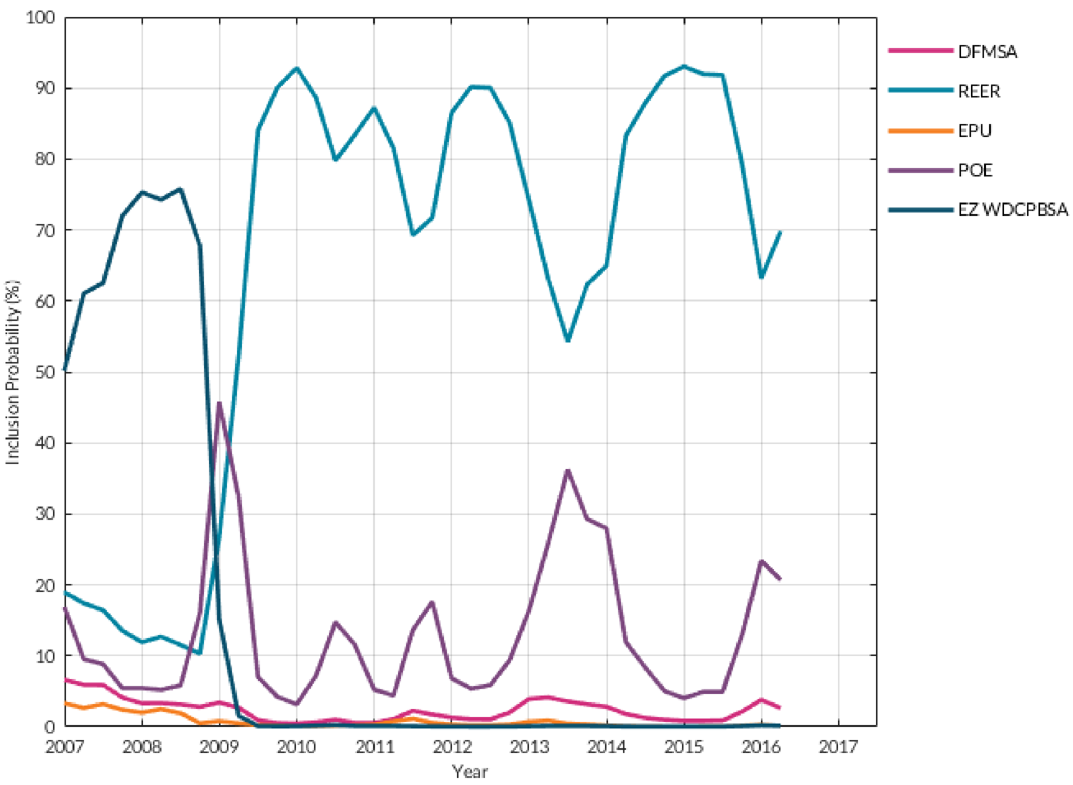
$$\mu_t = \mu_{t-1} + Q_t^{1/2} e_t$$

The estimation steps involve setting the initial conditions and normal inverse gamma priors via a training sample of 10 years, then drawing the stochastic volatility of the transitory components via the Metropolis Hastings procedure of Jacquier, Polson, and Rossi (2004), and the random walk component using the algorithm provided in Carter and Kohn (1994).

Forecast Performance

It is important to conduct a thorough analysis of the forecast accuracy compared with the outturn at various forecast horizons (i.e. $t...t+h$ step ahead forecasts). We then compare

Figure 4: External Variables, Inclusion Probabilities Over Time



these forecast errors with the accuracy of the forecasts conducted by the Central Bank of Ireland and in the European Central Bank Staff Projections.

In order to measure forecast accuracy, we assess the mean absolute percentage error (MAPE), given by:

$$MAPE = \frac{1}{n}\sum_{n=1}^{n} \left| \frac{\pi_t - \hat{\pi}_t}{\pi_t} \right| \tag{6}$$

where π_t is the actual outturn and $\hat{\pi}_t$ is the Forecast.

Table 1 details the MAPE from the median forecast at each horizon from the unobserved components model with stochastic volatility.

