Testing an Alternative Price-Setting Behavior in New Keynesian Phillips Curve: Extrapolative Price-Setting Mechanism

Yoonseok Choi*
Suffolk University

Sunghyun Kim**
Sungkyunkwan University and Suffolk University

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Abstract

Hybrid New Keynesian Phillips curve (NKPC) has been widely used in monetary policy literature (e.g. Gali and Gertler, 1999) as it contains both forward-looking and backward-looking components and therefore fits the data well. A typical backward-looking part of price setting behavior assumes that firms use the previous period's price. In this paper, we propose a generalized version of the hybrid NKPC by incorporating extrapolative (adaptive) price-setting mechanism in backward-looking part of the price setting behavior. We assume that when firms set the price at period t, they use information on price in period t-1 plus a portion of the change in prices between t-1 to t-2, which permits the trend in past price changes (partial error correction). Under this generalized setting, we derive reduced and structural NKPC explicitly. It turns out that the newly derived NKPC is a nesting model of the original hybrid NKPC in Gali and Gertler (1999). The empirical results show that the extrapolative component is strongly significant in explaining the inflation dynamics. In addition, the generalized version of the hybrid NKPC fits the data better than the original hybrid NKPC in terms of various measures for empirical performance such as AIC, BIC, root mean squared error and mean absolute error.

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Keywords: extrapolative price-setting, inflation dynamics, New Keynesian Phillips Curve, forward-looking, backward-looking.

* Department of Economics, Suffolk University, Boston, USA.E-mail: ychoi2@suffolk.edu.
** Corresponding Author. Department of Economics, Sungkyunkwan University, Seoul, Korea and Department of Economics, Suffolk University, Boston, MA, USA. Tel: 02-760-0421, E-mail: shenrykim@skku.edu.

1. Introduction

New Keynesian Phillips Curve (NKPC) has been widely used in monetary policy literature because it captures forward-looking behavior of rational agents. However, purely forward-looking model such as NKPC performs poorly in empirical test as it fails to capture inflation persistence observed in the data.[1] This empirical failure led economists to expand the standard NKPC by including a backward-looking price setting behavior as well as forward-looking part (Gali and Gertler, 1999). Concerning empirical performance, many studies have shown that this hybrid NKPC model, by emphasizing the role of lagged inflation to explain the intrinsic persistence of inflation, fits the data better than the purely forward-looking NKPC (e.g. Fuhrer and Moore 1995; Fuhrer 1997; Roberts 1997 and 2005; Gali et al. 2001; Christiano et al. 2005).

However, many hybrid NKPC models are based on ad-hoc inclusion of lags of inflation and use a reduced-form equation for estimation without structural model (e.g. Fuhrer 1997; Roberts 2005). Exceptions are, for example, Gali and Gertler (1999), Smets and Wouters (2003) and Sbordone (2006) who derive both structural and reduced-form equations based on hybrid NKPC models and therefore all structural parameters can be recovered and identified from the reduced-form equation.[2] The backward looking part in most previous papers assume that firms use a simple rule of thumb that depends on price information at time *t-1* only, which forces the model to have only one lag of inflation. Roberts (2005) points out, however, that there is no logical reason why only a single lag of inflation should be included for the backward-looking behavior because a single lag may not be enough to offer a good empirical description for inflation behavior.[3] In reality, it is reasonable to think that firms use more sophisticated price setting rules than a simple rule of thumb.

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[1] An unsatisfactory empirical result that the standard NKPC produces is the "disinflationary boom" argued by Ball (1994). In a completely forward-looking model, inflation can jump as a response to a shock to output and the model does not exhibit the intrinsic persistence of inflation. As Fuhrer and Moore (1995) and Fuhrer (1997) argue, the standard NKPC seems to fail to provide enough inertia in inflation and does not fit the post-war U.S. data well.

[2] Gali and Gertler (1999) assume that there are two types of firms that set their prices (forward-looking firms and backward-looking firms with a simple rule-of-thumb price setting rule). Smets and Wouters (2003) and Sbordone (2006) use the partial indexation assumption and derive the hybrid NKPC which contains one forward and one lagged inflations.

[3] Roberts (2005) introduces a general class of backward-looking component which is a lag polynomial of inflation similar to the accelerationist Phillips curve. He uses a simple four-quarter moving average of inflations for backward-looking behavior for the reduced-form equation. In addition to Roberts (2005), other researchers attempt to add additional lags of inflation. For example, see Moore (1995), Fuhrer (1997), Kozicki and Tinsley (2002).

This paper attempts to improve in these two aspects: an arbitrary model specification (ad hoc inclusion of lags of inflation) and the need for more sophisticated backward-looking pricing behavior. In particular, we assume that firms use price information in the two previous periods (extrapolative price-setting mechanism) and solve the structural model based on this extrapolative price setting behavior. As a result, we have two lags of inflation in the reduced-form NKPC and an additional structural parameter in the structural NKPC. We name this model as a generalized hybrid NKPC model (compared to hybrid NKPC à la Gali and Gertler, 1999). We first test whether the newly proposed price-setting rule presents a reasonable empirical validity using various test statistics and then test if the generalized hybrid NKPC performs better than the hybrid NKPC in various evaluation criteria for model fit.

Compared to "static or naïve" expectations formation adopted in Gali and Gertler (1999), the idea of the extrapolative price-setting mechanism is based on the extrapolative expectations formation. It states that the price-setting behavior at time *t* is a function of price at time *t-1* and the error component between prices in *t-1* and *t-2*, a partial correction added to permit the trend.[4]

We show that the generalized hybrid NKPC model is a nesting specification of the hybrid NKPC. We test for a zero restriction on the coefficients in the reduced-form and structural generalized hybrid NKPC. The Wald statistic rejects the null hypothesis of a zero restriction on estimated parameters, implying that the newly proposed NKPC is a reasonable model specification for inflation dynamics. Baseline estimation results show that the forward-looking component plays an important role in explaining current inflation and the slope coefficient of the labor share is positive, which is in line with the earlier findings. We find that the second lag of inflation (extrapolative coefficient) in the reduced-form (structural) equation is statistically meaningful. In addition, including the second lag of inflation reduces the role of forward-looking part and increases the role of backward-looking component. Estimate of the extrapolative coefficient (trend of change in prices) in the structural equation is highly significant and positive, implying that backward-looking firms tend to take account of the past trend in price changes when they set their prices. To test whether the generalized hybrid NKPC model performs better than the hybrid NKPC, we use various measures such as the Akaike information criterion (AIC) and the Bayesian information criterion (BIC), the root mean squared error

[4] Sometimes, it is called the "trend following" price expectations because it contains the change in recent prices reflecting the direction of price movements.

