The Effect of News Media on UK Consumers' Inflation Assessment

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Abstract

This paper examines the effect of unemployment news coverage on the inflation perceptions and expectations of the British public since 2000. It examines the existence of a 'cognitive' Phillips curve; as information concerning unemployment rises, are inflation perceptions or expectations affected? Analysing two distinct channels; intensity and tone, I find evidence that the intensity of news improves the accuracy of inflation perceptions, whereas front-page news coverage impairs inflation perception accuracy. However, taking news coverage as endogenous and employing Instrumental Variables regression, the hypothesis is rejected. I find little evidence of any effect of news on inflation expectations and conclude that this is evidence that inflation expectations are well anchored by another mechanism in the UK economy.

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1 Introduction

Economic policy, specifically monetary policy, relies upon understanding and exploiting the economic expectations of market participants. Indeed, Woodford (2005) claims that monetary policy consists purely of managing the expectations of market participants. Since its conception in the 1970s, the Rational Expectations Hypothesis has come to dominate macroeconomic theory. However, critics of this hypothesis, such as Ben Friedman, complain that such models lack 'a clear outline of the way in which economic agents derive the knowledge which they then use to formulate expectations' (Friedman, 1979; p24).

The motivation behind this paper derives from the concept of *The Economist's* 'R–Word Index' and the fear that the media creates negative economic opinions, thereby self perpetuating a decline in economic activity.[1] Benford of the Bank of England shows that UK inflation expectations are largely constructed using a 'backward rule-of-thumb' and acknowledges that 'around a quarter of [survey] respondents cited media reports as being a "very important" factor in influencing their perceptions of current inflation' (Benford, 2008:Q2). One surprising issue is the considerable disagreement of UK consumers' current perceptions of inflation with the actual rate, averaging 0.92% error between 2000 and end-2009. Disagreement considerably increases towards the end of the decade, a period of high media intensity concerning the economic situation. Intuitively, more media attention should improve consumers' awareness of the economic situation thereby improving the accuracy of inflation assessment: expectations and perceptions. This paper explicitly tests this hypothesis. Rather than concentrate singularly on consumers' expectations, an understanding the formulation of *current* inflation perceptions is as important for managing the beliefs of market participants. The policy implications of media coverage significantly affecting inflation assessment are large, specifically in terms of monetary policy as outlined by Woodford.

This paper examines the relationship between the intensity of unemployment news and the inflation assessment of the British public. The inherent endogeneity problem is countered through the use of an Instrumental Variables (IV) technique; to my knowledge, an approach unique among the literature. Moreover, this paper expands the literature by examining the existence of a 'cognitive' Phillips curve; does increased media intensity concerning unemployment affect the accuracy of inflation expectations or perceptions in the expected Phillips curve manner? I find evidence of a negative association between unemployment news intensity and the accuracy of consumers' perceptions; as media intensity increases, perception error falls, improving accuracy. This paper also finds an opposite relationship for front-page news; an impairment consumer inflation assessment. However, when employing a Two-Stage-Least-Squares (TSLS) instrumental variables approach neither hypothesis can be confirmed, precluding an explicit proof that media coverage *causes* impairment or improvement in inflation perceptions. Regarding inflation expectations, a relationship between news media and expectations cannot be confirmed, providing evidence that inflation expectations in the UK are well anchored by

[1] see 'The R-Word' on *www.economist.com* Jan 10, 2008

some other mechanism. Again, the endogeneity hypothesis of news intensity relative to inflation expectations cannot be rejected. This result is consistent with Benford's finding, that UK consumers use rules of thumb in determining their inflation assessment, exhibited by the significant relationship between realised inflation and expectations and perceptions.

Mankiw & Reis accept that the crux of New Keynesian economics, wage- and price-stickiness, and its subsequent Phillips curve framework, has trouble squaring with the facts. For example, it cannot explain why 'shocks to monetary policy have a delayed and gradual effect on inflation [and that] announced, credible disinflations cause booms rather than recessions' (Mankiw & Reis, 2002; p1). Hence, they propose a *sticky-information* model of expectation formation, where:

> Information diffuses slowly through the population [...] each period a fraction of the population updates itself on the current state of the economy and computes optimal [decisions] based on that information. The rest of the population continues to [make decisions] based on old plans and outdated information. [...] Although prices are always changing, pricing decisions are not always based on current information. (Mankiw & Reis, 2002; p3)

Building upon this theory, Reis (2006) and Sims (2003) developed the concept of 'rational inattention,' where agents rationally update their information set periodically as they face costs of 'acquiring, absorbing and processing information' (Reis, 2006; p1). Carroll (2003) subsequently expands this notion through his so-called 'epidemiological' model of informational diffusion; information 'spreads' through an economy. Carroll claims to provide a microfoundation for Mankiw & Reis' model, which this paper in turn develops.

2 Existing Literature & Theory

2.1 Sticky-Information & Inflation Expectations

This section examines the existing theoretical and empirical evidence for media's effect on consumers and introduces the model. The model is built upon Mankiw & Reis' *sticky-information Phillips curve*, in turn based on Calvo's (1983) sticky-price method. Mankiw & Reis demonstrate that inflation is a function of the output gap, weighted by the ratio of information-updaters to non-updaters, plus the infinite weighted sum of inflation and the change in the output gap. They elucidate that the crucial element of this model is that 'the relevant expectations are *past* expectations of *current* economic conditions' (Mankiw & Reis, 2002; p7).

$$\pi_t = \left[\frac{\alpha\lambda}{1-\lambda}\right] y_t + \lambda \sum_{j=0}^{\infty}(1-\lambda)^j E_{t-1-j}(\pi_t + \alpha\Delta y_t) \tag{1}$$

where α is the weight on the output gap, λ is the proportion of agents who update their information, y_t is the output gap and π_t is the quarterly inflation rate. E_{t-j} is the expectations operator made j periods ago.

Carroll's extension concentrates on the construction of inflation expectations. He makes the assumption that households form their expectations in a similar manner to Mankiw & Reis and claims that mean contemporaneous inflation expectations, $M_t(\pi_{t+1})$, are equal to the contemporaneous newspaper one-period forecast and the infinite sum, weighted by proportion of information-updaters, of lagged mean inflation expectations, thus:

$$M_t(\pi_{t+1}) = \lambda F_t(\pi_{t+1}) + [1-\lambda]\{\lambda F_{t-1}(\pi_t) + [1-\lambda](\lambda F_{t-2}(\pi_{t-1}) + ...)\} \tag{2}$$

or equivalently:

$$M_t(\pi_{t+1}) = \lambda F_t(\pi_{t+1}) + [1-\lambda]\{\lambda M_{t-1}(\pi_t)\} \tag{3}$$

where λ is the proportion of the population that update their information set each period.

Employing this model, Carroll examines whether an increase in informational availability – via the news media – increases the proportion of agents that update their inflation expectations. Formally, under the assumption that the media publishes a rational forecast provided by professional forecasters, Carroll tests whether the absolute error between consumer and professional inflation forecasts is affected by the intensity of news coverage on inflation. Standard T-tests confirm this hypothesis at the 5% level and Carroll determines an expectation 'speed of adjustment parameter' of around 0.25 (Carroll, 2003; p16).

2.2 The Model & Hypotheses

This paper combines these two models by examining the effect of newspaper coverage of economic activity on both consumers' inflation expectations and perceptions, under the assumption that expectations and perceptions are formed in an identical manner. Equations (1), (2) and (3) are essentially equivalent, aside from (1) contains an emphasis on the level of economic activity. Continuing Carroll's model extension, consumers are modeled as deriving their expectations in the same way as the agents in the Mankiw & Reis model, this paper takes the economic activity emphasis by examining the effect of media coverage of economic activity on the inflation assessment of consumers. Formally, from Equation (1):

$$M_t(\pi_{t+1}) = \lambda F_t(\pi_{t+1} + \alpha\Delta y_t) + [1-\lambda]\{\lambda M_{t-1}(\pi_t)\} \tag{4}$$

This invokes my investigation; are consumers' inflation expectations influenced by economic activity through a 'cognitive' Phillips curve channel? In other words, do consumers have an inherent Phillips curve relationship built into expectations of inflation? This broad theory allows me to posit testable hypotheses, laid out explicitly below.

