University of Leicester

DEPARTMENT OF ECONOMICS

THE NEW KEYNESIAN PHILLIPS CURVE AND LAGGED INFLATION: A CASE OF SPURIOUS CORRELATION?

Stephen G. Hall, University of Leicester, UK and Bank of Greece
George Hondroyiannis, Bank of Greece and Harokopio University
P.A.V.B. Swamy, U.S. Bureau of Labor Statistics
George S. Tavlas, Bank of Greece

Working Paper No. 08/26
August 2008

The New Keynesian Phillips Curve and Lagged Inflation: A Case of Spurious Correlation?*

Stephen G. Hall
Leicester University and Bank of Greece

George Hondroyiannis
Bank of Greece and Harokopio University

P.A.V.B. Swamy
U.S. Bureau of Labor Statistics

George S. Tavlas[†]
Bank of Greece

Abstract

The New Keynesian Phillips Curve (NKPC) specifies a relationship between inflation and a forcing variable and the current period's expectation of future inflation. Most empirical estimates of the NKPC, typically based on Generalized Method of Moments (GMM) estimation, have found a significant role for lagged inflation, producing a "hybrid" NKPC. Using U.S. quarterly data, this paper examines whether the role of lagged inflation in the NKPC might be due to the spurious outcome of specification biases. Like previous investigators, we employ GMM estimation and, like those investigators, we find a significant effect for lagged inflation. We also use time varying-coefficient (TVC) estimation, a procedure that allows us to directly confront specification biases and spurious relationships. Using three separate measures of expected inflation, we find strong support for the view that, under TVC estimation, the coefficient on expected inflation is near unity and that the role of lagged inflation in the NKPC is spurious.

JEL classification: C51; E31

Keywords: New Keynesian Phillips Curve; time-varying coefficients; spurious relaionships

---

* We thank Peter von zur Muehlen and Arnold Zellner for helpful comments. The views expressed are those of the authors and should not be interpreted as those of their respective institutions.

† Corresponding author: Economics Research Department, Bank of Greece, 21, El. Venizelos Ave, 102 50 Athens, Greece. Tel.++30210 320 2370; Fax: ++30210 320 2432. email: gtavlas@bankofgreece.gr

1. Introduction

The New Keynesian Phillips Curve (NKPC) is a key component of much recent theoretical work on inflation. Unlike traditional formulations of the Phillips curve, the NKPC is derivable explicitly from a model of optimizing behavior on the part of price setters, conditional on the assumed economic environment (e.g., monopolistic competition, constant elasticity demand curves, and randomly-arriving opportunities to adjust prices) (see Walsh, 2003, pp. 263-268). In contrast to the traditional specification, in the NKPC framework current expectations of future inflation, rather than past inflation rates, shift the curve (Woodford, 2003, p. 188). Also, the NKPC implies that inflation depends on real marginal cost, and not directly on either the gap between actual output and potential output or the deviation of the current unemployment rate from the natural rate of unemployment, as is typical in traditional Phillips curves (Walsh, 2003, p. 238). A major advantage of the NKPC compared with the traditional Phillips curve is said to be that the latter is a reduced-form relationship whereas the NKPC has a clear structural interpretation so that it can be useful for interpreting the impact of structural changes on inflation (Gali and Gertler, 1999).

Although the NKPC is appealing from a theoretical standpoint, empirical estimates of the NKPC have, by-and-large, not been successful in explaining the stylized facts about the dynamic effects of monetary policy, whereby monetary policy shocks are thought to first affect output, followed by a delayed and gradual effect on inflation (Mankiw, 2001, p. C59; Walsh, 2003, p. 241). To deal with what some authors (e.g., McCallum, 1999; Mankiw, 2001; Dellas, 2006a, b) believe to be inflation persistence in the data,[1] a response typically found in the literature is to augment the NKPC with lagged inflation - - on the supposition that lagged inflation receives weight in these equations because it contains information on the driving variables (i.e., the variables driving inflation) - - yielding a "hybrid" variant of the NKPC. A general result emerging from the empirical literature is that the coefficient on lagged inflation is positive and significant, with some authors (e.g., Fuhrer, 1997; Rudebusch, 2002; Rudd and Whelan, 2005) finding that inflation is predominantly backward looking.

[1] Roberts (1997), however, provided evidence suggesting that inflation is not sticky.

The hybrid NKPC, however, is itself subject to several criticisms. First, derivations of the hybrid specifications typically rely on backward looking rules-of-thumb, so that a “more coherent rationale for the role of lagged inflation” has yet to be provided (Gali, Gertler and Lopez-Salido, 2005, p. 1117). In effect we are loosing all the supposed advantages of the clear microfoundations. Second, the idea that the important role assigned to lagged inflation derives from its use as a proxy for expected future inflation is contradicted by the large estimates of the effects of lagged inflation obtained even in specifications that include the discounted sums of future inflations (Rudd and Whelan, 2005, p.1179).[2]

The contention made in this paper is that the standard model estimated within the NKPC paradigm is subject to a number of serious econometric problems and that these problems lead, not only to OLS being a biased estimator of the true underlying parameters, but that GMM is also subject to these problems in this instance. We will demonstrate below that, while GMM and instrumental variables can correctly deal with the standard problem of measurement error and endogeneity, if there is also missing variables and a misspecified functional form then no valid instruments will exist and GMM becomes inconsistent. Consequently, our argument is that the finding of a need for lagged inflation is a direct result of the biases caused by estimation problems rather than a flaw with the underlying economic theory. We will make this case, first, at a theoretical level, showing that economic theory clearly suggests both that the standard form of the NKPC is misspecified and that it is subject to omitted variables and misspecified functional form; hence, we will show that GMM is inconsistent. Second, we will apply an estimation procedure which is capable of yielding consistent estimates under these circumstances and which consistently finds a coefficient on expected inflation which is essentially unity.