(RMSE), the mean absolute error (MAE), the mean absolute percentage error (MAPC) and the Theil U statistics. Test statistics suggest that our model is more preferred by the data, implying that the effects of the second lag of inflation and extrapolative coefficient on current inflation cannot be disregard. These overall results are reasonably robust from sensitivity check.

This paper is organized as follows. In Section 2, we provide some pieces of evidence on the extrapolative behavior from various fields of literature. Section 3 derives the generalized hybrid NKPC. In Section 4, we describe the estimation method, its possible issue and the data. Section 5 presents the estimation results along with sensitivity analysis and Section 6 concludes.

2. Literature on Extrapolative Expectations

The particular form of price-setting mechanism assumed in this paper is motivated by the extrapolative expectations formation. Agents are said to have extrapolative beliefs (or show extrapolative behavior) when they place relatively high weights on the most recent past observation. A wide variety of early studies corroborates that many economic agents base their expectations on extrapolative beliefs. The earliest and influential work on the extrapolative expectations formation is Metzler (1941) and Goodwin (1947).[5] These two studies examine firms' economic behavior with extrapolative expectations. In particular, Metzler (1941) uses the extrapolative expectations formation to examine dynamic properties of business cycles using an inventory model with sales-output lags. Goodwin (1947) uses a simple cobweb model when producers use the extrapolative expectations formation to predict their future prices to examine dynamics of prices and markets. Johnson and Plott (1989) do experimental research on performance of different types of price expectations models to examine individual and market behaviors in four types of supply-lag auction and posted-price markets. Based on responses of the subjects who participate in the experiments, the results show that the sellers' behavior for posted price trading is fairly well explained by the extrapolative expectations formation.

Some studies empirically test if agents employ extrapolative scheme. Turnovsky (1970) uses the Livingston survey data to test which price expectations formation provides the best description of price movements and inflation dynamics. The results show that the price

[5] They formulate the extrapolative expectations explicitly in their papers but they did not name it the extrapolative expectations. Muth (1961) first called this type of expectations formation "extrapolative expectations."

movements can be well explained by the extrapolative scheme. Svendsen (1994) directly employs firms' survey data in Norway and find that firms base their expectations on the future prices and demand in an extrapolative manner. Reckwerth (1997) uses survey data on CPI in Germany to examine the relationship between inflation and output and find that the extrapolative coefficient is significant and well describes the inflation movement.

Recent research places an emphasis on the effect of heterogeneous expectations (e.g., interaction between rational and extrapolative expectations) on inflation dynamics. Pfajfar and Zakelj (2013) use a simple new Keynesian model to examine the effectiveness of monetary policy when there are different types of expectations (rational, adaptive, extrapolative and adaptive learning, etc) in the economy. Using experimental data, they show that a large portion of subjects uses the extrapolation rule which produces a high volatility of inflation and that the interaction between rational and extrapolative expectations play a crucial role in determining the performance of monetary policy.

Other studies actively discuss the importance of extrapolative expectations in the context of exchange rates and asset markets. Some studies use experimental and survey data to examine how agents form expectations on exchange rates movements including rational, static, extrapolative and adaptive expectations based on different horizons of exchange rates. Empirical evidence suggests that the extrapolative mechanism gives a better description on movements of exchange rates than other expectations formation such as rational or static expectations (e.g., Frankel and Froot 1987a and 1987b; Cavaglia et al. 1993; Chinn and Frankel 2000).

Some studies document that many individuals, even experts, tend to extrapolate the past performance in predicting future returns and show how extrapolative beliefs have effects on market behavior. If the recent past performance exhibits high returns, agents tend to expect the future returns to remain at the high level (De Bondt 1993; Sirri and Tufano 1998; Vissing-Jorgensen 2003). Some recent studies applied extrapolative expectations in explaining the recent housing market bubble and global financial crisis (Gerardi et al. 2008; Barberis 2011). Overall, a number of studies in various fields in economics demonstrate the important effects of extrapolative beliefs on market and economic behaviors.

3. Derivation of the Generalized Hybrid NKPC

In this section we construct a structural model that reflects extrapolative expectation in price setting behavior in order to obtain an econometric specification for parameter estimates in the generalized hybrid NKPC. We follow the notations in Gali and Gertler (1999) so that we can compare our results directly to those in their paper.

The optimal aggregate price level is expressed as a convex combination of the previous price level p_{t-1} and the optimal reset price $\bar{p}_t^*$,

$$(1) \qquad p_t = \theta p_{t-1} + (1-\theta)\bar{p}_t^*$$

Where $\bar{p}_t^*$ is the price selected by firms that are able to change price at time *t* and $1-\theta$ is the probability that firms may adjust price during this period. Following Gali and Gertler (1999), we assume that there are two types of firms when they update their prices. A portion $1-\omega$ of firms follows the Calvo's pricing rule, which is a "forward-looking price setting," whereas the other portion ω of firms employs a "backward-looking price rule." Then, the newly set price index can be expressed as

$$(2) \qquad \bar{p}_t^* = (1-\omega)p_t^F + \omega p_t^B$$

Forward-looking firms seek to maximize its discounted sum of profits under the sticky price setting in Calvo (1983). The first-order approximated version (first-order linearization) of the optimally updating pricing rule has the form of

$$(3) \qquad p_t^F = (1-\beta\theta)\sum_{i=0}^{\infty}(\beta\theta)^i E_t\{mc_{t+i}^n\},$$

where mc_t^n denotes a nominal marginal cost (forcing variable for the supply side), β is a discount factor for firms and θ indicates the probability of sticking to the previous price level.

For the formulation of "backward-looking" price, Gali and Gertler (1999) employ a very simple rule for setting the price $p_t^B = \bar{p}_{t-1}^* + \pi_{t-1}$, which depends only on the newly set price in the most recent period t-1 with a correction for inflation. In this paper, we consider an alternative price setting scheme for the backward-looking part, an extrapolative price setting scheme.