As Benford demonstrates, consumers themselves believe that the media plays an important role in determination of expectation formation. Intuitively, if media coverage of any incident increases, the total information about the incident rises, and more and more consumers become aware of it. In the 'rational inattention' literature, this increase in media content can be seen as improving informational availability, or lowering the costs of absorbing that information, hence increasing the likelihood that consumers' will update their information set. This in turn, following the *sticky-information* approach, can be seen as increasing λ in (4), thereby improving the average forecast, $M_t(\pi_{t+1})$. This paper will explicitly examine this concept, thus my primary hypothesis will be: *does increased media coverage of economic activity affect consumer inflation assessment? if so, is accuracy improved or impaired?*

It is clear, however, that media content is unlikely to provide perfectly accurate coverage. Profit maximising media firms compete not merely on accuracy of content, but rather through attention-grabbing stories; the media transmit what is demanded. This concept is widely acknowledged in Social Sciences, for example, DellaVigna & Kaplan (2006) and Marc (1996) both demonstrate that media bias or spin in US media significantly affects voting behaviour or political perceptions of economic competency, respectively. Therefore, complications stem from the concept of media bias; news providers compete through attention-grabbing coverage and there is a lack of incentives to publish the truth. In the economic literature, Doms & Morin demonstrate that there are 'periods when reporting on the economy has not been consistent with actual economic events' (Doms & Morin, 2004).

Alsem et al. measure media bias by asking economic professionals to analyse past publications. Examining the variation between consumer and producer confidence, they conclude that the existence of spin is weak, assuming producers are unaffected by media coverage. However, examining a Vector AutoRegressive (VAR) model, the authors claim that, as media spin affects consumer but not producer confidence their hypothesis is confirmed. The authors admit that determining spin this way suffers from the problem of professional hindsight (Alsem et al, 2004). Using a sophisticated media dataset, Lamla & Lein (2008) test whether the intonation of media reporting impairs the accuracy of consumers' forecasts via a media 'tone' variable; a significantly non-zero parameter on such a variable draws the conclusion of bias. Examining sophisticated media indices, Doms & Morin find a significant relationship between both media intensity and tone on consumer sentiment. The importance of media bias on inflation expectations must therefore be examined. The explicit mechanism is discussed at greater length in Section 3.2. For now, I define my second hypothesis as: *does accentuated media coverage of economic events have a significant effect on the accuracy of consumers' inflation assessment?*

One further problem is that of endogeneity, or reverse causality; does greater news intensity *cause* inflation expectation error, or do incorrect expectations induce greater news intensity? Lamla & Lein and Doms & Morin address this issue through the use of VAR techniques, where all variables are modeled endogenously. Lamla & Lein conclude that 'the volume channel has an impact on the [expectation error] but not vice versa', an observation backed up by Granger-causality tests (Lamla & Lein, 2008; p23). This paper will seek to counter this problem through the use of an Instrumental Variables technique. Intuitively, an instrumental variable must be inextricably connected with economic news intensity, but unrelated to potentially unobserved variables that affect the state of the economy, contained in the error term.

3 Data Methodology & Analysis

3.1 Dependent Variable: Inflation Expectations

The data on consumer inflation expectations comes from the Bank of England's quarterly GfK/NOP survey. Following Badarinza & Buchmann's approach, this paper will analyse the effect of media coverage on both current inflation perceptions and future expectations. The authors conclude that news intensity has a greater impact on the former (Badarinza & Buchmann, 2009) Therefore, I employ the median of the GfK/NOP survey response to the questions about current inflation expectations, which is equivalent to $M_t(\pi_{t+1})$ from Equation (2) and (3) above, and for inflation perceptions is $M_t(\pi_t)$.

Next I determine the consumers' observation and forecast error, which Carroll measures as the difference between the consumers' and professionals' inflation estimates, as do Lamla & Lein (2008), Sabrowski (2009) and Badarinza & Buchmann (2009). However, as Laster et al (1999) point out, the assumption that professionals provide unbiased, rational forecasts cannot be made with confidence. Furthermore, Branch (2004) suggests different methods to determine consumers' forecast error: perfect foresight; error between forecast and outcome, or between consumer forecasts and forecasts derived from the Central Bank's benchmark statistical model. This paper determines the error of consumers' inflation perceptions and expectations as the absolute difference between consumers' estimates and the actual outcome of inflation, the strictest form of the REH. Formally;

$$P_t^e(\pi_t) = \sqrt{(M_t(\pi_t) - \pi_t)^2}$$

and

$$E_t^e(\pi_{t+1}) = \sqrt{(M_t(\pi_{t+1}) - \pi_{t+1})^2}$$

where P_t^e is the perception error, E_t^e is the expectation error of a forecast made in period t.

The evolution of these variables is shown in Figure 1. It seems inflation expectations trails perceptions by one quarter until the beginning of the recent downturn, indicating that consumers do not use their previous expectation to determine their current perception. It is interesting to note, that even during the period of high inflation in the UK, consumer expectations remained fairly accurate, while perception error grew, especially around in the peak of the UK recession. As elucidated above, a key motivation for this paper is the fact that UK consumers are unaware of the current inflation rate. Furthermore, the mean squared error of inflation perceptions is 0.92 while for expectations is 0.69 for the entire sample, but mean errors are lower for a restricted

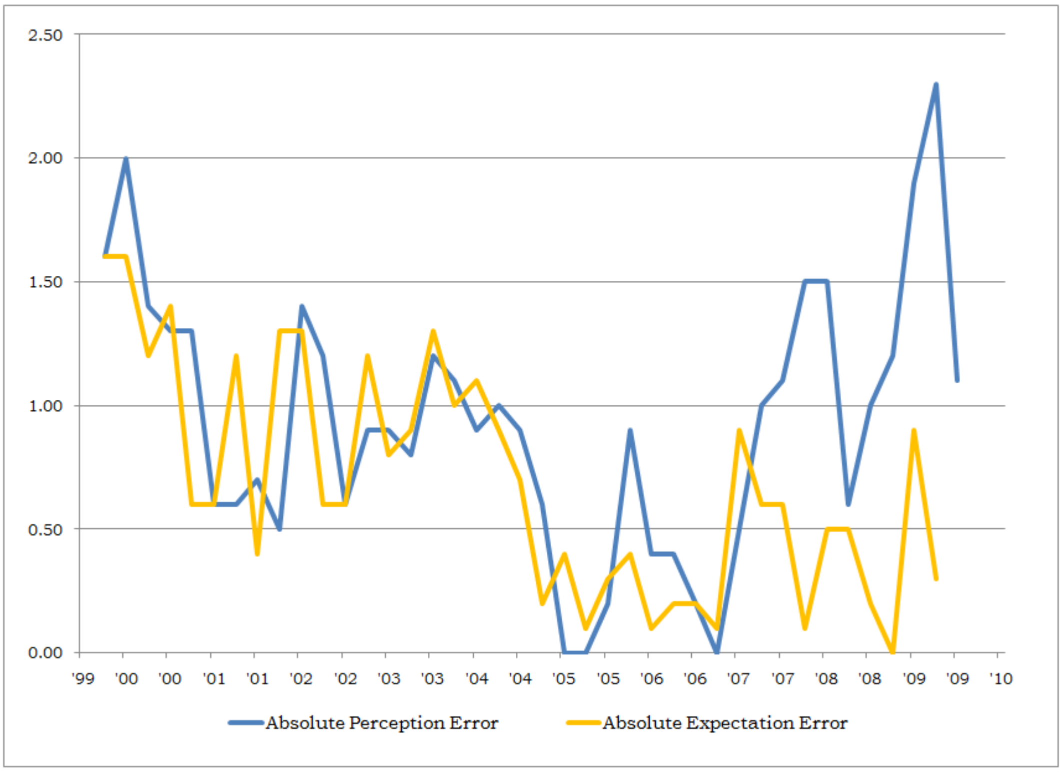

Figure 1: Absolute Errors of Inflation Perceptions & Expectations

sample (up to 2007Q3). Interestingly, expectation accuracy improves over the recessionary period, but perception accuracy falls. Ignoring the absolute value, consumers' perception error is repeatedly higher than the inflation outcome. Similarly for expectation error, except for a few occasions in 2006 and 2008. The origin of the error is interesting here; consumers almost always consistently over-estimate their inflation assessment, is this caused by economic news intensity? Examining the Auto-Correlation functions (ACF) of the series shows limited persistence which could present serial correlation issues. Box-Jenkins analysis suggests the inclusion of a lagged variable in the regression. Furthermore, Dickey-Fuller (DF) tests reject the unit root hypothesis at the 5% level and seasonality is also rejected.[2]