The remainder of this paper is divided into three sections. Section 2 briefly summarizes the theoretical derivation of the NKPK and stresses the simplifying assumptions which imply the misspecification of the model. It then goes on to outline the novel estimation strategy used in this paper, building on the work of Swamy,

[2] Not all researchers have obtained large estimates of lagged inflation. Gali, Gertler and Lopez-Salido, (2005) found that the coefficient of lagged inflation, while significant, was quantitatively modest (i.e., generally on the order of .35 to .37).

Tavlas, Hall and Hondroyiannis (2008). [3] We contrast our estimation approach with that of the generalized method of moments (GMM), which has been widely applied in previous empirical studies of NKPCs (e.g., Gali and Gertler, 1999; Gali, Gertler and Lopez-Salido, 2005; Linde, 2005). Section 3 presents empirical results of NKPCs using US quarterly data. We demonstrate that GMM produces the usual result of significant lagged inflation rates while our estimation approach reveals coefficients that are much more closely in line with the micro foundations. Section 4 concludes.

2. Theoretical considerations and empirical methodology

2.1 The NKPC is a misspecified model

The theoretical model underlying the NKPC can be derived from a model of price setting by monopolistically competitive firms (Gali and Gertler, 1999). Following Calvo (1983), firms are allowed to reset their price at each date with a given probability $(1-\theta)$, implying that firms adjust their price taking into account expectations about future demand conditions and costs, and that a fraction θ of firms keep their prices unchanged in any given period. Aggregation of all firms produces the following NKPC equation in log-linearized form

$$\dot{p}_t = \beta \mathrm{E}_t \dot{p}_{t+1} + \lambda_1 s_t + \eta_{0t} \qquad (1)$$

where $\dot{p}_t$ is the inflation rate, $\mathrm{E}_t \dot{p}_{t+1}$ is the expected inflation in period t+1 as it is formulated in period t, s_t is the (log of) average real marginal cost in per cent deviation from its steady state level, and η_{0t} is a random error term. The coefficient, β, is a discount factor for profits that is on average between 0 and 1, $\lambda_1 = \frac{(1-\theta)(1-\beta\theta)}{\theta}$ is a parameter that is positive; $\dot{p}_t$ increases when real marginal cost, which is a measure of excess demand, increases (as there is a tendency for inflation to increase). Since marginal cost is unobserved, in empirical applications real unit labor cost (ulc_t) is often used as its proxy.[4]

[3] Swamy, Tavlas, Hall and Hondroyiannis (2008) in turn draw on papers by Swamy and Tavlas (2007), Chang, Hallahan and Swamy (1992) and Chang, Swamy, Hallahan and Tavlas (2000).

[4] The coefficients and the error term of equation (1) are not unique because β, λ_1, and η_{0t} can be changed without changing equation (1) (Pratt and Schlaifer, 1984, p. 13).

If we look a little deeper into the microfoundations however we start to find a number of serious simplifications that lie behind this equation. Batini, Jackson and Nickell (2005) emphasize the underpinnings of the NKPC. They begin their derivation with a Cobb-Douglas production function in which capital is dropped in place of a variable labor-productivity rate. They then go on to assume a representative firm with a simple quadratic cost minimization objective function and derive a standard NKPC, which even then includes terms in employment. Later, in the same paper, they generalize the NKPC to an open economy case, at which point a number of extra variables play an important part, including foreign prices, exchange rates and oil prices. Given this derivation, it is clear that the standard NKPC involves the following simplifications:

- The basic functional form is misspecified. In the standard derivations the NKPC is a linearization of a theory based on quadratic costs and Cobb-Douglas technology. In fact, both of these assumptions are unrealistic. Cobb-Douglas technology is almost always rejected wherever it is tested, and so the real production function must be more complex. Similarly, quadratic objective functions are convenient, but far from realistic. Clearly, according to the theory the NKPC is a linear version of a much more complex non-linear model.
- The basic NKPC is subject to the omission of a potentially large number of omitted variables. Batini, Jackson and Nickell (2005) emphasize the need to include exchange rates, foreign prices, oil prices, employment and a labor productivity variable. The representative firm assumption could well mean that variables capturing firm heterogeneity are important.
- The variables used in the NKPC are almost certainly measured with error. For example unit labor costs can only be modeled as the labor share under Cobb-Douglas technology. A CES function would involve a much richer set of variables to properly capture the real wage, and even this function would be only an approximation as empirical support for CES technology is not overwhelming. Clearly, the representative firm assumption also suggests that average or total measures of labor share may not be the correct measure. Additionally there are well known problems in measuring inflation itself.

Thus, the case is very strong from a theoretical perspective that any of the standard NKPC models would be subject to measurement error, omitted variable bias, and a misspecified functional form.

The response of many authors to the poor estimation results often produced from the NKPC is to start to find largely 'add hoc' reasons for augmenting the NKPC with lags. Many authors assume that firms can save costs if prices are changed between price adjustment periods according to a rule of thumb. For example, Gali and Gertler (1999) assume that only a portion $(1-\rho)$ of firms are forward-looking and the rest are backward-looking. This implies that only a fraction $(1-\rho)$ of firms set their prices optimally and the rest employ a rule of thumb based on past inflation. Recently, Christiano, Eichenbaum and Evans (2005) assumed that all firms adjust their price each period but some are not able to re-optimize, so they index their price to lagged inflation. Under the above assumptions, the hybrid NKPC, which includes lagged inflation, can be derived as:

$$\dot{p}_t = \omega_f \mathrm{E}_t \dot{p}_{t+1} + \lambda_2 s_t + \omega_b \dot{p}_{t-1} + \eta_{1t} \qquad (2)$$

where $\dot{p}_{t-1}$ is the lagged inflation and η_{1t} is a random error term. The reduced form parameter λ_2 is defined as $\lambda_2 = (1-\rho)(1-\theta)(1-\beta\theta)\phi^{-1}$ with $\phi = \theta + \rho[1-\theta(1-\beta)]$. Finally, the two reduced form parameters, ω_f and ω_b, can be interpreted as the weights on "backward-" and "forward-looking" components of inflation and are defined as $\omega_f = \beta\theta\phi^{-1}$ and $\omega_b = \rho\phi^{-1}$, respectively. Unlike the "pure" NKPC, the hybrid NKPC is not derived from an explicit optimization problem.