The extrapolative price setting scheme (partial error correction mechanism) in period *t* consists of the price in period *t-1* plus a portion of the change in prices between *t-1* to *t-2*, which represents the correction added to permit the trend in past price changes. Hence, the extrapolative price setting mechanism is formulated as

$$\text{(4)} \qquad p_t^B = (\bar{p}_{t-1}^* + \pi_{t-1}) - \alpha[(\bar{p}_{t-1}^* + \pi_{t-1}) - (\bar{p}_{t-2}^* + \pi_{t-2})],$$

where α is an extrapolative coefficient (coefficient of a partial error correction term) capturing the trend (or direction) of changes in prices.[6] In this expectations formation, producers take account of both the past level of prices and direction of change of such prices. The parameter α is theoretically meaningful and admissible when it lies between -1 and 1. The equation (4) can be rewritten as

$$\text{(5)} \qquad p_t^B = (1-\alpha)(\bar{p}_{t-1}^* + \pi_{t-1}) + \alpha(\bar{p}_{t-2}^* + \pi_{t-2}).$$

This rewritten form of extrapolative price setting scheme is a convex combination of the newly reset prices at *t-1* and *t-2* with weight α on *t-2*. The respective price levels (i.e, prices in period *t-1* and *t-2*) are corrected with inflation corresponding to those periods. It is a "generalized" version of the static (simple rule of thumb) price setting scheme in Gali and Gertler (1999) because if the extrapolative coefficient (coefficient of partial error correction) α is equal to zero, equation (5) reduces to the hybrid NKPC in Gali and Gertler (1999). If α is not zero, the interpretation is as follows: (a) when $\alpha < 0$, firms extrapolate the past trend expecting that the trend would continue. In this case, firms tend to set their prices by expecting a rise in prices, which creates a further rise in prices in the future; (b) when $\alpha > 0$, firms expect that the trend in past price would revert. In this case, firms have an inclination to set their

[6] Metzler (1941) and Goodwin (1947) called this parameter the "coefficient of expectation."

prices in anticipation of a fall (rise) in prices after a rise (fall) in prices[7]; (c) when $\alpha = 0$, backward-looking firms do not consider the past trend when they set their prices.

If firms employ the extrapolative price-setting mechanism in (4), a variant of the hybrid NKPC curve can be derived as

(6) $$\pi_t = \eta_f E_t \pi_{t+1} + \eta_{b1} \pi_{t-1} + \eta_{b2} \pi_{t-2} + \varphi mc_t,$$

where

$$\eta_f = \frac{\beta\theta}{\Theta};\ \eta_{b1} = \frac{\omega[1-2\alpha+\alpha\theta(1-\beta)]}{\Theta};\ \eta_{b2} = \frac{\alpha\omega}{\Theta};\ \varphi = \frac{(1-\beta\theta)(1-\theta)(1-\omega)}{\Theta};$$

$$\Theta = \omega + \theta[1 - \omega + \beta\omega(1 - 2\alpha + \alpha\theta)].$$

The equation (6) shows how the structural parameters are related to the reduced-form parameters because each reduced-form parameter is a function of structural parameters. We refer to this newly derived equation as the generalized hybrid NKPC. Detailed derivation of this equation is in Appendix. If no firms use the backward-looking price setting rule (i.e. $\omega = 0$), this hybrid NKPC reduces to the standard purely forward-looking NKPC.

For the comparison purpose, the hybrid NKPC in Gali and Gertler (1999) is

(7) $$\pi_t = \gamma_f E_t \pi_{t+1} + \gamma_b \pi_{t-1} + \lambda mc_t,$$

where

$$\gamma_f = \frac{\beta\theta}{\phi};\ \gamma_b = \frac{\omega}{\phi};\ \lambda = \frac{(1-\beta\theta)(1-\omega)(1-\theta)}{\phi};\ \phi = \theta + \omega[1 - \theta(1 - \beta)].$$

We can easily verify that the original hybrid NKPC in (7) is a special case of the generalized

[7] In some literature, the case of $\alpha < 0$ is called "bandwagon" movement (or destabilizing movements), while that of $\alpha > 0$ is called "regressive" movement (or stabilizing movements). These terms are widely used in the literature studying the expectations hypothesis for exchange rate. For example, see Frankel and Froot (1987a and 1987b), Ito (1990) and Lai and Pauli (1992).

hybrid NKPC in (6) when $\alpha = 0$.

An important feature of our model is that the four structural parameters of the model can be fully recovered by estimating the reduced form equation which will be discussed in the next section, as in the case of hybrid NKPC in Gali and Gertler (1999). In other words, all the parameters in the reduced form equation are functions of structural parameters derived from the model. Also, many of previous studies that compare the relative importance of backward- and forward-looking parts have used an ad hoc version of backward-looking part in the model and their estimates could not provide information on structural parameters.

4. Estimation Method and Data

In order to deal with the expectation terms in estimating equations and to avoid the associated endogeniety issue, we use the generalized method of moments (GMM) technique. In order to check whether instruments are valid, we employ several statistical tests. We use the J-statistics to test the validity of over-identifying restrictions in the estimated model (for instruments exogeniety). Another important issue in IV estimation is weak instruments (for instruments validity).[8] For weak instrument tests, we use the Anderson-Rubin (AR) statistics (Anderson and Rubin, 1949) and Lagrange multiplier (LM) statistics proposed by Kleibergen (2002).[9]

Based on these tests, we estimate both the generalized hybrid NKPC in (6) and the typical hybrid NKPC in (7). For the GMM estimator, the moment conditions (orthogonality conditions) for two NKPCs are specified as follows:

(8) $E_t\left[\left(\pi_t - \eta_f E_t \pi_{t+1} - \eta_{b1}\pi_{t-1} - \eta_{b2}\pi_{t-2} - \varphi mc_t\right) z_t\right] = 0$ (generalized hybrid NKPC),

[8] Many studies show that simple estimations based on IVs are susceptible to weak instruments (identification) problem. For example, see Staiger and Stock (1997), Stock et al. (2002) and Kleibergen (2002).

[9] To perform these tests, we make use of two independent sufficient statistics developed by Moreira (2003) for two endogenous variables (expected future inflation and forcing variable). Under the null hypothesis of no weak instruments, both AR and LM statistics are asymptotically chi-squared distribution. The AR-type statistics are used by many researchers such as Dufour (2003), Dufour and Jasaik (2001), and Dufour et al. (2006). The AR-type statistics are particularly useful when there are weak or missing instruments. Some researchers show that the symptom of weak instruments arises in empirical work using NKPC-type models (see Ma 2002; Mavroeidis 2005; Dufour, et al. 2006; Nason and Smith 2008).

(9) $E_t[(\pi_t - \gamma_f E_t \pi_{t+1} - \gamma_b \pi_{t-1} - \lambda mc_t) z_t] = 0$ (hybrid NKPC),

where the vector z_t is the set of instruments at *t-1* and earlier.

