Economics Bulletin

Volume 35, Issue 2

The output gap and inflation in U.S. data: an empirical note

Anindya Biswas
Spring Hill College

Abstract

This paper analyzes the relationship between the output gap and inflation. This study uses a newly proposed flexible data-driven measure of the output gap and finds that such a distance weight-based measure of the ex-ante output gap (WAgap), has a significant and better in-sample relation with inflation in U.S from January, 1948 to August, 2013 compared to a prevalent ex-ante trend-based measure of the output gap. However, this study confirms the literature's conclusion that finding the out-of-sample/real-time predictability for inflation is most challenging, and the WAgap model provides only modest improvement over the benchmark historical mean model.

This paper is based on the second chapter of my dissertation and I am grateful to my advisor Dr. Evan W. Anderson for his valuable time, guidance, and comments and take responsibility for any remaining errors. The author is highly indebted to two anonymous referees of this journal for their interesting and constructive comments on an earlier version of the paper. The usual disclaimer, however, applies.
Citation: Anindya Biswas, (2015) "The output gap and inflation in U.S. data: an empirical note", *Economics Bulletin*, Volume 35, Issue 2, pages 841-845
Contact: Anindya Biswas - abiswas@shc.edu.
Submitted: May 17, 2014. **Published:** April 02, 2015.

The output gap and inflation in U.S. data: an empirical note[1]

1. Introduction

Keeping inflation at a tolerable level has been a major objective of the Fed as well as other central banks. The Fed achieves this goal primarily by devising an implicit policy for the targeted short-term nominal interest rate known as the federal funds rate. John B. Taylor (1993) summarized the above facts in a rule known as Taylor's rule. On many occasions, Taylor's rule accurately predicted the decisions of the Federal Open Market Committee regarding the federal funds rate. Owing to this rule, it is believed that the Fed's monetary policies are guided by the output gap and consequently, the output gap has an important relation to inflation.

There is a solid theoretical explanation for a relationship between the output gap and inflation. The output gap increases during expansions and decreases during recessions. When the output gap increases, usually there is inflationary pressure in an economy. This has led a number of researchers to specify a positive relationship between the output gap and inflation. This type of specification is based on the premise of the well-known backward-looking Phillips curve, which relates some measures of aggregate economic activities (i.e., the unemployment rate, output gap, etc.) along with lagged inflation term to current inflation. However, it is often found in the literature (Orphanides & van Norden, 2005) that a prediction of inflation from an ex-ante measure of the output gap is extremely difficult.

This paper studies the relationship between a newly proposed flexible data-driven and distance weighting based measure of the output gap, the weighted average output gap (WAgap), and inflation. The main objective of this study is to analyze the effectiveness of the WAgap compared to the quadratic trend-based output gap (QTgap) in explaining inflation in the U.S. economy. Both the WAgap and the QTgap are ex-ante and explained in detail in Biswas (2014). This study finds significant in-sample predictability of the WAgap for inflation, whereas the QTgap has no such predictability. However, this study confirms the literature's conclusion that finding the out-of-sample/real-time predictability for inflation is most challenging**,** and both the WAgap model and QTgap model provide only modest improvements over the benchmark historical mean model.

2. Framework

The WAgap considers the difference between period *t*'s output and the weighted average of the output up to period $t-1$. Following Ghysels, Santa-Clara, and Valkanov's (2006) and Ghysels, Sinko, and Valkanov's (2007), Biswas (2014) used a single parameter beta polynomial to specify a distance weighting scheme. Such a weighting scheme (following Anderson, Ghysels, & Juergen's, 2009 study) can be written succinctly as:

$$w_i = \frac{(i^{max}+1-i)^{\kappa-1}}{\sum_{j=1}^{i^{max}}(i^{max}+1-j)^{\kappa-1}} \qquad (1)$$

---

[1] The author is highly indebted to two anonymous referees of this journal for their interesting and constructive comments on an earlier version of the paper. The usual disclaimer, however, applies.

where w_i is the weight to the i^{th} prior lag and i^{max} is the maximum number of lags. A single parameter beta distribution is parsimonious because only one parameter κ needs to be estimated. It is also flexible because it can take different shapes depending on the value of κ.

The framework for the WAgap model is:

$$\pi_t = \mu_{wa} + \gamma_1^{wa} gap_{(t-2,t-3,....,t-s)}^{t-1}(\kappa) + \gamma_2^{wa}\pi_{prior}^{av} + \varepsilon_t \qquad (2)$$

where π_t=log(CPI_t) - log(CPI_{t-1}) is the inflation at time *t*, μ_{wa} denotes the constant term, $\gamma_1^{wa}$is the WAgap coefficient, κ is the hyperparameter used in a single parameter beta distribution for the weighting scheme given to the prior vintage (log of) industrial production index (IP) data to obtain the potential output and hence the WAgap, π_{prior}^{av} is the average of prior inflations,[2] γ_2^{wa} is the coefficient for the lagged inflation term and ε_t denotes a disturbance term.