Assuming rational expectations and that the error terms η_{1t}, t = 1, 2, …, are identically and independently distributed (i.i.d.), many researchers employ the GMM procedure to estimate the NKPC and/or its hybrid version. Under GMM estimation, $E_t \dot{p}_{t+1}$ is replaced by $\dot{p}_{t+1}$, which is actual inflation in t + 1, and the method of instrumental variables is used to obtain consistent estimates of the parameters of model (2), since $\dot{p}_{t+1}$ is correlated with η_{1t}. The instrumental variables are correlated with $\dot{p}_{t+1}$, ulc_t, and $\dot{p}_{t-1}$, but not with η_{1t}. The condition that $E(\eta_{1t}|z_{t-1})$ = 0, where z_{t-1} is a vector of instruments dated t-1 and earlier and is assumed to be orthogonal to η_{1t}, implies the following orthogonality condition:

$$\mathrm{E}_t\left\{(\dot{p}_t - \lambda_2\, ulc_t - \omega_f\, \dot{p}_{t+1} - \omega_b \dot{p}_{t-1})\, z_{t-1}\right\} = 0 \qquad (3)$$

In the next section, we will demonstrate that, given the multiple forms of misspecification to which the NKPC is subject, this GMM approach cannot be a consistent estimator.

2.2 A new estimation strategy

In this sub section, we outline an estimation strategy which can estimate some of the structural parameters of a relationship without specifying either the true or complete model.[5]

When studying the relation of a dependent variable, denoted by y_t^*, to a hypothesized set of K – 1 of its determinants, denoted by x_{1t}^*, …, $x_{K-1,t}^*$, where K-1 may be only a subset of the complete set of determinates of y_t^*, a number of problems may arise. Any specific functional form may be incorrect and may therefore lead to specification errors resulting from functional-form biases. Another problem that can arise in investigating the relationship between the dependent variable and its determinants is that x_{1t}^*, …, $x_{K-1,t}^*$ may not exhaust the complete list of the determinants of y_t^*, in which case the relation of y_t^* to x_{1t}^*, …, $x_{K-1,t}^*$ may be subject to omitted-variable biases. In addition to these problems, the available data on y_t^*, x_{1t}^*, …, $x_{K-1,t}^*$ may not be perfect measures of the underlying true variables, causing errors-in-variables problems. In what follows, we propose the correct interpretations and an appropriate method of estimation of the coefficients of the relationship between y_t^* and x_{1t}^*, …, $x_{K-1,t}^*$ in the presence of the foregoing problems.

Suppose that T measurements on y_t^*, x_{1t}^*, …, $x_{K-1,t}^*$ are made and these measurements are in fact, the sums of "true" values and measurement errors: y_t = y_t^* + v_{0t}, x_{jt} = x_{jt}^* + v_{jt}, j = 1, …, K-1, t = 1, …, T, where the variables y_t, x_{1t}, …, x_{Kt} without an asterisk are the observable variables, the variables with an asterisk are the unobservable "true" values, and the v's are measurement errors. Also, given the

[5] The discussion below draws on Swamy, Tavlas, Hall and Hondroyiannis (2008).

possibilities that the functional form we are estimating may be misspecified and there may be some important variables missing from x_{1t}, …, $x_{K-1,t}$, we need a model which will capture all these potential problems.

It is useful at this point to clarify what we believe is the main objective of econometric estimation. In our view, the objective is to obtain unbiased estimates of the effect on a dependent variable of changing one independent variable holding all others constant. That is to say, we aim to find an unbiased estimate of the partial derivative of y_t^* with respect to any x_{jt}^*. This interpretation of course is the standard one usually placed on the coefficients of a typical econometric model, but validy of this interpretation depends crucially on the assumption that the conventional model gives unbiased coefficients, which, of course, is not the case in the presence of model misspecification.

One way to proceed is to specify a set of time-varying coefficients which provide a complete explanation of the dependent variable y. Consider the relationship

$$y_t = \gamma_{0t} + \gamma_{1t} x_{1t} + \cdots + \gamma_{K-1,t} x_{K-1,t} \tag{4}$$

which we call "the time-varying coefficient (TVC) model". (Note that this equation is formulated in terms of the observed variables). As this model provides a complete explanation of y, all the misspecification in the model, as well as the true coefficients must be captured by the time-varying coefficients. Note that, if the true functional form is non-linear, the time-varying coefficients may be thought of as the partial derivatives of the true non-linear structure and so they are able to capture any possible function. These coefficients will also capture the effects of measurement error and omitted variables. The trick is to find a way of decomposing these coefficients into the biased and the bias-free components.

It is important to stress, that while we start from a time varying coefficient model, and this technique is sometimes referred to as TVC estimation, the objective here is not to simply estimate a model with changing coefficients. We start from (4) because this is a representation of the underlying data generation process, which is correct. This is the case simply because, if the coefficients can vary at each point in time, they are able to explain 100 percent of the variation in the dependent variable. In the case of the TVC procedure followed in this paper, however, we then decompose these varying coefficients into two parts, a consistent estimate of the true structural partial derivative and the remaining part which is due to biases from the various misspecifications in the model. If the true model is linear, we would get back to a constant coefficient model. If the true model is non-linear, the partial derivative will be varying with the models variables and parameters and the coefficient will then vary over time to reflect this circumstance. The key point is that the TVC technique used here produces consistent estimates of structural relationships in the presence of model misspecification.