To implement the GMM, we use the iterative GMM based on the heteroskedasticity and autocorrelation consistent (HAC) estimator for estimating the weighting matrix using Bartlett kernel proposed by Newey-West (1987).[10] We start with the baseline set of instruments as in Gali and Gertler (1999), which consists of 6 instruments (inflation, labor share, output gap, spread between long and short interest rate, wage inflation and inflation on commodity price) with four lags. It turns out, however, that these sets of instruments are rejected by the AR and LM tests, which shows the presence of weak instruments documented by earlier studies. Therefore, we use three lags of 6 instruments instead of four lags, which passed the weak instrument tests (labeled as baseline IV set 1 in Table 1). Given that a large number of instruments are more likely to yield incorrect estimates and inference in finite sample and that different choices of instruments may produce different results, we provide additional estimation results using various sets of IVs (labeled as IV sets 2 to 5 in Table 1). These additional IV sets include inflation, labor income share and output gap as common variables and use different combinations for the rest of the variables.[11]

We apply a wide variety of model selection criteria to evaluate the empirical performance of the two hybrid NKPC models. We use two most commonly used model selection criteria for selecting competing models; AIC and BIC.[12] We also consider RMSE, MAE, MAPE and Theil U statistics.[13] The closer the values of RMSE, MAE and MAPE are to zero, the better the empirical performance is in terms of a model fit. For the Theil U measure, a high value implies a poor model fit. We use the Wald test for the hypothesis test with a zero restriction for both the

[10] We use the baseline IV set to find the optimal bandwidth which turns out to be 10. This number is lower than 12 used in Gali and Gertler (1999).

[11] Lags of endogenous variables (inflation and labor income share) are typically used as IVs in a time-series models. For the use of output gap as an instrument, see, for example, Fuhrer and Moore (1995), Fuhrer (1997), Estrella and Fuhrer (2002), Neiss and Nelson (2005).

[12] The AIC is known to work better than BIC in small samples. However, the fact that the AIC tend to select an overparameterized model leads us to use an alternative criterion, BIC. The BIC tend to choose a more parsimonious model than the AIC.

[13] Unlike the RMSE placing more weights on large errors due to its quadratic nature, MAE and MAPE put equal weights on large and small errors. Since we do not include an intercept term following typical NKPC papers (e.g., Gali and Gertler 1999) and R^2 with no intercept term may mislead the interpretation of empirical results, we use the Theil U statistic in place of R^2.

reduced-form and structural form NKPCs.

All the data are obtained from the Federal Reserve Economic Data (FRED) at the Federal Reserve Bank of St. Louis. We use the quarterly data from 1960:1 to 2007:4. The starting point of the data is 1960:1 to be comparable with Gali and Gertler (1999).[14] We set the ending point of the data at 2007:4 to avoid the financial crisis period.

Inflation is defined as the percentage change of the GDP deflator (series ID: GDPDEF). We use the labor income share of nonfarm business sector (series ID: PRS85006173) as a proxy for the real marginal cost, constructed by two methods−log of HP-filtered and log of quadratic detrended labor share.[15] Output gap is constructed by log deviation of real GDP (series ID: GDPC1), measured by HP-filtered and quadratic detrending techniques. Unit labor cost (ULC) of nonfarm business sector (series ID: ULCNFB) is employed to obtain the wage inflation, which is defined as the percent change of ULC. Commodity price inflation is measured by a percentage change of the producer price index of all commodities (series ID: PPIACO). We also use spread between long (series ID: INTGSBUSM193N) and short (series ID: FEDFUNDS) interest rates.

5. Estimation Results

In this section, we present the estimation results of both reduced-form and structural NKPCs to evaluate the overall performance of our model in comparison to the hybrid NKPC in Gali and Gertler (1999).

5.1. Parameter estimation

Table 2 reports the estimation results using the baseline instruments (IV set 1 in Table 1). The overall results from the two reduced-form specifications (generalized hybrid NKPC and hybrid NKPC) exhibit that all the estimates are highly significant. The forward-looking

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[14] Earlier empirical evidence also indicates that there seems to be a structural break in inflation around 1960 (see Turnovsky 1970).

[15] See Gali and Gertler (1999), Gali et al. (2001) and Sbordone (2002), etc. These studies argue that real unit labor costs are a driving force for inflation dynamics. Gali and Gertler (1999) use the percent deviation of real marginal costs from its steady state, while we use the two widely used detrending measures. For the same procedure as ours, see Mihailov et al. (2011) and Coroneo et al. (2011).

component in the generalized hybrid NKPC (η_f) are around 0.75 and 0.71 with the HP-filtered labor share (LS1) and the quadratically detrended labor share (LS2), respectively. The same coefficient in the hybrid NKPC (γ_f) is around 0.80 with both LS1 and LS2. The backward-looking components in both generalized hybrid NKPC (sum of η_{b1} and η_{b2}) and hybrid NKPC (γ_b) are much smaller than the forward-looking coefficients around 0.2 ~ 0.3. This suggests that the forward-looking component plays a more important role than the backward-looking part in accounting for inflation dynamics, which is in line with earlier findings as in Gali and Gertler (1999), Gali et al. (2001), Sbordone (2002) and Gali et al. (2005), etc.[16]

In the generalized hybrid NKPC, the coefficient on the second lag of inflation (η_{b2}) is positive and significant around 0.08 ~ 0.11.[17] Therefore, the estimate of the backward-looking (forward-looking) part in the generalized hybrid NKPC is larger (smaller) than that in the hybrid NKPC with both measures of labor share. Using extrapolative pricing scheme reduces (increases) the role of forward-looking (backward-looking) part in explaining inflation dynamics. We also perform the Wald test for zero restriction on coefficient on the second lag of inflation η_{b2}. The test statistics show that we cannot reject the null of zero coefficient, implying that the second lag of inflation has a predictive power in explaining inflation dynamics, which is consistent with the earlier findings (e.g., Fuhrer and Moore 1995; Fuhrer 1997; Roberts 1997 and 2005). The slope coefficients on the labor share (φ and λ) are positive in both models, but only the coefficients with LS1 are significant.

Nest, we present the estimation results of the structural models focusing on the role of the extrapolative coefficient (price trend), α. With both LS1 and LS2, α is highly significant at 0.25 and 0.28, respectively. The Wald test statistics strongly rejects the null of zero coefficient on the price trend α. The significant and positive estimates of the price trend imply that backward-looking firms consider the past trend of prices when they set their prices, suggesting that the data favor the generalized hybrid NKPC more than the hybrid NKPC.

The estimate of the discount factor β is around 0.99 in both models irrespective of labor share measure. This estimate is more reasonable than that in Gali and Gertler (1999) and Gali

[16] The size of the forward-looking (backward-looking) components in both reduced-form equations is slightly higher (lower) than those in Gali and Gertler (1999) and Gali et al. (2001). This is because we use different sample periods and measures for some variables.