Table 1: Average Forecast Error By Horizon 2006-2017 : UCSV

	March	**September**
HICP year t	1.22	1.20
HICP year t+1	1.05	1.15

The forecasts from the UCSV model perform well. Indeed, the univariate model outpeforms the forecasts of both the Central Bank and the ECB. Table 2 describes the forecast errors of the Eurosystem staff "macroeconomic projection exercise" for Ireland. These forecasts are carried about by the ECB country experts in consultation with staff at the National Central Bank.

Table 2: Average Forecast Error By Horizon 2006-2017 : Eurosystem MPE Staff Projections

	March	**September**
HICP year t+1	1.44	1.30
HICP year t+2	1.28	1.28

Table 3 shows the mean absolute percentage error for the *Bank's* ECB *Broad Macroeconomic Projection Exercise*. The December forecasts for the current year have had, not surprisingly, a high degree of accuracy. When it comes to the one and two year horizons however, the forecast performance is broadly similar to that of the eurosystem MPE projections.

Table 3: Average Forecast Error By Horizon 2006-2017 : CBI Eurosystem Staff Projections

	June	**December**
HICP year t	0.73	0.06
HICP year t+1	1.43	1.05
HICP year t+2	1.20	1.35

Table 4 describes the MAPE of the inflation forecasts published in the Bank's *Quarterly Bulletin*. These forecasts are published at a higher frequency (four times per year). Overall, the forecast accuracy for the current year (i.e. forecasts published in 2018 for 2018) are positive and (intuitively) improve as more data becomes available as the year progresses. The error declines from 0.65 percentage points in the first quarter to 0.17 in the fourth. [8]

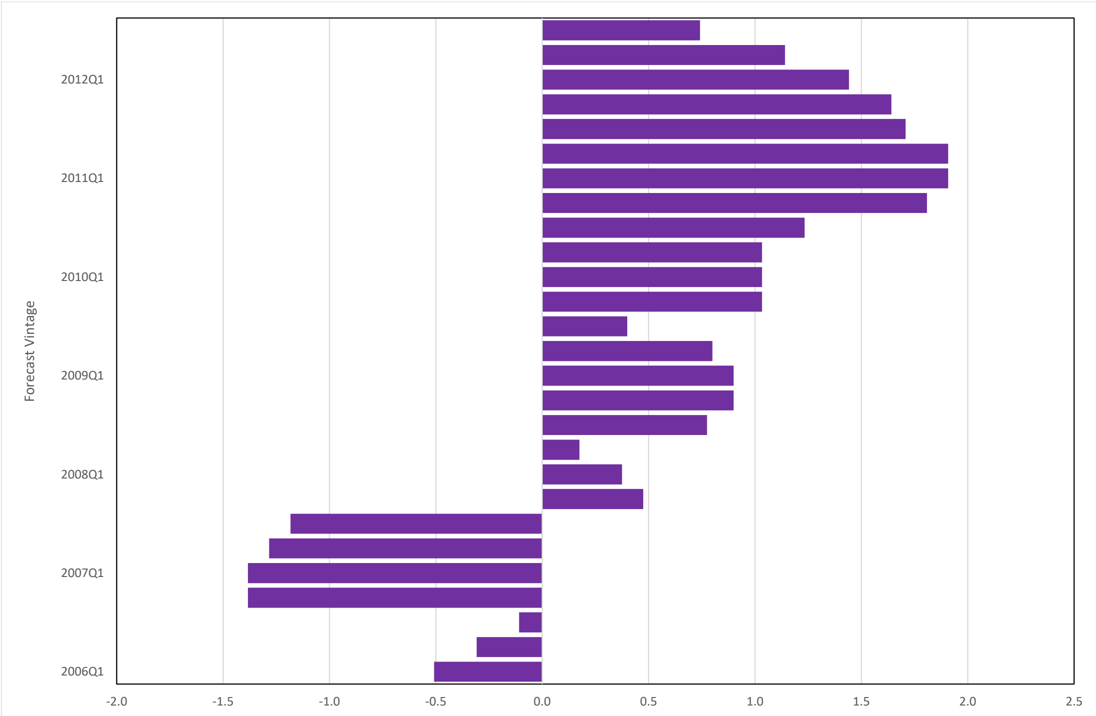
Table 4: Average Forecast Error by Horizon 2006-2017: Central Bank Quarterly Bulletins

	Q1	**Q2**	**Q3**	**Q4**
HICP year t	0.65	0.47	0.27	0.17
HICP year t+1	1.21	1.17	1.06	1.01
Goods year t	1.14	0.78	0.40	0.17
Goods year t+1	2.59	2.42	1.97	1.76
Services year t	0.53	0.36	0.18	0.26
Services year t+1	0.59	0.69	0.60	0.74

Note: The table should be interpreted as thus: Forecasts of aggregate HICP published in the first quarter for the current year are, on average, inaccurate by 0.65 percentage points in absolute terms.