For empirical implementation, model (4) has to be embedded in a stochastic framework. To do so, we need to answer the question: What are the correct stochastic assumptions about the TVC's of (4)? We believe that the correct answer is: the correct interpretation of the TVC's and the assumptions about them must be based on an understanding of the model misspecification which comes from any (i) omitted variables, (ii) measurement errors, and (iii) misspecification of the functional form. We expand on this argument in what follows.

Notation and Assumptions Let m_t denote the total number of the determinants of y_t^*. The exact value of m_t cannot be known at any time. We assume that m_t is larger than K-1 (that is, the number of determinants is greater than the determinants for which we have observations) and possibly varies over time.[6] This assumption means that there are determinants of y_t^* that are excluded from equation (4) since equation (4) includes only K-1 determinants. Let x_{gt}^*, $g = K, \ldots, m_t$, denote these excluded determinants. Let α_{0t}^* denote the intercept and let both α_{jt}^*, $j = 1, \ldots, K\text{-}1$, and α_{gt}^*, $g = K, \ldots, m_t$, denote the other coefficients of the regression of y_t^* on all of its determinants. The true functional form of this regression determines the time profiles of α^* s. These time profiles are unknown, since the true functional form is unknown. Note that an equation that is linear in variables accurately represents a non-linear equation, provided the coefficients of the former equation are time-varying with time profiles determined by the true functional form of the latter equation. This type of representation of a non-linear equation is convenient, particularly when the true functional form of the non-linear equation is unknown. Such a representation is not subject to the criticism of misspecified functional form. For $g = K, \ldots, m_t$, let λ_{0gt}^*

[6] That is, the number of determinants is itself time-variant.

denote the intercept and let λ^*_{jgt}, j = 1, …, K-1, denote the other coefficients of the regression of x^*_{gt} on x^*_{1t}, …, $x^*_{K-1,t}$. The true functional forms of these regressions determine the time profiles of λ^*s.

The following theorem gives the correct interpretations of the coefficients of equation (4):

Theorem 1 *The intercept of (4) satisfies the equation,*

$$\gamma_{0t} = \alpha^*_{0t} + \sum_{g=K}^{m_t} \alpha^*_{gt}\lambda^*_{0gt} + \mathrm{v}_{0t}\,, \tag{5}$$

and the coefficients of (4) other than the intercept satisfy the equations,

$$\gamma_{jt} = \alpha^*_{jt} + \sum_{g=K}^{m_t} \alpha^*_{gt}\lambda^*_{jgt} - \left(\alpha^*_{jt} + \sum_{g=K}^{m_t} \alpha^*_{gt}\lambda^*_{jgt}\right)\left(\frac{\mathrm{v}_{\mathrm{jt}}}{\mathrm{x}_{\mathrm{jt}}}\right) \qquad (j = 1, \ldots, K\text{-}1) \tag{6}$$

Proof See Swamy and Tavlas (2001, 2007).

Thus, we may interpret the TVC's in terms of the underlying correct coefficients, the observed explanatory variables and their measurement errors. It should be noted that, by assuming that the λ^*s in equations (5) and (6) are possibly nonzero we do not require that the determinants of y^*_t included in (4) be independent of the determinants of y^*_t excluded from (4). Pratt and Schlaifer (1988, p. 34) show that this condition is "meaningless". By the same logic, the usual exogeneity assumption of independence between a regressor and the disturbances of an econometric model is "meaningless" if the disturbances are assumed to represent the net effect on the dependent variable of the determinants of the dependent variable excluded from the model. The real culprit appears to be the interpretation that the disturbances of an econometric model represent the net effect on the dependent variable of the unidentified determinants of the dependent variable excluded from the model. In other words, if we make the classical econometric assumption that the error term is an IID process, then standard techniques go through in the usual way. If however we interpret the error term as a function of the misspecification of the model, then it becomes impossible to assert its conditional independence from the included regressors and standard techniques such as instrumental variables are no longer consistent.

By assuming that the α^*s and λ^*s are possibly time-varying, we do not *a priori* rule out the possibility that the relationship of y_t^* with all of its determinants and the regressions of the determinants of y_t^* excluded from (4) on the determinants of y_t^* included in (4) are non-linear. Note that the last term on the right-hand side of equations in (6) implies that the regressors of (4) are correlated with their own coefficients.[7]

Theorem 2 *For j* = 1, …, *K*-1, *the component* α_{jt}^* *of* γ_{jt} *in (6) is the direct or bias-free effect of* x_{jt}^* *on* y_t^* *with all the other determinants of* y_t^* *held constant and is unique.*

Proof It can be seen from equation (6) that the component α_{jt}^* of γ_{jt} is free of omitted-variables bias $(=\sum_{g=K}^{m_t}\alpha_{gt}^*\lambda_{jgt}^*)$, measurement-error bias $(=-\left(\alpha_{jt}^*+\sum_{g=K}^{m_t}\alpha_{gt}^*\lambda_{jgt}^*\right)\times\left(\mathrm{v}_{\mathrm{jt}}/x_{jt}\right))$, and of functional-form bias, since we allow the α^*s and λ^*s to have the correct time profiles. These biases are not unique being dependent on what determinants of y_t^* are excluded from (4) and the v_{jt}. However, the γ_{jt} are unique when their correct interpretations given by (5) and (6) are adopted (see Swamy and Tavlas 2007, p. 300). Note that α_{jt}^* is the coefficient of x_{jt}^* in the correctly specified relation of y_t^* to all of its determinants. Hence α_{jt}^* represents the direct, or bias-free, effect of x_{jt}^* on y_t^* with all the other determinants of y_t^* held constant. The direct effect is unique because it represents a property of the real world that remains invariant against mere changes in the language we use to describe it (see Basmann 1988, p. 73; Pratt and Schlaifer 1984, p. 13; Zellner 1979, 1988). In effect the direct effect is a consistent estimator of the derivative of x_{jt}^* with respect to y_t^*, it is essentially simply a number and is therefore unique.