[17] This result is different from Gali and Gertler (1999) who show that the coefficients on the lagged inflation terms are quite small.

et al. (2001) where estimated β is around 0.85. The estimate of θ which represents a portion of firms sticking to the old average prices (price rigidity) is around 0.81 with LS1 and around 0.92 ~ 0.97 with LS2 in both models. These results imply that the average period in which prices are fixed (average price duration) is about 4 with LS1 and 10 with LS2, which is in line with existing works (e.g., Kashyap 1995; Blinder et al. 1998; Klenow and Malin 2010).[18]

The estimate for the portion of backward-looking firms ω is highly significant in all cases. In the case of the generalized hybrid NKPC, it is 0.36 (0.51) with LS1 (LS2), while it is 0.19 (0.24) with LS1 (LS2) in the hybrid NKPC. These results suggest that the portion of backward-looking firms is much larger in the generalized hybrid NKPC than in the hybrid NKPC.

5.2. Tests for model fit

In this section, we check the empirical fit of the two models by testing if the newly proposed model is more preferred by the data. We employ various measures to test model performance. The main criteria that we employ are AIC and BIC. Table 2 shows that both AIC and BIC measures (with both LS1 and LS2) from the generalized hybrid NKPC are smaller than those from the hybrid NKPC, implying that the data favor the generalized hybrid NKPC model. In addition, other criteria such as RMSE, MAE, MAPE, and Theil U from the generalized hybrid NKPC are smaller than those from the hybrid NKPC, which also imply that the data favor the generalized hybrid NKPC.

Next, we test instruments exogeneity and instruments relevance using the J test and AR and LM test statistics. In Table 2, J statistics indicate that we cannot reject the null hypothesis that the over-identifying assumption is satisfied, implying that the instruments that we use for the baseline estimation are valid. AR and LM test statistics indicate that we cannot reject the null of no weak instruments.[19]

The summary of the baseline results is as follows. First, the forward-looking behavior is more important than the backward-looking behavior for explaining inflation movements regardless of the model specification. Second, the estimate of the second lag of inflation

[18] Other studies document shorter periods of the price duration of 2~3 quarters (e.g., Gali et al. 2001). Estimated duration ranges from 2-3 quarters to several years, depending on the choice of methodology and data.

[19] Though the LM test in the case of H (LS1) in Table 2 rejects the null of no weak instruments at five percent level, the AR test gives strong support for the use of our instruments in all cases.

(extrapolative coefficient) in the reduced-form (structural) equation is highly significant, and the Wald test suggests that the estimated coefficient is statistically different from zero. Further, all the measures of model fit suggest that the data favor the generalized hybrid NKPC model and the additional lag of inflation plays an important role in providing useful insights into the nature of inflation dynamics.

5.3. Sensitivity analysis

In this section, we examine whether our baseline results are robust to different sets of IVs. Tables 3 to 6 present estimation results using IV sets 2 through 5 defined in Table 1. Overall, for all four IV specifications, the estimated parameter values in both reduced form and structural form equations are similar to those in the baseline case and the main results hold through different sets of IVs: the additional lag of inflation is statistically different from zero, implying that the second lag of inflation has a significant effect on current inflation. In the structural form equation, the estimates of the extrapolative coefficient are highly significant and positive.

The test statistics for model fit show that the AIC and BIC criteria favors the generalized hybrid NKPC in all cases except for the case with the IV set 4 with LS2. Other test measures such as RMSE and MAE also favor the generalized hybrid NKPC except for MAPE measures with IV sets 3, 4 and 5 with LS2. Overall, the sensitivity check suggests that our baseline results are fairly robust to different sets of instruments.

6. Conclusion

In this paper, we prove the validity of the extrapolative pricing behavior by empirically testing the significance of the second lag of inflation in both reduced-form and structural-form generalized hybrid NKPC. Our model is more general and empirically better fit that the typical hybrid NKPC model widely used in the literature since Gali and Gertler (1999). We also confirm that magnitude of the forward-looking part in hybrid NKPC is large and plays an important role in accounting for the nature of inflation dynamics, which is in line with previous literature. In the structural model, all the estimated coefficients are highly significant and fairly similar to those reported in earlier studies. In particular, the extrapolative coefficient (trend of change in prices) is statistically significant and positive, implying that the backward-looking firms tend to take account of the past trend of prices when setting the current price.

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Appendix: Derivation of the generalized hybrid NKPC

The following equations are used to derive the generalized hybrid NKPC.

(A.1) Evolution of aggregate price level: $p_t = \theta p_{t-1} + (1-\theta)\bar{p}_t^*$

(A.2) Heterogeneous price-setting rule: $\bar{p}_t^* = (1-\omega)p_t^F + \omega p_t^B$

(A.3) Optimal price setting rule (forward-looking part): $p_t^F = (1-\beta\theta)\sum_{i=0}^{\infty}(\beta\theta)^i E_t mc_{t+i}^n$

(A.4) Extrapolative price-setting scheme (backward-looking part):

$$p_t^B = (1-\alpha)(\bar{p}_{t-1}^* + \pi_{t-1}) + \alpha(\bar{p}_{t-2}^* + \pi_{t-2})$$

Plugging (A.4) into (A.2) and arranging it for p_t^F yield

(A.5) $p_t^F = \frac{1}{1-\omega}[\bar{p}_t^* - \omega(1-\alpha)(\bar{p}_{t-1}^* + \pi_{t-1}) - \alpha\omega(\bar{p}_{t-2}^* + \pi_{t-2})]$.

Converting (A.3) into a recursive form and substituting (A.5) generate

(A.6) $\omega(\bar{p}_t^* - \bar{p}_{t-1}^*) + (1-\omega)\bar{p}_t^* + \alpha\omega(\bar{p}_{t-1}^* - \bar{p}_{t-2}^*) - \omega(1-\alpha)\pi_{t-1} - \alpha\omega\pi_{t-2}$

$$= \beta\theta E_t[(\bar{p}_{t+1}^* - \bar{p}_t^*) + (1-\omega)\bar{p}_t^* + \alpha\omega(\bar{p}_t^* - \bar{p}_{t-1}^*) - \omega(1-\alpha)\pi_t - \alpha\omega\pi_{t-1}]$$

$$+ (1-\beta\theta)(1-\omega)mc_t^n.$$

Arranging (A.1) for $\bar{p}_t^*$ and using the lagged value $\bar{p}_{t-1}^*$ give

(A.7) $\bar{p}_t^* - \bar{p}_{t-1}^* = \frac{\pi_t - \theta\pi_{t-1}}{1-\theta}$.