3.2 Independent Variables: News Media Coverage & Controls

The media dataset is constructed using the Dow Jones Factiva news database, examining coverage from the UK's largest non-tabloid weekday newspapers; the *Daily Express*, the *Daily Mail*, the *Daily Telegraph*, the *Financial Times*, the *Guardian*, the *Independent* and *the Times*. In this way, at least 50% of the UK's newspaper circulation is captured.[3] Unfortunately, tabloid newspapers are not stored on Factiva, so top-selling newspapers such as *the Sun* or *the Mirror* are missing from the analysis. The Factiva database allows searches to be run of news articles since 2000. All articles are categorised by Dow Jones Intelligent Indexing^{TM}, which for

[2]see Appendix for explicit results

[3]'ABCs: National Daily Newspaper Circulation, December 2009', The *Guardian*, accessed April 28, 2010

our purposes include; 'Economic Performance/Indicators' with subcategories such as 'Employment/Unemployment', etc. To determine the media variables a search was run for articles either within a specific category, or containing a certain word or phrase, and the number of hits for each quarter 2000Q1 - 2009Q4 was taken.

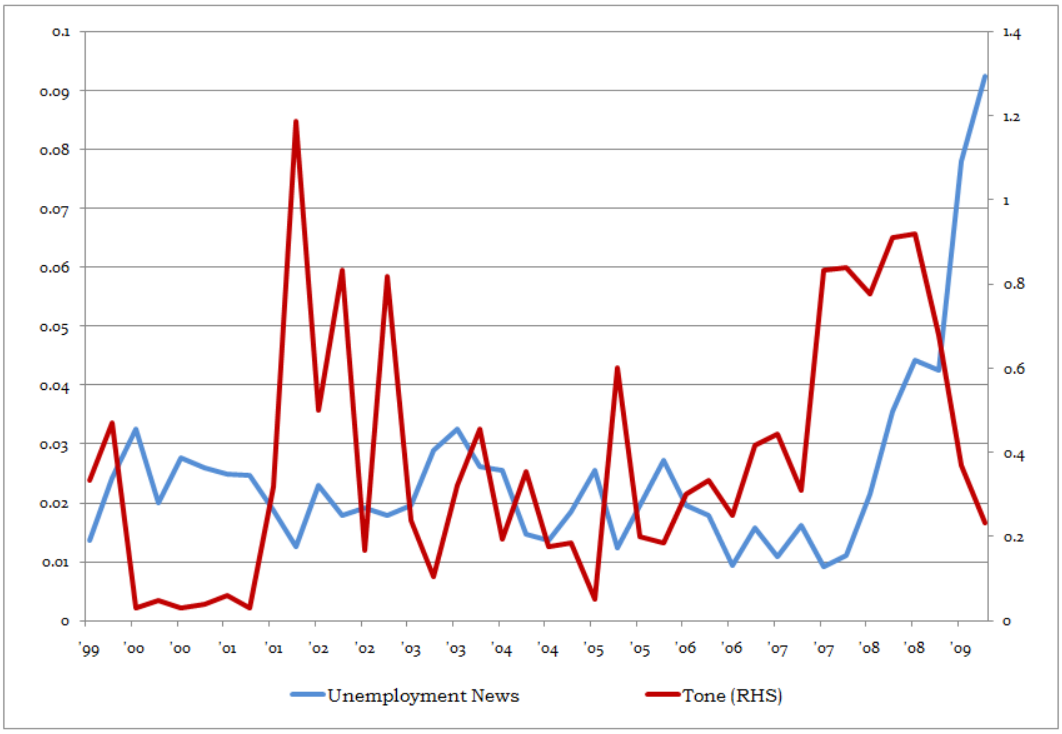

Figure 2: Evolution of Independent Variables

Since I examine the concept of a 'cognitive' Phillips curve, I take unemployment as the archetypal measure for economic activity. Following Badarinza & Buchmann and Lamla & Lein, this paper improves on Carroll's basic news intensity measure through creation of a ratio; the number of articles concerning unemployment relative to the quantity of articles in Factiva's 'Economic News' category. Here, the *tone* variable is defined as the number of articles containing the word 'unemployment' that are published on the front-page, relative to the total number of articles concerning unemployment. Logs are taken to reduce variances and produce elasticities. The evolution of these variables is shown in Figure 2. Surprisingly, despite the low economic growth around late-2001, unemployment news intensity did not increase substantially, perhaps because unemployment was falling at the time. Contrastingly, the intensity of front-page articles containing 'unemployment' spiked at the end of 2001 and remained volatile until mid-2003. The period 2003 – 2007 is quiet in terms of economic news and unemployment continued to fall. From the onset of the 2007 financial crisis, media intensity grew; front-page news quickly rises before falling back again, this could be evidence that continuous front-page news about unemployment is not sustainable in the market; the public do not continue to demand such stories. However, the unemployment news intensity has continued to rise. This could be due to the general acknowledgment that unemployment lags economic growth.

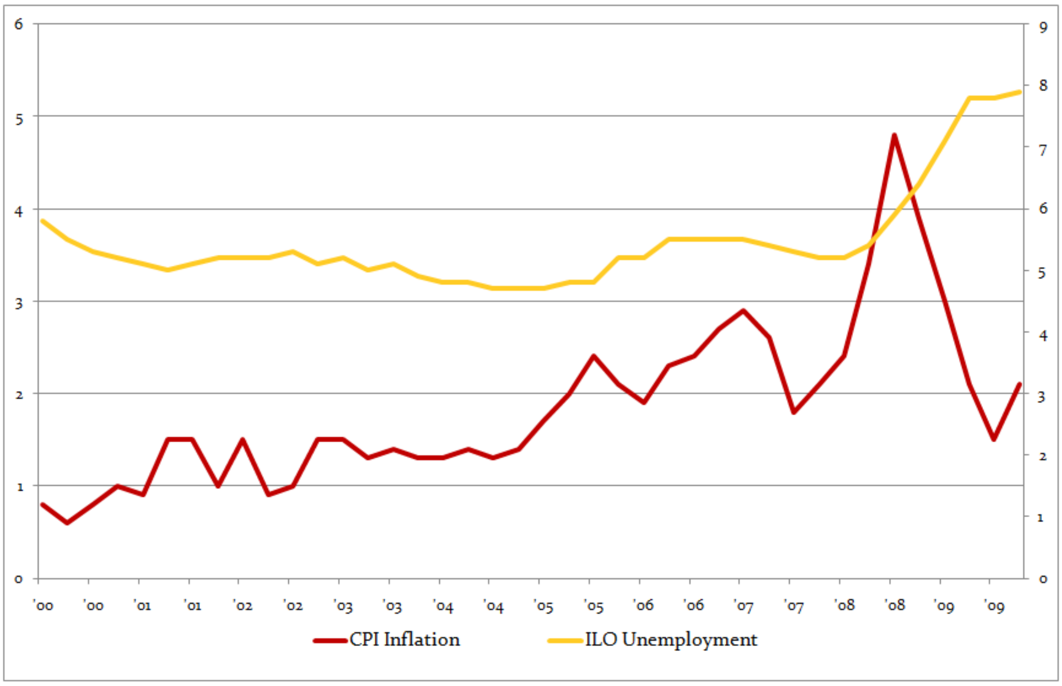

Figure 3: Evolution of Control Variables

Economic control variables may also be required to negate bias from omitted variables and, regarding inflation, 'if media just report what is happening in the real world, this would imply that no extra effect of media would be present' (Lamla & Lein, 2008; p23). The model includes controls for quarterly UK ILO unemployment rate and CPI inflation. All data is taken from the Office of National Statistics (ONS).