The direct effect α_{jt}^* is constant if the relationship between y_t^* and all of its determinants are linear; alternatively, it is variable if the relationship is non-linear. We

[7] These correlations are typically ignored in the analyses of state-space models. Thus, inexpressive conditions and restrictive functional forms are avoided in arriving at equations (5) and (6) so that Theorem 1 can easily hold; for further discussion and interpretation of the terms in (5) and (6), see Swamy and Tavlas (2001, 2007) and Hondroyiannis, Swamy and Tavlas (2008).

often have information from theory as to the right sign of α^*_{jt}. Any observed correlation between y_t and x_{jt} is spurious if α^*_{jt} = 0 (see Swamy, Tavlas and Mehta 2007).[8]

A key implication of (5) and (6) is that, in the presence of a misspecified functional form and omitted variables, the errors in a standard regression will contain the difference between the right-hand side of (4) and the right-hand side of the standard regression with the errors suppressed. So the errors will contain the included x variables. This means that the orthogonality condition (of the form of (3)) of GMM and instrumental variables cannot be met as the errors contain exactly the same variables that we require the instruments to have a strong correlation with. In effect, if the instruments are highly correlated with the x variables, they cannot be uncorrelated with the errors as these errors contain exactly the same x variables.

Swamy, Tavlas, Hall and Hondroyiannis (2008) go on to show how a TVC model may be estimated and then the time varying coefficients decomposed to give unbiased estimates of the true parameters of a model which is misspecified in terms of its functional form, its variables and measurement error. The key to this decomposition is to use a set of variables, called coefficient drivers, which explain the time variation in the coefficients. Some of these variables should be correlated with any true variation in the direct effect while other drivers *should be correlated* with the biases that are present. Once this is achieved by removing the effect on the coefficients which come from the second set of variables (i.e., the biased variables) we remove the bias and obtain a consistent estimate of the underlying direct effect. This second set of coefficient drivers then act rather like the dual of conventional instruments. The key difference however is that these drivers should be correlated with the misspecification rather than uncorrelated, as in the case with instruments, and this should be much easier to achieve in a real world situation.

The normal use of the TVC approach requires an intercept as this term represents three components, the ‘true’ intercept (α^*_{0t}), the net effect of the portions of excluded variables remaining after the effect of the true values of included

[8] We use the term spurious in a more general sense than Granger and Newbold’s (1974), where it strictly applies to linear models with non-stationary error terms. Here we mean any correlation which is observed between two variables when the true direct effect is actually zero.

explanatory variables have been removed($\sum_{g=K}^{m_t} \alpha^*_{gt} \lambda^*_{0gt}$), and the measurement error in the dependent variable (v_{0t}). As equation (5) shows. However in the special case of the Phillips curve this is not necessary. The reason for this is that when we have a unit coefficient on expected inflation the equation effectively becomes a forward difference in inflation. This means that all the variables must be mean zero without a constant if inflation is not to contain a deterministic trend, which would imply a permanent rise or fall in inflation. Thus in this case, the theory suggests that the true constant should be zero, the net effect of omitted variables should also be zero and the net measurement error in the dependent variable should again be zero. To check this we estimated all the TVC models including a constant and in every case the constant proved to be insignificant. We will therefore not report these results.

2.3 The NKPC and TVC estimation

Section 2.1 argued that the NKPC is subject to a misspecified functional form, omitted variables and measurement error. Section 2.2 demonstrated that in the simultaneous presence of all three sources of misspecification no valid instruments could exist for instrumental variable estimation. It therefore follows that, in the case of the NKPC, GMM is not a consistent estimator and therefore it is hardly surprising that some of the reported results are so poor. For example, in Gali and Gertler (1999) the Hansen J statistic suggests that the instruments are extremely poor, as we would expect from the above arguments. TVC estimation, however, goes on from the arguments set out above to specify a set of parametric equations for the time variation in the coefficients as a function of observed variables; the coefficient drivers mentioned above. It can then be formerly shown that, by decomposing these drivers into two subsets, we may remove the bias component from the time varying coefficient and get back to the unbiased underlying true effect. We can do this without fully specifying the set of exogenous variables and without knowing the correct functional form. The key to all this is the properties of the coefficient drivers; the important thing to realize here is that a good set of coefficient drivers is a set of variables that are correlated with the misspecification in the model. Crucially, it is much easier to find a good set of coefficient drivers than a good set of instruments (which in this specific case cannot exist)

Apart from the general theoretical problems with the NKPC outlined above, there are some specific reasons why in the case of US data standard estimation would be problematic. During the past two decades, several interrelated factors appear to have contributed to a nonlinear structure (or, equivalently, a linear structure with changing coefficients) of the U.S. economy, including the following. First, there was a substantial fall in inflation in the 1990s and the first half of the 2000s, compared with the 1970s and early 1980s, reflecting the focus of monetary policy on achieving price stability,[9] increased globalization, which led to competitive pressures on prices, and an acceleration of productivity, beginning in the mid-1990s, that helped contain cost pressures. Second, the increased role of the services sector and an improved trend in productivity growth beginning in 1995 appear to have led to a changing non-accelerating inflation rate of unemployment (NAIRU), so that a given inflation rate has been associated with a lower unemployment rate in the latter 1990s and early 2000s, compared with the 1970s (Sichel, 2005, pp. 131-132). Third, a structural decline in business-cycle volatility appears to have occurred beginning in the mid-1980s (Gordon, 2005). This decline has been attributed to such factors as the improved conduct of monetary policy and innovations in financial markets that allow for greater flexibility and dampen the real effects of shocks (Jermann and Quadrini, 2006). The implication of these changes for estimation of econometric models was noted by Greenspan (2004, p. 38), who argued: “The economic world in which we function is best described by a structure whose parameters are continuously changing … An ongoing challenge to the Federal Reserve … is to operate in a way that does not depend on a fixed economic structure based on historically … [fixed] coefficients.”