Substituting (A.7) into (A.6) yields

(A.8) $\omega\pi_t - \theta\omega\pi_{t-1} + \alpha\omega\pi_{t-1} - \alpha\theta\omega\pi_{t-2} - \omega\pi_{t-1} + \alpha\omega\pi_{t-1} + \theta\omega\pi_{t-1} - \alpha\theta\omega\pi_{t-1}$

$$- \alpha\omega\pi_{t-2} + \alpha\theta\omega\pi_{t-2} = \beta\theta E_t\pi_{t+1} - \beta\theta^2\pi_t + \alpha\beta\theta\omega\pi_{t-1} - \alpha\beta\theta^2\omega\pi_{t-1} - \beta\theta\omega\pi_t$$

$$+ \alpha\beta\theta\omega\pi_t + \beta\theta^2\omega\pi_t - \alpha\beta\theta^2\omega\pi_t - \alpha\beta\theta\omega\pi_{t-1} + \alpha\beta\theta^2\omega\pi_{t-1}$$

$$- (1-\beta\theta)(1-\theta)(1-\omega)\bar{p}_t^* + (1-\beta\theta)(1-\theta)(1-\omega)mc_t^n.$$

(A.1) can be expressed as $\bar{p}_t^* = \frac{p_t - \theta p_{t-1}}{1-\theta}$. Plugging this equation into (A.8) gives

$$\text{(A.9)}\quad \omega\pi_t - \theta\omega\pi_{t-1} + \alpha\omega\pi_{t-1} - \alpha\theta\omega\pi_{t-2} - \omega\pi_{t-1} + \alpha\omega\pi_{t-1} + \theta\omega\pi_{t-1} - \alpha\theta\omega\pi_{t-1}$$

$$- \alpha\omega\pi_{t-2} + \alpha\theta\omega\pi_{t-2} = \beta\theta E_t\pi_{t+1} - \beta\theta^2\pi_t + \alpha\beta\theta\omega\pi_{t-1} - \alpha\beta\theta^2\omega\pi_{t-1} - \beta\theta\omega\pi_t$$

$$+ \alpha\beta\theta\omega\pi_t + \beta\theta^2\omega\pi_t - \alpha\beta\theta^2\omega\pi_t - \alpha\beta\theta\omega\pi_{t-1} + \alpha\beta\theta^2\omega\pi_{t-1}$$

$$- (1-\beta\theta)(1-\theta)(1-\omega)\left(\frac{1}{1-\theta}\right)[\theta\pi_t + (1-\theta)p_t] + (1-\beta\theta)(1-\theta)(1-\omega)mc_t^n.$$

$$- (1-\beta\theta)(1-\omega)\theta\pi_t - (1-\beta\theta)(1-\theta)(1-\omega)p_t$$

$$\text{(A.10)}\quad \omega\pi_t - \theta\omega\pi_{t-1} + \alpha\omega\pi_{t-1} - \alpha\theta\omega\pi_{t-2} - \omega\pi_{t-1} + \alpha\omega\pi_{t-1} + \theta\omega\pi_{t-1} - \alpha\theta\omega\pi_{t-1}$$

$$- \alpha\omega\pi_{t-2} + \alpha\theta\omega\pi_{t-2} = \beta\theta E_t\pi_{t+1} - \beta\theta^2\pi_t + \alpha\beta\theta\omega\pi_{t-1} - \alpha\beta\theta^2\omega\pi_{t-1}$$

$$- \beta\theta\omega\pi_t + \alpha\beta\theta\omega\pi_t + \beta\theta^2\omega\pi_t - \alpha\beta\theta^2\omega\pi_t - \alpha\beta\theta\omega\pi_{t-1} + \alpha\beta\theta^2\omega\pi_{t-1}$$

$$- (1-\beta\theta)(1-\omega)\theta\pi_t + (1-\beta\theta)(1-\theta)(1-\omega)(mc_t^n - p_t).$$

Cancelling out and collecting the same terms generate

$$\text{(A.11)}\quad (\omega - 2\alpha\beta\theta\omega + \beta\theta\omega + \alpha\beta\theta^2\omega + \theta - \theta\omega)\pi_t = \beta\theta E_t\pi_{t+1}$$

$$+ (\omega - 2\alpha\omega + \alpha\theta\omega - \alpha\beta\theta\omega)\pi_{t-1} + \alpha\omega\pi_{t-2} + (1-\beta\theta)(1-\theta)(1-\omega)mc_t.$$

Arranging all the terms yields the generalized hybrid NKPC as follows:

$$\text{(A.12)}\quad \pi_t = \eta_f E_t\pi_{t+1} + \eta_{b1}\pi_{t-1} + \eta_{b2}\pi_{t-2} + \varphi mc_t,$$

where

$$\eta_f = \frac{\beta\theta}{\Theta};\ \eta_{b1} = \frac{\omega[1-2\alpha+\alpha\theta(1-\beta)]}{\Theta};\ \eta_{b2} = \frac{\alpha\omega}{\Theta};\ \varphi = \frac{(1-\beta\theta)(1-\theta)(1-\omega)}{\Theta};$$

$$\Theta = \omega + \theta[1 - \omega + \beta\omega(1 - 2\alpha + \alpha\theta)].$$

Table 1. Sets of instrumental variables (IVs)

IV set	***List of Instrumental Variables (IVs)***
IV set 1	inflation, labor share, output gap, long-short spread of interest rates, wage inflation, inflation on commodity price
IV set 2	inflation, labor share, output gap, long-short spread of interest rates, wage inflation
IV set 3	inflation, labor share, output gap, wage inflation, inflation on commodity price
IV set 4	inflation, labor share, output gap, long-short spread of interest rates
IV set 5	inflation, labor share, output gap, wage inflation

Note: 1. All the instruments have three lags.
2. IV set 1 is used for the baseline case.
3. For IV set 5, we use the same variables as in Gali et al. (2001) except for the number of lags.