From Figure 3 the distortion from the economic crisis in the late 2000s can be clearly seen. Examining the ACFs for persistence explains very little, but a DF test does not permit rejection of a unit root. Following Perron (1989), this could be as a result of a 'one-time change in the level or in the slope of the trend function', leading to under-rejection of the null hypothesis of no unit root (Perron, 1989). As unemployment is non-stationary after 2008Q1, I restrict the sample to check for robustness of the results in section 4.1.

	Mean	Median	Max	Min	Std. Dev.	Obs.
$P_t^e(\pi_t)$	0.62	0.64	1.19	0	0.30	39
$E_t^e(\pi_{t+1})$	0.49	0.47	0.96	0	0.27	39
$news_t$	-3.87	-3.93	-2.55	-4.68	0.44	39
$tone_t$	-1.91	-1.67	-0.22	-3.64	0.84	39
CPI_t	1.84	1.50	4.80	0.60	0.90	39
UN_t	5.39	5.20	7.80	4.70	0.73	39
$cric_t$	-1.89	-1.86	-1.48	-2.62	0.21	39
$sport_t$	0.776	0.77	0.85	0.68	0.04	39
$political_t$	10.75	10.77	10.96	10.55	0.10	39

Table 1: Descriptive Statistics

3.3 Instrumental Variables

As elucidated above, the inherent endogeneity issue within the model must be controlled for. This paper utilises an Instrumental Variables (IV) approach, rather than using the lagged independents *news* and *tone*. IV theory expounds that the instrument must satisfy two conditions; relevance and exogeneity. The former concerns correlation with the potentially endogenous variable, while the latter imposes no correlation with with the error term. For my model, this implies that any instrument must be correlated with unemployment news but uncorrelated with factors that affect the state of the economy, which will be picked up by the error term. Again, the instruments are news media measures, but here composed of stories regarding 'Cricket' and 'Sport' relative to the total number of news articles (*cric* and *sport*, respectively). A third instrument is constructed as total 'General/Political News' ($political_t$). Given an external constraint on the number of pages in a newspaper, an increase in unemployment news should be associated with less coverage of other news; hence the negative correlation shown. Although *cric* is positively correlated with unemployment news, cricket news may increase in order to compensate readers for the emphasis on economic news. Furthermore, the inevitable seasonality of sporting news also helps to satisfy my exogeneity assumption. I explicitly test for exogeneity using the Durbin-Wu-Hausman test below. The evolution of these instruments is shown in Figure 4.

Stock & Yogo (2002) have shown that weak instruments can produce biased IV estimators and distorted hypothesis tests. Following the authors, the instruments are weak 'if the bias of the IV estimator, relative to the bias of ordinary least squares (OLS), could exceed a certain threshold b, for example 10%' (Stock & Yogo, 2002) Since I employ Two-Stage Least Squares (TSLS) estimation, I examine the first-stage F-statistic, with the Stock & Yogo critical values. The critical value in my case, with 2 potentially endogenous variables (*tone* and *news*), six instruments (3 instruments, 2 controls & constant), and a 10% bias tolerance, is 8.67 (Stock & Yogo, 2002; p21). The weakness of the instruments is tested explicitly in Section 4.

	$P_t^e(\pi_t)$	$E_t^e(\pi_{t+1})$	$news_t$	$tone_t$	CPI_t	UN_t	$cric_t$	$sport_t$	$political_t$
$P_t^e(\pi_t)$	1	0.440	0.324	0.287	-0.341	0.412	-0.267	-0.011	-0.275
$E_t^e(\pi_{t+1})$	0.440	1	0.025	-0.016	-0.607	-0.208	-0.191	0.260	-0.205
$news_t$	0.324	0.025	1	-0.272	-0.089	0.542	0.282	-0.107	-0.215
$tone_t$	0.287	-0.016	-0.272	1	0.343	0.251	-0.083	-0.213	-0.026
CPI_t	-0.341	-0.607	-0.089	0.343	1	0.317	0.178	-0.347	-0.090
UN_t	0.412	-0.208	0.542	0.251	0.317	1	0.026	-0.049	-0.034
$cric_t$	-0.267	-0.191	0.282	-0.083	0.178	0.026	1	-0.248	0.178
$sport_t$	-0.011	0.260	-0.107	-0.213	-0.347	-0.049	-0.248	1	0.092
$political_t$	-0.275	-0.205	-0.215	-0.026	-0.090	-0.034	0.178	0.092	1

Table 2: Variable Correlation Matrix

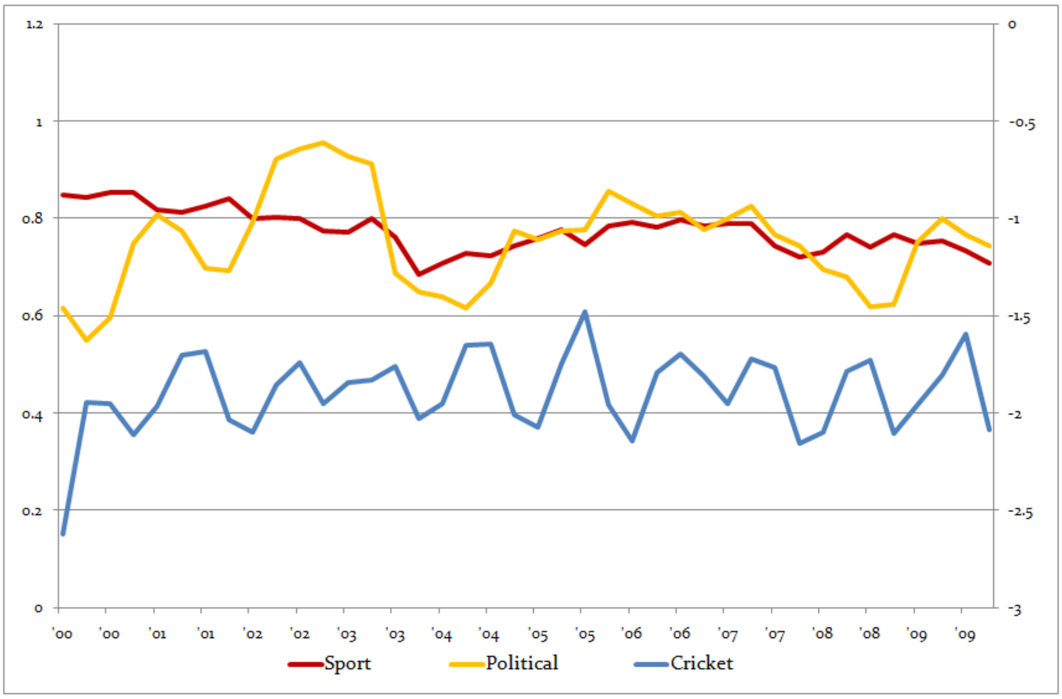

Figure 4: Evolution of Instrumental Variables

4 Regression Analysis

Now I develop the model from Equation (4) into a regression model and introduce the estimation procedure. Employing the recent literature of weak instruments, I finalise my Instrumental Variables model. From my first hypothesis, testing the effect of unemployment news intensity on consumers' inflation perceptions and expectations I determine my first model thus:

$$P_t^e(\pi_t) = \alpha + \beta_1 news_t + \gamma Control_t + \epsilon_{1t} \tag{5}$$

The variable of interest is clearly β_1, and from my hypothesis of a 'cognitive' Phillips curve, I expect the coefficient to be negative, signifying that increased media intensity of unemployment induces consumers to revise their inflation perceptions towards the actual rate. I again test the primary hypothesis, this time for inflation expectations, using a similar argument.

$$E_t^e(\pi_{t+1}) = \alpha + \beta_1 news_t + \varphi Control_t + \epsilon_{2t} \tag{6}$$

I now introduce the *tone* variable. Intuitively, unemployment news published on the front-page is likely to receive greater attention and indeed greater readership than less pronounced articles. Therefore, from my second hypothesis, I expect the coefficient on *tone* to induce more substantial revisions to consumers' inflation perceptions and expectations. The outcome of the sign of the coefficient is currently ambiguous; a positive coefficient implies that front-page news actually has adverse effects on consumers' beliefs. It is possible that the news intensity and *tone* variables may be collinear, but as their correlation is only -0.25, this shouldn't be an issue.