Here, the WAgap is calculated as $gap_{(t-2,t-3,....,t-s)}^{t-1}(\kappa) = \log(IP_{t-2}) - \sum_{i=1}^{s} w_i(\log(IP_{t-2-i}))$,[3] and the weighting parameter κ is estimated jointly with μ_{wa}, γ_1^{wa} and γ_2^{wa}in the above set up given by equation 2. Selection of the optimum lag length in the WAgap model is data-driven as it is determined by the value of κ. This is a major departure from most other lag-based forecasting models where researchers usually choose lag lengths by guessing. Decaying weighting pattern is obtained when κ is greater than one. The construction of the WAgap is more general; it does not involve any explicit restriction in the in-sample analysis for a decaying pattern. But decaying weighting pattern has emerged in this study's empirical analysis, commensurate with the intuition that distant observations of output has smaller impact on the present output. Another distinguish feature of the WAgap is that it does not include any future information, and, hence, avoids the well-known "look-ahead" bias (Welch & Goyal, 2008) problem of common trend-based measure of the output gap.

The framework for the QTgap model is

$$\pi_t = \mu_{qt} + \gamma_1^{qt}\overline{gap}_{t-2,t-3,....,t-s}^{t-1} + \gamma_2^{qt}\pi_{prior}^{av} + \varphi_t \qquad (3)$$

where, $\overline{gap}_{t-2,t-3,....,t-s}^{t-1} = \log(IP_{t-2}) - QT\ fitted\ value\ (IP_{t-2})$, μ_{qt} denotes the constant term, γ_1^{qt} is the QTgap coefficient γ_2^{qt} is the coefficient for the lagged inflation term, and $\varphi_t$is a disturbance term. In this analysis, the predictability of both types of gap is determined from the statistical significance of the respective gap coefficients.

3. Data

The full-sample study period covers 1948 to August-2013, involving 788 and 262 total observations for monthly and quarterly inflation, respectively. In line with the literature, the urban consumer price index (series CPIAUCSL) from the Federal Reserve Economic Data (FRED) was considered as the basis for measuring inflation. Quarterly inflation data were obtained from the quarterly CPI series which was calculated from the monthly CPI series by geometrically averaging. The IP index is one of the common aggregate economic indicators for

---

[2] Although, researchers usually consider only the first lag of inflation in this context, however, this study differs slightly by considering average of prior inflations to incorporate information about current inflation in other prior inflations in addition to only the first lag of current inflation.

[3] To predict inflation at *t* the WAgap is calculated from the vintage IP series at *t - 1* and because of publication lag such data are available up to *t - 2* and this study considers prior IP data until *(t - s)*th period.

output data and, unlike GDP, is available monthly. In Choi, Hauser, and Kopecky's (1999), Cooper and Priestley's (2009), Ghysels and Wright's (2009) work, among that of many others, the IP index is considered as a basis for measuring the aggregate output and hence, the output gap. This analysis used the vintage version of the IP index series from the ArchivaL Federal Reserve Economic Data (ALFRED) website in order to construct both types of output gap series. Mean and standard deviation of IP growth based on the vintage IP series published on 2013:M7[4] for the periods from 1927:M1 to 2013:M6 were 0.0028 and 0.0183 respectively.

4. In-Sample Analysis

This analysis used US inflation in levels rather than changes in inflation and found that the inflation series was stationary. The null hypothesis of a unit-root in the well-known ADF test for the level of inflation was rejected at the conventional level of significance over the full-sample period from 1948:M1 to 2013:M8. The values of the ADF-test statistic for inflation are -14.416 (-2.860) and -6.458 (-2.880) at the monthly and quarterly frequencies, respectively. Critical values at 95% are in parenthesis. The WAgap is more positively related to inflation than the QTgap. The correlation between the WAgap and inflation during the full-sample period is 0.10 and 0.11 at the monthly and quarterly frequencies, respectively, whereas the correlation between the QTgap and inflation is only 0.04 and 0.03 at those frequencies.

The WAgap coefficients are 0.022 (0.006) and 0.037 (0.013) with respect to monthly and quarterly inflation, respectively for the full sample period. Robust standard errors from the Quasi-Maximum Likelihood Estimation (QMLE) are given in brackets. The corresponding coefficients for the QTgap model are 0.003 (0.002) and 0.009 (0.005). The in-sample predictability of both types of output gap is determined from the statistical significance through the QMLE standard errors of the respective gap coefficients. The better forecasting accuracy of the WAgap is evident from the higher as well as the significant values of the WAgap coefficients compared to the corresponding QTgap coefficients. The coefficient for the lagged inflation term is almost the same (roughly equal to 0.8) in both the models, and is highly significant. This result is not surprising because many other studies in related contexts have found significant predictability of the lagged inflation term for current inflation. In short, this in-sample analysis identifies a strong relationship between inflation and the output gap that is based on a distance-weighted average method (See Table 1).