Table 2. Baseline estimation results using IV set 1

Reduced-form equations										
	Reduced-form generalized hybrid NKPC						***Reduced-form hybrid NKPC***			
LIS	η_f	η_{b1}	η_{b2}	φ	*J-Stat*	*W-Stat*	γ_f	γ_b	λ	*J-Stat*
LS1	0.745***	0.168***	0.083**	0.021**	7.239	5.019	0.805***	0.190***	0.025**	7.866
	(0.043)	(0.047)	(0.037)	(0.011)	(0.925)	(0.025)	(0.044)	(0.045)	(0.011)	(0.929)
LS2	0.710***	0.173***	0.113***	0.003	7.826	10.225	0.797***	0.199***	0.001	9.095
	(0.041)	(0.046)	(0.036)	(0.004)	(0.898)	(0.001)	(0.045)	(0.045)	(0.005)	(0.873)

Structural equations										
	Structural generalized hybrid NKPC						***Structural hybrid NKPC***			
LIS	β	θ	ω	α	*J-Stat*	*W-Stat*	β	θ	ω	*J-Stat*
LS1	0.996***	0.814***	0.363***	0.248***	7.239	9.823	0.992***	0.827***	0.193***	7.865
	(0.014)	(0.047)	(0.083)	(0.079)	(0.925)	(0.002)	(0.011)	(0.040)	(0.052)	(0.929)
LS2	0.992***	0.923***	0.514***	0.285***	7.826	20.495	0.993***	0.969***	0.240***	9.095
	(0.018)	(0.068)	(0.099)	(0.063)	(0.898)	(0.000)	(0.011)	(0.111)	(0.064)	(0.873)

Measures for model performance								
	AIC	***BIC***	***RMSE***	***MAE***	***MAPE***	***TheilU***	***AR***	***LM***
GH (LS1)	476.275	489.199	0.259	0.198	25.804	0.230	0.746	3.479
							(0.748)	(0.062)
H (LS1)	484.337	494.031	0.265	0.200	25.947	0.236	0.685	2.083
							(0.821)	(0.149)
GH (LS2)	471.471	484.395	0.255	0.196	25.705	0.227	0.800	3.917
							(0.690)	(0.048)
H (LS2)	482.119	491.813	0.263	0.198	25.896	0.235	0.736	3.391
							(0.769)	(0.066)

*Note: 1. ***, ** and * denote the significance levels at 1%, 5% and 10%, respectively.*

2. LIS denote for labor income share. LS1 and LS2 denote the HP-filtered labor share and the quadratically-detrended labor share respectively. GH denotes for the generalized hybrid NKPC and H denotes for the hybrid NKPC.

3. J-Stat denotes for J Statistics and W-Stat denotes for Wald statistics.

4. Parentheses below the coefficient estimates indicate the standard errors, whereas parentheses below statistics indicate p-values.

Table 3. Sensitivity check using IV set 2

Reduced-form equations										
	Reduced-form generalized hybrid NKPC						***Reduced-form hybrid NKPC***			
LIS	η_f	η_{b1}	η_{b2}	φ	*J-Stat*	*W-Stat*	γ_f	γ_b	λ	*J-Stat*
LS1	0.708***	0.176***	0.112***	0.022**	6.870	7.566	0.807***	0.188***	0.0280**	7.714
	(0.048)	(0.048)	(0.041)	(0.011)	(0.810)	(0.006)	(0.0500)	(0.051)	(0.012)	(0.807)
LS2	0.665***	0.179***	0.154***	0.003	7.118	15.591	0.767***	0.229***	0.002	9.004
	(0.043)	(0.047)	(0.039)	(0.004)	(0.789)	(0.000)	(0.047)	(0.047)	(0.005)	(0.703)
Structural equations										
	Structural generalized hybrid NKPC						***Structural hybrid NKPC***			
LIS	β	θ	ω	α	*J-Stat*	*W-Stat*	β	θ	ω	*J-Stat*
LS1	1.002***	0.790***	0.448***	0.280***	6.870	17.766	0.992***	0.817***	0.188***	7.712
	(0.019)	(0.052)	(0.102)	(0.066)	(0.810)	(0.0000)	(0.011)	(0.040)	(0.058)	(0.807)
LS2	0.996***	0.893***	0.649***	0.316***	7.119	36.771	0.993***	0.940***	0.279***	9.004
	(0.028)	(0.074)	(0.118)	(0.052)	(0.789)	(0.000)	(0.012)	(0.063)	(0.068)	(0.703)

Measures for model performance								
	AIC	***BIC***	***RMSE***	***MAE***	***MAPE***	***TheilU***	***AR***	***LM***
GH (LS1)	470.804	483.728	0.255	0.196	25.614	0.226	0.891	3.432
							(0.562)	(0.064)
H (LS1)	485.004	494.698	0.265	0.200	26.008	0.236	0.768	1.599
							(0.706)	(0.206)
GH (LS2)	466.265	479.189	0.252	0.193	25.527	0.224	0.983	3.719
							(0.465)	(0.054)
H (LS2)	476.233	485.926	0.259	0.195	25.579	0.231	0.824	3.112
							(0.643)	(0.078)

*Note: 1. ***, ** and * denote the significance levels at 1%, 5% and 10%, respectively.*

2. LIS denote for labor income share. LS1 and LS2 denote the HP-filtered labor share and the quadratically-detrended labor share respectively. GH denotes for the generalized hybrid NKPC and H denotes for the hybrid NKPC.

3. J-Stat denotes for J Statistics and W-Stat denotes for Wald statistics.

4. Parentheses below the coefficient estimates indicate the standard errors, whereas parentheses below statistics indicate p-values.

Table 4. Sensitivity check using IV set 3

Reduced-form equations										
	Reduced-form generalized hybrid NKPC						***Reduced-form hybrid NKPC***			
LIS	η_f	η_{b1}	η_{b2}	φ	*J-Stat*	*W-Stat*	γ_f	γ_b	λ	*J-Stat*
LS1	0.760***	0.165***	0.071*	0.021*	7.029	3.318	0.806***	0.189***	0.026**	7.337
	(0.055)	(0.056)	(0.039)	(0.011)	(0.797)	(0.069)	(0.053)	(0.052)	(0.011)	(0.835)
LS2	0.719***	0.176***	0.102***	0.002	7.686	7.328	0.769***	0.227***	0.002	8.648
	(0.048)	(0.054)	(0.038)	(0.004)	(0.741)	(0.007)	(0.049)	(0.048)	(0.005)	(0.733)

Structural equations										
	Structural generalized hybrid NKPC						***Structural hybrid NKPC***			
LIS	β	θ	ω	α	*J-Stat*	*W-Stat*	β	θ	ω	*J-Stat*
LS1	0.996***	0.818***	0.329***	0.232**	7.029	6.216	0.992***	0.823***	0.191***	7.336
	(0.014)	(0.049)	(0.094)	(0.093)	(0.797)	(0.013)	(0.012)	(0.040)	(0.061)	(0.835)
LS2	0.991***	0.927***	0.484***	0.269***	7.686	13.326	0.992***	0.952***	0.278***	8.647
	(0.018)	(0.069)	(0.105)	(0.074)	(0.741)	(0.000)	(0.013)	(0.075)	(0.072)	(0.733)

Measures for model performance								
	AIC	***BIC***	***RMSE***	***MAE***	***MAPE***	***TheilU***	***AR***	***LM***
GH (LS1)	478.704	491.628	0.260	0.199	25.905	0.231	0.810	2.968
							(0.650)	(0.085)
H (LS1)	484.677	494.370	0.265	0.200	25.979	0.236	0.723	1.731
							(0.753)	(0.188)
GH (LS2)	472.397	476.657	0.256	0.196	25.720	0.227	0.895	3.630
							(0.557)	(0.057)
H (LS2)	485.322	486.350	0.260	0.196	25.581	0.231	0.798	3.239
							(0.672)	(0.072)

*Note: 1. ***, ** and * denote the significance levels at 1%, 5% and 10%, respectively.*

2. LIS denote for labor income share. LS1 and LS2 denote the HP-filtered labor share and the quadratically-detrended labor share respectively. GH denotes for the generalized hybrid NKPC and H denotes for the hybrid NKPC.