Consequently I define my tonal models:

$$P_t^e(\pi_t) = \alpha + \beta_1 news_t + \beta_2 tone_t + \varphi Control_t + \epsilon_{3t} \tag{7}$$

$$E_t^e(\pi_{t+1}) = \alpha + \beta_1 news_t + \beta_2 tone_t + \varphi Control_t + \epsilon_{4t} \tag{8}$$

To define the IV estimation, I must outline the first stage regression; the instrument list. I include all exogenous regressors (control variables) and instruments defined above, thus:

$$news_t = \alpha + \gamma_1 cric_t + \gamma_2 sport_t + \gamma_3 total_t + \varphi Control_t + \epsilon_{Rt} \tag{9}$$

The results of these regressions are displayed in Table 3 below.

4.1 Robustness

Preliminary estimation of the above models allows refinement of the specification. I check for serial correlation or heteroscedasticity in the standard errors. From running Equation (5), the Durbin-Watson statistic indicates positive serial correlation of order 1, confirmed by the Breusch-Godfrey LM test; consistent with the Box-Jenkins result from above. Unsurprisingly, the same is true of Equation (7). I counter this through inclusion of a lagged dependent variable. Examining Equations (6) and (8) permits rejection of serial correlation in both inflation expectations models. Both the ARCH-LM test and White's test reject heteroscedasticity in models (5), (6) and (7). However, model (8) exhibits CPI-dependent heteroscedasticity; employing White's robust standard errors, the T-stat of CPI falls, but the coefficient remains significant in OLS but not so for TSLS. Furthermore, by restricting the dataset to pre-2008Q1, I implicitly check the stability of the results. The Chow stability test is ineffective owing to the size of the dataset. In the restricted regressions, the coefficients change slightly, but not substantially.

I briefly examine the specification of the IV models, by comparing TSLS with OLS. If the coefficients are substantially different, or indeed have opposite signs, then the instruments may be ill-specified. For model (5), the coefficients all keep the same sign, the controls remain almost identical, but the magnitude of $news$ increases. The same is true for model (6), but the $news$ coefficient increases by larger degree. In model (7) too, the coefficients on $tone$ and $news$ increase in magnitude indicating that OLS causes a downward bias in both news measures.

Here, the instruments are tested for exogeneity, via the Durbin-Wu-Hausman test. I estimate the reduced-form equation, by regressing the endogenous variable on all exogenous regressors and procure the residuals (ϵ_{Rt} from (9)). Then by including these residuals in the simple OLS regression, I test the hypothesis that the coefficient on the residual series is zero. Formally, and by using Equation (5) as an example:

$$P_t^e(\pi_t) = \alpha + \beta news_t + \varphi Control_t + \psi \epsilon_{Rt} + \epsilon_{1t}$$

Eq.	Dep. Var	$news_t$	$tone_t$	1st-Lag	Cons.	CPI_t	UN_t	F-Stat	S.E.	$R^2(\bar{R}^2)$	D-W Stat
OLS (5)	$P^e_t(\pi_t)$	-0.156	–	0.563	-1.372	-0.148	0.245	12.94	0.187	0.610	1.785
		(-1.697)*		(4.679)***	(-2.400)**	(-3.781)***	(4.001)***	(P:0.00)***		(0.563)	
TSLS (5)	$P^e_t(\pi_t)$	-0.572	–	1.693	-3.905	-0.105	0.278	2.708	0.363	-0.470	1.837
		(-1.048)		(1.652)	(-1.223)	(-1.209)	(1.808)*	(P:0.04)**		(-0.648)	
OLS (6)	$E^e_t(\pi_{t+1})$	-0.014	–	–	0.660	-0.202	0.049	7.568	0.222	0.400	1.721
		(-0.138)			(1.140)	(-3.079)***	(0.752)	(P:0.00)***		(0.347)	
TSLS (6)	$E^e_t(\pi_{t+1})$	0.247	–	–	1.902	-0.174	-0.022	7.061	0.237	0.313	1.64
		(1.358)			(1.757)*	(-2.278)**	(-0.209)	(P:0.00)***		(0.253)	
OLS (7)	$P^e_t(\pi_t)$	-0.015	0.123	0.502	-0.167	-0.170	0.182	15.103	0.166	0.703	2.019
		(-0.157)	(3.134)***	(4.617)***	(-0.263)	(-4.787)***	(3.142)***	(P:0.00)***		(0.656)	
TSLS (7)	$P^e_t(\pi_t)$	-0.241	0.354	1.275	-0.788	-0.196	0.140	2.364	0.358	-0.390	1.745
		(-0.361)	(0.848)	(1.133)	(-0.163)	(-1.430)	(0.631)	(P:0.062)*		(-0.607)	
OLS (8)†	$E^e_t(\pi_{t+1})$	0.112	0.095	–	1.513	-0.215	0.000	7.006	0.213	0.459	1.844
		(-1.075)	(2.033)*		(2.703)**	(-3.540)***	(0.005)	(P:0.00)***		(0.394)	
TSLS (8)†	$E^e_t(\pi_{t+1})$	0.273	0.061	–	2.252	-0.188	-0.042	5.804	0.227	0.390	1.716
		(1.478)	(0.291)		(1.615)	(-2.032)*	(-0.405)	(P:0.00)***		(0.316)	
First Stage		Cons.	$cric_t$	$sport_t$	$political_t$	CPI_t	UN_t	F-Stat	S.E.	$R^2(\bar{R}^2)$	D-W Stat
OLS (9)	$news_t$	9.741	0.703	-1.725	-1.205	0.225	0.452	12.000	0.319	0.638	1.460
		(1.867)	(2.689)**	(-1.326)	(-2.292)**	(-3.498)***	(6.860)***	(P:0.00)***		(0.585)	

Table 3: OLS & TSLS Regression Results from Equations 5 to 8. T-Stats in parenthesis; ***=1% significance, **=5% and *=10%.
† indicates heteroscedastic-robust standard errors

$$H_o : \psi = 0 \qquad\qquad H_a : \psi \neq 0$$

Estimation of this model, as well as a similar model built from Equation (6), does not allow rejection of the hypothesis above and I conclude that the assumed exclusion restrictions are sufficient for these instruments. Furthermore, following the 'weak' instruments issues raised in Section 3.3, it is clear from Table 3 that the F-Stat of the first-stage regression is substantially greater than 8.78 at 12.0. Thus, I can conclude that my instruments are neither weak nor endogenous and can comfortably continue to use the instruments laid-out above.

4.2 Preliminary Findings

This section presents a brief discussion of the results displayed in Table 3. From the OLS regression of model 5, I find evidence in favour of my primary hypothesis; an increase in unemployment news intensity is associated, on average, with a 0.156% improvement in consumers' inflation perception, through an increase in informational availability. Conversely, an increase in the realised rate of unemployment is associated with a decline in the accuracy of perceived inflation. One interesting result is that an increase in the actual level of inflation is associated with an improvement in perception accuracy. Examining the effect of *tone*, the most notable result is that the coefficient on *tone* is positive; an increase in front-page unemployment news intensity is associated, on average, with a 0.123% impairment of consumers' inflation perception. The coefficient on *news* has fallen to zero, however. Despite the increase in informational availability, the negative connotation associated with front-page news deteriorates the accuracy of consumers' perceptions.