[8]Fourth quarter forecasts are generally published in October using data up to August

Figure 5: HICP Year $(t+1)$ Forecast Errors



Source: Authors' calculations

At the longer horizon $(t+1)$ the forecast performance, understandably, begins to decline. However, it is noteworthy that the source of the forecast error appears to lie largely in the forecast for goods prices. This may reflect the ongoing debate in Ireland about the persistent negative inflation in non-energy industrial goods driven mainly by declines in the prices of clothing and footwear.

Figure 5 displays the aggregate HICP year $t+1$ forecast errors over time. It is clear that in large part the mean forecast error is driven by a persistent overestimation during the financial crisis; in particular between 2008 and 2011. This is unsurprising given that this period was marked by sharp declines in aggregate inflation, as well as a strongly elevated degree of uncertainty around key variables used in the Central Bank's inflation models such as GDP, interest rates, and the performance of the labour market.

Conclusion

This Letter shows that while external variables remain the most important determinants of Irish inflation, domestic factors have become increasingly important in recent years. This underscores the finding of Gerlach *et al.* that the Phillips curve is a useful model for Ireland.

The importance of external factors however helps explain the weakness in Irish inflation in recent years despite the strength of output growth. The depreciation of the euro/sterling exchange rate, as well as the fall in oil prices, have exerted downward pressure on prices that have outweighed domestic developments. We also show that the Central Bank's published forecasts outperform the univariate unobserved components model with stochastic volatility in a forecast horizon less than twelve months, but over longer forecast horizons the UCSV performs best. This validates the use of expert judgement over the short-term forecasts.

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Table 5: Data Appendix

Variable Name	Description	Unit	Source
HEUF	HICP, all items excluding energy and unprocessed food (2015=100)	Price Index	Eurostat
ULCHN	Nominal Unit Labour Cost Based on Hours Worked, Total Economy (2010=100)	Index	Eurostat
CPESA	Compensation per Employee	Euros	ECB
DFMSA	Implicit Price Deflator, Imports (2010 = 100), Annualised Rate	Price Index	OECD
URXSA	Unemployment Rate, Total populaton, ILO definition	Percentage	Eurostat
NAIRU	Non-accelerating inflation rate of unemployment	Percentage	OECD
REER	Real Effective Exchange Rate Based on CPI (Index, 2010 = 100), Broad	Index	BIS
POE E	Crude Oil, Dated Sullom Voe EUR per BBL	Price	Thomson Reuters
EPU	Economic Policy Uncertainty	Index	Jonathan Rice (2019)
PLS1	Potential Labour Supply (Unemployed plus discouraged workers)	% Working Age Pop	CSO
PLS2	Potential Labour Supply (All individuals in Potential Additional Labour Force (PALF)	% Working Age Pop	CSO
PLS3	Potential Labour Supply (PALF + Discouraged + Outside labour force not in education	Percentage of Working Age Population	CSO
NEI	Non Employment Index	Percentage of Working Age Population	Byrne and Conefrey (2017)
U6	Broader Measure of Labour Supply		Eurostat
EIS1	Inflation Swap - Spot 1 year	Rate	
FIS1Y1Y	1 Year in 1 Year Implied Forward Inflation Swap	Rate	Bloomberg
FIS5Y5Y	5 Years in 5 Years Implied Forward Inflation Swap	Rate	Bloomberg
SPA1	Inflation Forecast of One Year Ahead	%YoY	ECB
SPA2	Inflation Forecast of Two Years Ahead	%YoY	ECB
SPA3	Inflation Forecast of Five Years Ahead	%YoY	ECB
WDCPBSA	World Industrial Production (import weight, 2005 = 100)	Index	Datastream