Under fixed-coefficient estimation methods, dummy variables are typically used to capture changes in economic structure, such as a change in policy regime. This approach, however, involves several problems. First, it assumes that any changes in structure occurred at a given, known date, whereas changes in structure may have a gradual effect and/or take place with a lag. Second, structural changes may not only

[9] Greenspan (2004) argued that this focus reflected increased political support for stable prices, which was a consequence of, and reaction to, the unprecedented peacetime inflation of the 1970s.

change the coefficients, but can also change the error distribution. For example, adding a dummy variable to an equation is likely to change the variance of the error.

How does TVC estimation deal with structural changes? Consider the case in which a dummy variable is used to capture a change in structure. Unlike fixed-coefficient estimation, under which the dummy variable is added to the regression, in TVC estimation the dummy variable first appears as a coefficient driver and so the coefficient may discreetly change at the appropriate point in time. This is a much more flexible approach to structural change as any of the included regressor coefficients may capture the change as appropriate to the data rather than restricting the change to a simple change in intercept.

3. Data and empirical results

In this section, we contrast the results for some standard NKPC estimates with those obtained from the TVC approach. In the case of standard GMM results, we try to replicate the usual findings (not to improve or correct them) in order to demonstrate that the data we are using yield the usual results. We will then go on to demonstrate that, over a range of data periods, the TVC approach actually gives much stronger support to the standard NKPC models, although, of course, without assuming they are the entire story.

All the estimates reported below are based on quarterly U.S. data either over the period 1970:1 – 2002:4, to compare with most of the literature and because of data limitations (noted below), or 1970:1-2007:4, as the latest available data set. We use three measures of expected inflation, the first is the projected change in the implicit GDP deflator, contained in the Fed's Federal Open Market Committee (FOMC) *Greenbook.* The *Greenbook* forecasts appear to incorporate efficiently a large amount of information from all sectors of the economy as well as Fed officials' judgmental adjustments. *Greenbook* forecasts, however, are available only with a multi-year lag (more than five years), so that our estimation period ends in 2002:4. The second measure of expected inflation used is the consensus group median forecasts of inflation from the Survey of Professional Forecasters (consensus forecasts) conducted by the Federal Reserve Bank of Philadelphia. The final measure of inflation is the actual future realization of inflation which rests on the usual rational expectations assumption combined with GMM estimation.

The other data are as follows. Inflation ($\dot{p}_t$) is the annualized quarterly per cent change in the implicit GDP deflator. Real unit labor cost (ulc), is estimated using the deviation (x_{2t}) of the (log) of the labor income share from its average value; the labor income share is the ratio of total compensation of employees in the economy to nominal GDP. The CPI inflation rate (used as an instrument) is the annualized quarterly per cent change in consumer price index.[10] Wage inflation is the annualized quarterly per cent change in hourly earnings in manufacturing. The interest rate is the three month t-bill rate.[11]

Our estimation procedure was the following: In line with much of the literature, we estimated a hybrid model using GMM, the results of which are used as a benchmark with which to compare the results based on TVC estimation. Our aim is to assess whether the results reported in the literature - - namely, that the inclusion of lagged inflation is needed in the Phillips curve specification and that the coefficient on expected inflation, while significant, is well-below unity, results typically based on GMM - - reflect specification biases. Given the probability of measurement error in all three of our measures of expected inflation we use GMM estimation in all the standard estimates. In an attempt to keep our GMM estimates as close to the standard literature as possible we use a standard set of instruments in equation (3); four lags of inflation, two lags of real unit labor cost variable, four lags of consumer price index (CPI) inflation, four lags of wage inflation and the t-bill rate. The standard errors of the estimated parameters were modified using a Barlett or quadratic kernel with variable Newey-West bandwidth. In addition, prewhitening was used. In all cases the J-statistic was used to test overidentifying restrictions of the model (Greene, 2003, p. 155).

As mentioned, coefficient drivers play a crucial role under the TVC procedure used in this study. Four coefficient drivers were used: z_{0t} = the constant term, z_{1t} = the change in the t-bill rate in period $t-1$, z_{2t} = the change in CPI inflation in period $t-1$, and z_{3t} = the change in wage inflation in the manufacturing sector in period $t-1$. The reported estimates from TVC estimation that correct for all specification

[10] Apart from the *Greenbook* forecasts, the source of the foregoing data is the Datastream OECD *Economic Outlook*.

[11] The data on wages and the t-bill rate are from *the International Financial Statistics* (*IFS*).

biases, yielding what we call "bias-free" effects, are estimated using the constant term and the change in the t-bill rate in the previous period. That is the constant term and the lagged change in the t-bill rate are used to absorb specification biases, yielding the bias-free effects.

Table 1 presents the main empirical results for the period up to 2002 using the two direct measures of expectation, the *Greenbook* (panel A) and the consensus forecasts (panel B) [12]. In both cases the GMM results include highly significant lagged inflation effects. If these are not included then the marginal cost term ceases to be significant. The TVC results present a strong contrast to this. In both cases the lagged inflation effect is insignificant (and in one case it is actually negative which strongly confirms our view that the lagged effect does not belong in the equation) and when this effect is removed from the equation the coefficient on expected inflation becomes almost exactly one (1.005 and 0.978). In both cases the marginal cost terms are highly significant.