[4] M1 means January, M2 means February,…., etc.

Table 1. In-sample prediction analysis

Panel 1.1: Monthly inflation from 1948:M1 to 2013:M8

Model	**μ**	γ_1	γ_2	**κ**	**LL**
WAgap	0.0003 (0.0002)	0.022 (0.006)	0.834 (0.051)	74.041 (0.888)	4224.629
QTgap	0.0005 (0.0002)	0.003 (0.002)	0.824 (0.050)	() (-)	4218.893

Panel 1.2: Quarterly inflation from 1948:Q1 to 2013:Q2

WAgap	0.001 (0.001)	0.037 (0.013)	0.810 (0.060)	37.016 (29.457)	1202.688
QTgap	0.002 (0.001)	0.009 (0.005)	0.802 (0.063)	() (-)	1199.969

Note. This table provides the main results of the in-sample prediction analysis of inflation from the two models. Estimates of parameters are reported with QMLE standard errors in parentheses. LL stands for the value of the log likelihood function.

5. Real-Time Analysis

This study considers a real-time forecast evaluation of these two models from 1970:M1 to 2013:M8 and from 1970:Q1 to 2013:Q2 for monthly and quarterly frequencies, respectively. The Mean Absolute Errors (MAEs) are uniformly lower both in the WAgap and the QTgap models compared to those in the benchmark historical mean model and both of them have high correlation between the actual and the predicted inflations (CORR). These results indicate that at these frequencies, both the WAgap and QTgap models predict inflation better than the benchmark historical mean model. However, it is evident that the improvement in the MAE is rather modest compared to the benchmark model, which confirms the result of the relevant literature that predicting inflation in the OOS context is most challenging.

Table 2: Out sample prediction analysis

Periods	Evaluation criterion	HIS_{mean}	QTgap	WAgap
1970:M1-2013:M8	MAE	0.0027	0.0018	0.0018
1970:M1-2013:M8	CORR		0.6226	0.6215
1970:Q1-2013:Q2	MAE	0.0068	0.0037	0.0037
1970:Q1-2013:Q2	CORR		0.7684	0.7647

Note. This table reports the results of one-period-ahead forecast comparisons of inflation at three frequencies. In each case, two models, the WAgap and the QTgap, were compared with the historical mean model, HIS_{mean}.

6. Conclusion

This analysis shows that the WAgap has a significant role in explaining inflation and that the lagged WAgap is a useful predictor for inflation. The WAgap captures the output fluctuations in the economy better than the QTgap, which in turn raises the in-sample predictive accuracy of the WAgap regarding inflation. So the finding regarding the WAgap is congruent with the idea that the higher the output gap in the previous period, the greater the inflation in the present period. The contribution of this study is to add precision to this idea by establishing the relationship between a new, flexible, data-driven, and ex-ante measure of the output gap and inflation. This study exclusively focuses on the impact of the output gap, by far the most important business-cycle indicating macroeconomic variable, on inflation. Future study will include other macroeconomic variables, such as money supply, different measures of interest rates, etc. into the analysis with a goal of improving the real-time forecast of inflation.

References

Anderson, E. W., Ghysels, E., & Juergens, J. L. (2009). The impact of risk and uncertainty on expected returns. Journal of Financial Economics, 94 (2), 233-263.

Biswas, A. (2014). The output gap and expected security returns. Review of Financial Economics, 23(3), 131−140.

Choi, J. J., Hauser, S., & Kopecky, K. J. (1999). Does the stock market predict real activity? Time series evidence from the G-7 countries. Journal of Banking and Finance, 23, 1771-1792.

Cooper, I., & Priestley, R. (2009). Time-varying risk premiums and the output gap. The Review of Financial Studies, 22 (7), 2801-2833.

Ghysels, E., Santa-Clara, P., & Valkanov, R. (2006). Predicting volatility: Getting the most out of return data sampled at different frequencies. Journal of Econometrics, 131, 59-95.

Ghysels, E., Sinko, A., & Valkanov, R. (2007). MIDAS regressions: Further results and new directions. Econometric Reviews, 26, 53-90.

Ghysels, E., & Wright, J. (2009). Forecasting Professional Forecasters, Journal of Business and Economic Statistics, 27, 504-516.

Orphanides, A. & van Norden, S. (2005). The reliability of inflation forecasts based on output gap estimates in real time. Journal of Money, Credit, and Banking, 37, 583-601

Taylor, J. B. (1993). Discretion versus policy rules in practice. Carnegie-Rochester Conference Series on Public Policy, 39, 195-214.

Welch, I., & Goyal, A. (2008). A Comprehensive Look at The Empirical Performance of Equity Premium Prediction. The Review of Financial Studies, 23, 1455-1508.