The TSLS regressions however, tell a different story. The rate of inflation is the sole statistically significant coefficient in each regression, while the parameter values remain largely the same. From this, it is clear that the associations outlined above are largely as a result of possible reverse-causality in the model; increased media intensity may improve consumers' perceptions, but alternatively, inaccurate consumer perceptions could lead to more intense media coverage. Thus I reject my hypotheses with regard to UK consumer inflation perceptions; while I find an association between unemployment news and perception accuracy, I am unable to confirm my hypotheses that media intensity explicitly *causes* improvement or impairment in inflation assessment.

From the outset, the results from models (6) and (8) oblige rejection of my primary hypothesis; increased media intensity appears to have no statistically significant effect on UK inflation expectations. However, increased front-page news is associated with an impairment inflation expectations accuracy. Consistent with before, an increase in the true inflation rate improves consumer forecast accuracy, but the realised rate of unemployment is no longer a significant factor. The unemployment rate has no significant effect on consumer inflation expectations. The TSLS results are almost identical except now the coefficient on *tone* is insignificant. Again, OLS biases the coefficients on the news measures downwards. Since no *news* variables significantly affect expectation error, I conclude that inflation expectations are determined by some mechanism other than news media. The result that inflation has a limited effect adds to the conviction that expectations in the UK are well anchored.

4.3 Analysis of Regression Results

Although I am forced to reject my hypotheses, many of my findings are concurrent with the existing literature on the effect of the news media and with the sticky-information hypothesis. Carroll (2003), Badarinza & Buchmann (2009) and Lamla & Lein (2009) all find that increased media coverage significantly improves consumer inflation assessment efficiency. Furthermore, the differing signs of the *news* and *tone* variables is consistent with Lamla & Lein's findings; an increase in accentuated news impairs the accuracy of consumers' inflation perceptions. My results also find that news intensity has a greater effect on perceptions than expectations, which Badarinza & Buchmann also find. Sadly however this paper must reject the hypothesis of a causal relationship and the concept of a 'cognitive' Phillips curve.

The fact that this paper finds almost no causal relationship between news and consumer inflation assessment is likely to be because expectations and perceptions are well anchored in the UK economy. Kelly (2008) has shown that British expectations are well anchored to the actual rate and my conclusions cannot reject this. As the actual rate of inflation is significant in all perception models, (5) and (7), the results are also evidence in favour of Benford's conclusion that consumers use rules of thumb in their perceptions of inflation. This conclusion also is concurrent with Kelly, as the actual rate of inflation plays a significant role in affecting consumer accuracy.

5 Concluding Remarks

5.1 Problems & Extensions

One important consideration of my regressions is the extremely small sample, likely to lead to biased estimators. The most important aspect here is the frequency of the series; quarterly. It is a stretch to believe that newspaper articles printed three months prior are likely to have as great an impact as more recent information. With more frequent data, not only can bias be negated, but the endogeneity issue can be solved through using simple lags of news intensity. In my case, using news from up to six months before the consumer forecast is made, appears at best erroneous, especially since Doms & Morin have shown that the effect of the media is short-lived (Doms & Morin, 2004; p28). Because of this, I believe that improving the dataset could lead to more robust results. Firstly, my dependent variable has a very low frequency because surveys are costly. Barclays BASIX survey would improve this variable. The frequency of the remainder of the data could be increased in a straight-forward manner.

Furthermore, my news media variables are crude relative to others used in the literature. Lamla & Lein use Mediatenor™, which provides sophisticated analysis of media content, including tone and bias. Doms & Morin create indices from Factiva based on various criteria. To improve the media dataset, using recent technological advances I could use Google News™, a modern database of news articles, or even Google Insights™, which provides statistics on Google searches as a proxy for information. The downside with this is that the data only goes back a few years, despite the higher frequency. One issue I have neglected is the readership of each newspaper; I have assumed that as the information is available to all, that there is equal access; unlikely as consumers have preferences over their source of news. Ideally the media data would be weighted by newspaper circulation, or even examining different papers directly. Also, given a more sophisticated dataset, it would be interesting to test for non-linearity in the *tone* variable.

This research could be built upon in several ways. Firstly, Mankiw & Reis' model assumes an unrealistic Phillips curve; that inflation is dependent on the contemporaneous output gap. Under the prior assumption that information disseminates slowly, it is limiting to solely examine contemporaneous unemployment news. Given the hypothesis of a 'cognitive' Phillips curve, different Phillips curve dimensions could be tested using different lag lengths for news. In my case, the dataset frequency is a severe constraint to this. Similarly, further work could examine the role of news in determining inflation assessment over the transmission mechanism, by controlling for interest rate changes.

Another avenue of exploration would be to examine heterogeneous expectations of actors. This paper has concentrated on the expectations and perceptions of UK consumers, but it would be simple to explore the relationship of news on financial agents. Perceptions and expectations measures could be constructed from inflation-linked bond data. This data is also a much higher frequency.

5.2 Conclusion

This paper has attempted to examine the effect of news regarding unemployment on UK consumers' inflation assessment in terms of current perceptions and future expectations. While I find an association that a greater intensity of news improves inflation perception accuracy and front-page news impairs it, I am unable to concretely claim a causal relationship due to the inherent endogeneity. I find a small association between news and consumer expectations, which I cannot confirm either. My findings are in agreement with Benford in that UK consumers use rules of thumb in their assessments of inflation, and also with Kelly that expectations are well anchored in the economy. From these findings, the Bank of England can assume that their credibility and the anchoring of expectations are unaffected by news intensity about unemployment.

6 Bibliography

[1] Alsem, K-J., Brakman, S., Hoogduin, L., & Kuper, G. (2004): 'The Impact of Newspapers on Consumer Confidence: Does Spin Bias Exist?', *CESinfo Working Paper Series*, No. 1328

[2] Badarinza, C. & Buchmann, M. (2009): 'Inflation Perceptions and Expectations in The Euro Area: The Role of News', *ECB Working Paper Series*, No. 1088

[3] Benford, J. (2008): 'Public Attitudes to Inflation and Interest Rates', *Bank of England Quarterly Bulletin*, 2008:Q2

[4] Branch, W. A. (2004): 'The Theory of Rationally Heterogeneous Expectations: Evidence From Survey Data on Inflation Expectations', *The Economic Journal*, No. 114

[5] Calvo, G. A. (1983): 'Staggered Prices in a Utility Maximizing Framework', *Journal of Monetary Economics*, No.12, pp. 383–398

[6] Carroll, C. D. (2003): 'Macroeconomic Expectations of Households & Professional Forecasters', *Quarterly Journal of Economics*, Vol. 118 No. 1

[7] DellaVigna, S. & Kaplan, E. (2006): 'The Fox News Effect: Media Bias & Voting', *NBER Working Paper Series*, No. 12169

[8] Doms, M. & Morin, N. (2004): 'Consumer Sentiment, the Economy, and the News Media', *Working Papers in the Finance and Economics Discussion Series*, No. 51

[9] Friedman, B. (1979): 'Optimal Expectations and the Extreme Information Assumptions of "Rational Expectations" Macromodels', *Journal of Monetary Economics*, Vol. 5

[10] Kelly, R. (2008): 'The Causal Relationship between Inflation and Inflation Expectations in the United Kingdom', *Bank of England MPC Unit*, Discussion Paper No. 24

[11] Lamla, M. J. & Lein, M. (2008): 'The Role of Media for Consumers' Inflation Expectation Formation', *KOF Working Paper Series*, No. 201

[12] Laster, D., Bennett, P., & Geoum I. S. (1999): 'Rational Bias in Macroeconomic Forecasts', *The Quarterly Journal of Economics*, Vol. 114, No. 1, pp. 293-318

[13] Mankiw, N. G. (2001): 'The Inexorable and Mysterious Trade-off Between Inflation and Unemployment', *Economic Journal*, Vol. 111, No. 471, C45-C61

[14] Mankiw, N. G. & Reis, R. (2002): 'Sticky Information Versus Sticky Prices: A Proposal to Replace the New Keynesian Phillips Curve', *Quarterly Journal of Economics*, Vol. 117, No. 4

[15] Mankiw, N. G., Reis, R. & Wolfers, J. (2003): 'Disagreement about Inflation Expectations', *NBER Macroeconomics Annual*, ed. by Gertler, M. and Rogoff, K. MIT Press, Cambridge, MA.