Table 2 shows the results for the full period to 2007:4 for the two cases of the consensus forecast (panel B) and using the actual future value to proxy the expected value for inflation (panel A). The picture here is very similar. In both cases, the GMM results find that lagged inflation is significant and cannot be dropped and the term on expected inflation is well below unity. If lagged inflation is dropped then the marginal cost term becomes insignificant. When we consider the TVC results, even in the presence of a lagged inflation term the estimated coefficient on expected inflation is virtually one (1.00 and 0.852); the lagged inflation terms in both cases is highly insignificant and when we remove it we find coefficients on expected inflation of 1.036 and 0.968. In the odd case of using actual future value to proxy the expected value for future inflation we find the marginal cost term to be significant if lagged inflation is included and to be insignificant otherwise. Contrary, in the case of consensus forecast the marginal cost term is significant either when lagged inflation is included or excluded.

These results are almost exactly as we would have expected. Given the theoretical approximations made in the formal derivation of the NKPC our theory

[12] All the coefficient estimates from the TVC estimation reported are the time average of the coefficient estimates

suggests the GMM is not a consistent estimation technique. We have applied the TVC estimation strategy and found parameter estimates for the effect of expected inflation that are much closer to our theoretical expectations along with suitable significant effects for the effect of marginal costs provided correct coefficient drivers are used to compute bias-free effects. We would emphasize that we are not stating that this is the complete formulation of the Phillips curve. There may be other effects which are important. The TVC approach does not require a complete specification of the equation to derive consistent estimates of the structural effects considered.

4. Conclusions

This paper has provided a clear-cut empirical experiment. Using GMM, we were able to replicate results typically found in the literature in which lagged inflation has a positive and significant coefficient in the NKPC framework, producing a hybrid NKPC. Under GMM, incorporating lagged inflation and, alternatively, one of three measures of expected inflation in the Phillips relation, the coefficients on the lagged inflation variable and expected inflation sum to near unity, yielding a long-run vertical Phillips relation. Are these results spurious? TVC estimation provides a straightforward method of addressing this question. Our results strongly suggest that the role found by previous researchers for lagged inflation in the NKPC is the spurious outcome of specification biases. Moreover, our results are not dependent on a particular measure of inflation expectations or sample period. Each of the measures used provided a similar set of results.

This finding can have significant policy implications; the correct setting of monetary policy requires a clear understanding of the dynamics of inflation. The results provided here imply that inflation is much less sluggish and persistent than the standard finding might suggest. This would mean that the path of interest rates to optimally combat shocks to inflation would be substantially different to that implied by the conventional results. In conclusion, this paper offers strong support to the standard micro founded theory which lies behind the NKPC and this has important implications for monetary policy.

Table 1			
Estimation of NKPC for USA 1970:1-2002:4			
Panel A: Greenbook forecasts-based specification			
	GMM (1)	TVC bias-free effect without constant (2)	TVC bias-free effect without constant (3)
Greenbook forecast of $\dot{p}_{t+1}$	0.820*** [10.69]	0.933*** [9.60]	1.005*** [9.94]
ulc_t (marginal costs)	0.244*** [3.45]	0.227*** [2.84]	0.370*** [7.22]
$\dot{p}_{t-1}$	0.378*** [8.07]	0.068 [0.74]	-
$\bar{R}^2$	0.83	0.99	0.99
J-test	0.93		
Panel B: Consensus forecasts-based specification			
	GMM (1)	TVC bias-free effect without constant (2)	TVC bias-free effect without constant (3)
Consensus forecasts of $\dot{p}_{t+1}$	0.653*** [9.49]	1.003*** [8.19]	0.978*** [31.96]
ulc_t (marginal costs)	0.355*** [5.37]	0.296** [5.05]	0.332** [6.53]
$\dot{p}_{t-1}$	0.319*** [6.87]	-0.004 [-0.03]	-
$\bar{R}^2$	0.83	0.99	0.99
J-test	0.93		

Notes: Figures in brackets are t-statistics. ***, **,* indicate significance at 1%, 5%, and 10% level respectively. The estimates in columns (2) and (3) are obtained using four coefficient drivers: a constant term, the change in the t-bill rate in period t-1, the change in CPI inflation rate in period t-1 and the change in wage inflation in period t-1. The bias-free effects are estimated using the constant term and the change in the t-bill rate in the previous period.

Table 2			
Estimation of NKPC for USA 1970:1-2007:4			
Panel A: Actual inflation-based specification			
Variables	GMM (1)	TVC bias-free effect without constant (2)	TVC bias-free effect without constant (3)
$\dot{p}_{t+1}$	0.830*** [19.05]	1.000*** [20.90]	1.036*** [32.10]
ulc_t (marginal costs)	0.086*** [3.27]	0.112*** [2.61]	0.021 [0.28]
$\dot{p}_{t-1}$	0.164*** [3.92]	0.011 [0.25]	-
$\bar{R}^2$	0.79	0.99	0.99
J-test	0.83		
Panel B: Consensus forecasts-based specification			
	GMM (1)	TVC bias-free effect without constant (2)	TVC bias-free effect without constant (3)
Consensus forecasts of $\dot{p}_{t+1}$	0.848*** [11.40]	0.852*** [8.01]	0.968*** [31.21]
ulc_t (marginal costs)	0.282*** [4.06]	0.322*** [2.92]	0.500*** [2.45]
$\dot{p}_{t-1}$	0.186*** [2.61]	0.046 [0.31]	-
$\bar{R}^2$	0.80	0.99	0.99
J-test	0.87		

Notes: Figures in brackets are t-statistics. ***, **, * indicate significance at 1%, 5%, and 10% level respectively. The estimates in columns (2) and (3) are obtained using four coefficient drivers: a constant term, the change in the t-bill rate in period t-1, the change in CPI inflation rate in period t-1 and the change in wage inflation in period t-1. The bias-free effects are estimated using the constant term and the change in the t-bill rate in the previous period.