3. J-Stat denotes for J Statistics and W-Stat denotes for Wald statistics.

4. Parentheses below the coefficient estimates indicate the standard errors, whereas parentheses below statistics indicate p-values.

Table 5. Sensitivity check using IV set 4

Reduced-form equations										
	Reduced-form generalized hybrid NKPC						***Reduced-form hybrid NKPC***			
LIS	η_f	η_{b1}	η_{b2}	φ	*J-Stat*	*W-Stat*	γ_f	γ_b	λ	*J-Stat*
LS1	0.696***	0.190***	0.110**	0.017	6.542	5.972	0.747***	0.248***	0.019*	7.677
	(0.052)	(0.064)	(0.045)	(0.0110)	(0.587)	(0.015)	(0.061)	(0.062)	(0.012)	(0.567)
LS2	0.661***	0.197***	0.139***	0.003	6.857	9.659	0.700***	0.296***	0.002	8.527
	(0.046)	(0.059)	(0.045)	(0.004)	(0.552)	(0.002)	(0.052)	(0.052)	(0.004)	(0.482)
Structural equations										
	Structural generalized hybrid NKPC						***Structural hybrid NKPC***			
LIS	β	θ	ω	α	*J-Stat*	*W-Stat*	β	θ	ω	*J-Stat*
LS1	0.999***	0.807***	0.475***	0.269***	6.542	10.669	0.991***	0.833***	0.274***	7.677
	(0.019)	(0.061)	(0.108)	(0.082)	(0.587)	(0.001)	(0.012)	(0.049)	(0.087)	(0.567)
LS2	0.992***	0.903***	0.643***	0.294***	6.855	18.228	0.991***	0.946***	0.395***	8.527
	(0.028)	(0.082)	(0.121)	(0.069)	(0.552)	(0.000)	(0.015)	(0.082)	(0.095)	(0.482)

Measures for model performance								
	AIC	***BIC***	***RMSE***	***MAE***	***MAPE***	***TheilU***	***AR***	***LM***
GH (LS1)	468.478	481.402	0.253	0.194	25.442	0.225	0.692	1.970
							(0.733)	(0.161)
H (LS1)	472.785	482.478	0.257	0.194	25.354	0.229	0.581	1.370
							(0.846)	(0.242)
GH (LS2)	464.782	477.706	0.251	0.193	25.421	0.223	0.757	2.177
							(0.671)	(0.140)
H (LS2)	465.063	474.757	0.252	0.190	25.048	0.224	0.649	2.308
							(0.788)	(0.129)

*Note: 1. ***, ** and * denote the significance levels at 1%, 5% and 10%, respectively.*

2. LIS denote for labor income share. LS1 and LS2 denote the HP-filtered labor share and the quadratically-detrended labor share respectively. GH denotes for the generalized hybrid NKPC and H denotes for the hybrid NKPC.

3. J-Stat denotes for J Statistics and W-Stat denotes for Wald statistics.

4. Parentheses below the coefficient estimates indicate the standard errors, whereas parentheses below statistics indicate p-values.

Table 6. Sensitivity check using IV set 5

Reduce-form equations										
	Reduced-form generalized hybrid NKPC						*Reduced-form hybrid NKPC*			
LIS	η_f	η_{b1}	η_{b2}	φ	*J-Stat*	*W-Stat*	γ_f	γ_b	λ	*J-Stat*
LS1	0.761***	0.144**	0.091**	0.022*	6.390	4.335	0.839***	0.157**	0.031**	6.737
	(0.066)	(0.062)	(0.044)	(0.011)	(0.604)	(0.037)	(0.064)	(0.063)	(0.012)	(0.665)
LS2	0.690***	0.166***	0.142***	0.003	6.876	12.200	0.751***	0.245***	0.003***	8.464
	(0.053)	(0.057)	(0.041)	(0.004)	(0.550)	(0.000)	(0.055)	(0.054)	(0.005)	(0.488)
Structural equations										
	Structural generalized hybrid NKPC						*Structural hybrid NKPC*			
LIS	β	θ	ω	α	*J-Stat*	*W-Stat*	β	θ	ω	*J-Stat*
LS1	0.998***	0.811***	0.347***	0.279***	6.390	9.822	0.994***	0.814***	0.151**	6.736
	(0.014)	(0.052)	(0.116)	(0.089)	(0.604)	(0.002)	(0.012)	(0.039)	(0.068)	(0.665)
LS2	0.994***	0.906***	0.585***	0.316***	6.876	25.215	0.992***	0.930***	0.300***	8.463
	(0.024)	(0.072)	(0.127)	(0.063)	(0.550)	(0.000)	(0.013)	(0.055)	(0.082)	(0.488)

Measures for model performance								
	AIC	***BIC***	***RMSE***	***MAE***	***MAPE***	***TheilU***	***AR***	***LM***
GH (LS1)	479.924	492.849	0.261	0.200	26.040	0.232	0.930	2.365
							(0.504)	(0.124)
H (LS1)	492.250	501.943	0.271	0.204	26.425	0.241	0.812	0.775
							(0.628)	(0.379)
GH (LS2)	469.547	482.471	0.254	0.195	25.676	0.226	1.073	3.082
							(0.379)	(0.079)
H (LS2)	473.397	483.091	0.257	0.194	25.451	0.229	0.898	2.622
							(0.541)	(0.105)

*Note: 1. ***, ** and * denote the significance levels at 1%, 5% and 10%, respectively.*

2. LIS denote for labor income share. LS1 and LS2 denote the HP-filtered labor share and the quadratically-detrended labor share respectively. GH denotes for the generalized hybrid NKPC and H denotes for the hybrid NKPC.

3. J-Stat denotes for J Statistics and W-Stat denotes for Wald statistics.

4. Parentheses below the coefficient estimates indicate the standard errors, whereas parentheses below statistics indicate p-values.