[16] Marc, H. J. (1996): 'The Media's Role in Forming Voters' National Economic Evaluations in 1992', *American Journal of Political Science*, Vol. 40, No. 2, pp. 372–375

[17] Perron, P. (1989): 'The Great Crash, the Oil Price Shock, and the Unit Root Hypothesis' *Econometrica*, Vol. 57, No. 6, pp. 1361-1401

[18] Reis, R. (2006): 'Inattentive Consumers', *Journal of Monetary Economics*, Vol. 53, No. 8

[19] Sabrowski, H. (2009): 'Inflation News Coverage and the Impact on Inflation Expectations Across Demographic Groups', PhD Thesis, accessed at *http://www.addegem-asso.fr/docs/PapersDMM2009/4.pdf*

[20] Sims, C. A. (2003): 'Implications of Rational Inattention', *Journal of Monetary Economics*, Vol. 50 No. 3, pp665-690

[21] Woodford, M. (2005): 'Central-Bank Communication and Policy Effectiveness', *FRB Kansas City Symposium on 'The Greenspan Era: Lessons for the Future'*, Jackson Hole, Wyoming, August 25-27 2005

7 Appendix

Unit Root Tests

Variable	Level (+Intercept)	Stationary?	Restricted Sample	Level (& Intercept)	Stationary?
$P_t^e(\pi_t)$	-3.159146 (0.0301)	Yes	–		
$E_t^e(\pi_{t+1})$	-3.400817 (0.0170)	Yes	–		
$NEWS_t$	-2.233905 (0.1982)	No	2009Q2	-3.105158 (0.0348)	Yes
$TONE_t$	-4.267693 (0.0017)	Yes	–		
CPI_t	-0.463159 (0.8872)	No	ΔCPI_t	-5.331811 (0.0001)	Yes
UN_t	-0.075460 (0.9445)	No	2008Q1	-2.663800 (0.0921)	Yes
$cric_t$	-7.693153 (0.000)	Yes	–		
$sport_t$	-18.75187 (0.0001)	Yes			
$total_t$	-4.054674 (0.0031)	Yes			

Table 4: DF Unit Root Tests. P-Values in Parentheses; using Mackinnon (1991) Critical Values

Seasonality Tests

Variable	Cons	Seas(Q2)	Seas(Q3)	Seas(Q4)	Seasonal?
$P_t^e(\pi_t)$	0.639428	0.005645	-0.028587	-0.081066	No
	(6.717905)***	(0.041935)	(-0.212374)	(-0.616404)	
$E_t^e(\pi_{t+1})$	0.444944	0.125966	0.029665	0.022368	No
	(5.089498)***	(1.018844)	(0.239936)	(0.180917)	
$NEWS_t$	-3.993666	0.111814	0.293101	0.226430	No
	(-25.16013)***	(0.498108)	(1.305699)	(1.008696)	
$TONE_t$	-1.787935	-0.165024	-0.045709	-0.261115	No
	(-6.590007)***	(-0.430097)	(-0.119130)	(-0.680535)	
CPI_t	1.790000	0.020000	0.100000	0.046364	No
	(6.162968)***	(0.048691)	(0.243457)	(0.115532)	
UN_t	5.380000	0.060000	0.100000	0.174545	No
	(20.23192)***	(0.159548)	(0.265913)	(0.475062)	
$cric_t$	-2.072943	0.288140	0.367075	0.047124	Yes
	(-47.15891)***	(4.635155)***	(5.904953)***	(0.758056)	
$sport_t$	0.775936	0.009012	-0.003966	-0.080021	No
	(19.23694)***	(0.157988)	(-0.069518)	(-1.435816)	
$total_t$	10.76081	0.004735	-0.028390	-0.005109	No
	(329.4124)***	(0.102497)	(-0.614542)	(-0.110581)	

Table 5: Seasonality Checks. T-Stats in Parentheses; ***=1% significance, **=5% and *=10%.

Regression Results

Dependent Variable: LGAP_P
Method: Least Squares
Date: 04/12/10 Time: 18:31
Sample (adjusted): 2000Q1 2009Q2
Included observations: 38 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LGAP_P(-1)	0.563551	0.120432	4.679403	0.0000
LNEWS	-0.156612	0.092264	-1.697423	0.0990
CPI	-0.148456	0.039260	-3.781324	0.0006
UN	0.245393	0.061196	4.009934	0.0003
C	-1.372392	0.571703	-2.400535	0.0222

R-squared	0.610674	Mean dependent var	0.600607
Adjusted R-squared	0.563483	S.D. dependent var	0.283123
S.E. of regression	0.187058	Akaike info criterion	-0.392721
Sum squared resid	1.154688	Schwarz criterion	-0.177249
Log likelihood	12.46170	F-statistic	12.94045
Durbin-Watson stat	1.785865	Prob(F-statistic)	0.000002

Dependent Variable: LGAP_P
Method: Two-Stage Least Squares
Date: 04/12/10 Time: 18:38
Sample (adjusted): 2000Q1 2009Q2
Included observations: 38 after adjustments
Instrument list: INSTOTAL INSCRIC INSSPORT CPI UN C

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LGAP_P(-1)	1.693055	1.024586	1.652430	0.1079
LNEWS	-0.572035	0.545823	-1.048022	0.3022
CPI	-0.105776	0.087477	-1.209183	0.2352
UN	0.278046	0.153709	1.808909	0.0796
C	-3.905739	3.192257	-1.223504	0.2298

R-squared	-0.470090	Mean dependent var	0.600607
Adjusted R-squared	-0.648282	S.D. dependent var	0.283123
S.E. of regression	0.363488	Sum squared resid	4.360082
F-statistic	2.707969	Durbin-Watson stat	1.837535
Prob(F-statistic)	0.046946		

Figure 5: Regression Results for Model (5), OLS and TSLS respectively

Dependent Variable: LGAP_E
Method: Least Squares
Date: 04/12/10 Time: 18:30
Sample (adjusted): 2000Q1 2009Q2
Included observations: 38 after adjustments
White Heteroskedasticity-Consistent Standard Errors & Covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LNEWS	0.014222	0.102727	0.138445	0.8907
CPI	-0.202035	0.065602	-3.079689	0.0041
UN	0.049537	0.065825	0.752559	0.4569
C	0.660098	0.578749	1.140560	0.2620

R-squared	0.400384	Mean dependent var	0.494336
Adjusted R-squared	0.347477	S.D. dependent var	0.274628
S.E. of regression	0.221842	Akaike info criterion	-0.074405
Sum squared resid	1.673266	Schwarz criterion	0.097972
Log likelihood	5.413697	F-statistic	7.567647
Durbin-Watson stat	1.721260	Prob(F-statistic)	0.000524

Dependent Variable: LGAP_E
Method: Two-Stage Least Squares
Date: 04/12/10 Time: 18:42
Sample (adjusted): 2000Q1 2009Q2
Included observations: 38 after adjustments
White Heteroskedasticity-Consistent Standard Errors & Covariance
Instrument list: INSCRIC INSSPORT INSTOTAL CPI UN C

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.901611	1.082125	1.757293	0.0879
LNEWS	0.246978	0.181758	1.358831	0.1831
CPI	-0.174904	0.076780	-2.278008	0.0291
UN	-0.022145	0.105769	-0.209370	0.8354