References

Basmann, R. L., 1988. Causality tests and observationally equivalent representations of econometric models. Journal of Econometrics 39, 69-104.

Batini, N., Jackson, B., Nickell, S., 2005. An open economy new Keynesian Phillips curve for the U.K. Journal of Monetary Economics 52, 1061-1071.

Calvo, G., 1983. Staggered prices in a utility-maximizing framework. Journal of Monetary Economics 12 (3), 383-398.

Chang, I., Hallahan, C., Swamy, P. A. V. B., 1992. Efficient computation of stochastic coefficient models. In: Amman, H. M., Belsley, D. A., Pau, L. F. (Eds.), Computational Economics and Econometrics, London: Kluwer Academic Publishers.

Chang, I., Swamy, P. A. V. B., Hallahan, C., Tavlas, G. S., 2000. A computational approach to finding causal economic laws. Computational Economics 16, 105-136.

Christiano, L., Eichenbaum, M., Evans, C., 2005, Nominal rigidities and the dynamic effects of a shock to monetary policy. Journal of Political Economy 113, 1- 45.

Dellas, H. 2006a. Monetary shocks and inflation dynamics in the New Keynesian model. Journal of Money, Credit and Banking 38 (2), 543-51.

Dellas, H. 2006b. Inflation inertia in the New Keynesian model. Mimeo., University of Bern.

Fuhrer, J. C., 1997. The (un)importance of forward –looking behavior in price setting. Journal of Money, Credit and Banking 29, 338-350.

Gali, J., Gertler, M., 1999. Inflation dynamics: a structural econometric approach. Journal of Monetary Economics 44 (2), 195-222.

Gali, J., Gertler, M., Lopez-Salido, J. D., 2005. Robustness of the estimates of the hybrid New Keynesian Phillips curve. Journal of Monetary Economics 52, 1107-1118.

Greene, W. H., 2003. Econometric analysis, 5th edition, Upper Saddle River, New Jersey: Prentice Hall.

Gordon, R., 2005. What caused the decline in U.S. business cycle volatility? NBER Working Paper No. 11777.

Granger C. W. J., Newbold, P., 1974. Spurious regressions in econometrics. Journal of Econometrics 2, 111-20.

Greenspan, A., 2004. Risk and uncertainty in monetary policy. American Economic Review, Papers and Proceedings 94, 33-40.

Hondroyiannis, G., Swamy, P.A.V.B., Tavlas, G. S, 2008. A note on the new Keynesian Phillips curve in a time-varying coefficient environment: some European evidence. Macroeconomic Dynamics 12, forthcoming.

Jermann, U., Quadrini, V., 2006. Financial innovations and macroeconomic volatility. NBER Working Paper No. 12308.

Linde, J., 2005. Estimating New-Keynesian Phillips curves: a full information maximum likelihood approach. Journal of Monetary Economics 52, 1135-52

Mankiw, N.G., 2001. The inexorable and mysterious trade-off between inflation and unemployment. The Economic Journal 111, C45-C61.

McCallum, B.T., 1999. Recent developments in monetary policy analysis: The roles of theory and evidence. Journal of Economic Methodology 6, 171-198

Pratt, J. W., Schlaifer, R., 1984, On the nature and discovery of structure. Journal of the American Statistical Association 79, 9-22.

Pratt, J. W., Schlaifer, R., 1988. On the interpretation and observation of laws. Journal of Econometrics 39, 23-52.

Roberts, J.M., 1997. Is inflation sticky? Journal of Monetary Economics 39, 173-96.

Rudebusch, G.D., 2002. Assessing nominal income rules for monetary policy with model and data uncertainty. Economic Journal 112, 402-432.

Rudd, J., Whelan, K., 2005. New tests of the New Keynesian Phillips curve. Journal of Monetary Economics, 52, 1167-1181.

Sichel, D., 2005. Where did the productivity growth go? Inflation dynamics and the distribution of income: comments. Brookings Papers on Economic Activity No. 2, 128-135.

Swamy, P. A. V. B., Tavlas, G. S., 1995. Random coefficient models: theory and applications. Journal of Economic Surveys 9, 165-182.

Swamy, P. A. V. B., Tavlas, G. S., 2001. Random coefficient models. In: Baltagi, B. H. (Ed.), A companion to theoretical econometrics, Malden: Blackwell.

Swamy, P. A. V. B., Tavlas, G. S., 2007. The new Keynesian Phillips curve and inflation expectations: re-specification and interpretation. Economic Theory, 31,293-306.

Swamy, P.A.V.B., Tavlas, G.S., Mehta, J.S., 2007. Methods of distinguishing between spurious regressions and causality. Journal of Statistical Theory and Applications 1, 83-96.

Swamy, P. A. V. B., Tavlas, G. S., Hall, S. G., Hondroyiannis G., 2008. Estimation of parameters in the presence of model misspecification and measurement error. Mimeo.

Walsh, C. E., 2003. Monetary theory and policy, 2nd ed., Cambridge, MA: MIT Press.

Woodford, M., 2003. Interest and prices. Princeton: Princeton University Press.

Zellner, A., 1979. Causality and econometrics. In Three Aspects of Policy and Policymaking, K. Brunner and A. H. Meltzer, eds., Amsterdam: North-Holland, pp. 9-54.

Zellner, A., 1988. Causality and causal laws in economics. Journal of Econometrics 39, 7-21.