R-squared	0.313536	Mean dependent var	0.494336
Adjusted R-squared	0.252966	S.D. dependent var	0.274628
S.E. of regression	0.237364	Sum squared resid	1.915620
F-statistic	7.061927	Durbin-Watson stat	1.639105
Prob(F-statistic)	0.000816		

Figure 6: Regression Results for Model (6), OLS and TSLS respectively

Dependent Variable: LGAP_P
Method: Least Squares
Date: 04/12/10 Time: 18:37
Sample (adjusted): 2000Q1 2009Q2
Included observations: 38 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LGAP_P(-1)	0.501980	0.108715	4.617404	0.0001
LNEWS	-0.014727	0.093558	-0.157406	0.8759
LTONE	0.123844	0.039442	3.139891	0.0036
CPI	-0.170114	0.035535	-4.787220	0.0000
UN	0.182098	0.057955	3.142069	0.0036
C	-0.167530	0.636332	-0.263274	0.7940

R-squared	0.702371	Mean dependent var	0.600607
Adjusted R-squared	0.655866	S.D. dependent var	0.283123
S.E. of regression	0.166088	Akaike info criterion	-0.608659
Sum squared resid	0.882727	Schwarz criterion	-0.350092
Log likelihood	17.56451	F-statistic	15.10326
Durbin-Watson stat	2.019764	Prob(F-statistic)	0.000000

Dependent Variable: LGAP_P
Method: Two-Stage Least Squares
Date: 04/12/10 Time: 18:40
Sample (adjusted): 2000Q1 2009Q2
Included observations: 38 after adjustments
Instrument list: INSTOTAL INSCRIC INSSPORT CPI UN C

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LGAP_P(-1)	1.275478	1.125295	1.133461	0.2654
LNEWS	-0.240850	0.665611	-0.361848	0.7198
LTONE	0.354603	0.418057	0.848216	0.4026
CPI	-0.196001	0.137035	-1.430302	0.1623
UN	0.140289	0.222308	0.631056	0.5325
C	-0.788484	4.842081	-0.162840	0.8717

R-squared	-0.390445	Mean dependent var	0.600607
Adjusted R-squared	-0.607702	S.D. dependent var	0.283123
S.E. of regression	0.358986	Sum squared resid	4.123866
F-statistic	2.364952	Durbin-Watson stat	1.745875
Prob(F-statistic)	0.061915		

Figure 7: Regression Results for Model (7), OLS and TSLS respectively

Dependent Variable: LGAP_E
Method: Least Squares
Date: 04/12/10 Time: 18:41
Sample (adjusted): 2000Q1 2009Q2
Included observations: 38 after adjustments
White Heteroskedasticity-Consistent Standard Errors & Covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LNEWS	0.112417	0.104539	1.075355	0.2900
LTONE	0.094677	0.046556	2.033630	0.0501
CPI	-0.215993	0.061014	-3.540083	0.0012
UN	0.000343	0.063226	0.005420	0.9957
C	1.513163	0.559675	2.703647	0.0108

R-squared	0.459257	Mean dependent var	0.494336
Adjusted R-squared	0.393712	S.D. dependent var	0.274628
S.E. of regression	0.213838	Akaike info criterion	-0.125119
Sum squared resid	1.508978	Schwarz criterion	0.090353
Log likelihood	7.377255	F-statistic	7.006778
Durbin-Watson stat	1.844387	Prob(F-statistic)	0.000337

Dependent Variable: LGAP_E
Method: Two-Stage Least Squares
Date: 04/12/10 Time: 18:43
Sample (adjusted): 2000Q1 2009Q2
Included observations: 38 after adjustments
White Heteroskedasticity-Consistent Standard Errors & Covariance
Instrument list: INSCRIC INSSPORT INSTOTAL CPI UN C

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	2.252318	1.394016	1.615705	0.1157
LNEWS	0.273042	0.184629	1.478867	0.1487
LTONE	0.060861	0.208596	0.291766	0.7723
CPI	-0.188197	0.092586	-2.032670	0.0502
UN	-0.042356	0.104480	-0.405398	0.6878

R-squared	0.390352	Mean dependent var	0.494336
Adjusted R-squared	0.316456	S.D. dependent var	0.274628
S.E. of regression	0.227054	Sum squared resid	1.701260
F-statistic	5.804777	Durbin-Watson stat	1.716391
Prob(F-statistic)	0.001189		

Figure 8: Regression Results for Model (8), OLS and TSLS respectively

Dependent Variable: LNEWS
Method: Least Squares
Date: 03/25/10 Time: 11:09
Sample: 2000Q1 2009Q4
Included observations: 40

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	7.705124	5.168407	1.490812	0.1455
INSCRIC	0.600428	0.236388	2.540014	0.0160
INSSPORT	0.214752	0.145181	1.479202	0.1486
INSTOTAL	-1.195416	0.468272	-2.552821	0.0155
CPI	-0.113148	0.062124	-1.821311	0.0776
UN	0.390790	0.085398	4.576095	0.0001
LTONE	-0.179578	0.059781	-3.003949	0.0051

R-squared	0.719300	Mean dependent var	-3.835829
Adjusted R-squared	0.668263	S.D. dependent var	0.495378
S.E. of regression	0.285321	Akaike info criterion	0.487224
Sum squared resid	2.686467	Schwarz criterion	0.782778
Log likelihood	-2.744489	F-statistic	14.09385
Durbin-Watson stat	1.379975	Prob(F-statistic)	0.000000

Dependent Variable: LNEWS
Method: Least Squares
Date: 04/12/10 Time: 19:11
Sample (adjusted): 2000Q1 2009Q4
Included observations: 40 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	9.741094	5.774021	1.687056	0.1007
INSCRIC	0.703804	0.261697	2.689389	0.0110
INSSPORT	-1.725400	1.300652	-1.326565	0.1935
INSTOTAL	-1.204904	0.525530	-2.292740	0.0282
CPI	-0.225435	0.064442	-3.498283	0.0013
UN	0.452415	0.065942	6.860850	0.0000

R-squared	0.638325	Mean dependent var	-3.835829
Adjusted R-squared	0.585137	S.D. dependent var	0.495378
S.E. of regression	0.319072	Akaike info criterion	0.690684
Sum squared resid	3.461445	Schwarz criterion	0.944016
Log likelihood	-7.813675	F-statistic	12.00139
Durbin-Watson stat	1.460335	Prob(F-statistic)	0.000001

Figure 9: Regression Results for the Reduced Form Model and the First Stage Regression

Variable	Description	Data Source & Info
$P_t^e(\pi_t)$	The mean square error of the UK consumers' current inflation perceptions relative to the realised rate.	Bank of England GfK/Nop Quarterly Survey of 4000 people
$E_t^e(\pi_{t+1})$	The mean square error of the UK consumers' contemporaneous inflation expectations relative to one-period ahead realised rate.	Bank of England GfK/NOP Quarterly Survey of 4000 people
$NEWS_t$	Number of newspaper articles containing the word 'unemployment' in the text, relative to the total number of articles in the 'Economic News' section.	Dow Jones Factiva database, $www.factiva.com$, Quarterly data, logged
$TONE_t$	Number of newspaper articles containing the word 'unemployment' in the text, printed on the front-page, relative to the total number of articles containing 'unemployment' in them.	Dow Jones Factiva database, $www.factiva.com$, Quarterly data, logged
CPI_t	The UK CPI 12-month inflation rate	Office for National Statistics, quarterly
UN_t	The UK ILO Unemployment rate	Office for National Statistics, quarterly
$cric_t$	Number of newspaper articles under the 'Cricket' category, relative to the total number of newspaper articles.	Dow Jones Factiva database, $www.factiva.com$, Quarterly data, logged
$sport_t$	Number of newspaper articles under the 'Sport' category, relative to the total number of newspaper articles.	Dow Jones Factiva database, $www.factiva.com$, Quarterly data, logged
$total_t$	Total number of newspaper articles under the 'General/Political News' category.	Dow Jones Factiva database, $www.factiva.com$, Quarterly data, logged

Table 6: List of Variables