How Important is Forward-Looking Behavior in New-Keynesian Models?

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Abstract: We assess the empirical relevance of forward-looking behavior in a standard New-Keynesian model of the macroeconomy. We find that forward-looking behavior explains a small fraction of the variation in this model. The portion of movements in inflation, consumption, and investment attributable to movements in the expected present-discounted value of their respective driving processes is small. Only the dynamics for the real wage depend significantly on forward-looking behavior. Overall, we conclude that the ability of the New-Keynesian model to match some empirical facts appears to rely mostly on the model's embedded inertia.

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Purpose of the paper

We provide an empirical assessment of the dynamic stochastic general equilibrium model featured in Christiano, Eichenbaum, and Evans (2005). This model has been shown to successfully replicate the dynamic response of nominal and real quantities to monetary policy shocks and to productivity shocks (see Christiano, Eichenbaum, and Evans, 2005, and Altig, Christiano, Eichenbaum, and Linde, 2004). It is still an open question, though, whether the model is a good approximation to the data from a more general standpoint. Del Negro, Schorfheide, Smets, and Wouters (2004) argue that, while misspecified, the model is a useful tool for quantitative analysis at the policymaking stage. [...]

In this paper, we consider a test of the model that focuses on its forward-looking features. These features play a prominent role in the model's structural equations. Essentially, expectations of current and future interest rates affect current aggregate demand, and expectations of current and future activity affect current inflation and wages. This intertemporal specification generates present-value relationships for key macroeconomic variables such as inflation, the real wage, consumption, and investment. These relationships can be thought of taking the form:

$$y_t - \gamma y_{t-1} = \lambda \sum_{i=0}^{\infty} \zeta^i E_t x_{t+i} + \varepsilon_t \ , \qquad (1)$$

where y is the structural variable (i.e., inflation, the real wage, consumption, or investment), x is a driving process, and E_t denotes expectations as of time t. The error term ε denotes some form of misspecification in the relationship or a shock to

y not embedded in the driving process.[1] The lagged value for y captures the inertial response of the structural variables to shocks observed in empirical vector autoregression (VAR) studies. The inertial response of consumption is usually attributed to habits in consumption expenditures, while the inertial response of inflation, the real wage, and investment is largely motivated on empirical grounds by adjustment costs and/or by some form of deviations from an optimizing behavior. The parameters γ, λ, and ζ are model structural parameters. In short, ζ plays the role of a discount factor, γ governs the degree of "backwardness" in spending and pricing decisions, and λ is the elasticity with which the structural variable responds to present discounted movements in the driving process.

When equation (1) is interpreted as a relationship for inflation, the equation says that inflation is a function of past inflation and of the present discounted value of current and future real marginal costs. When the structural variable is the real wage, equation (1) relates the real wage to its value in the previous period and to the present discounted value of the expected marginal rate of substitution between consumption and leisure. For consumption, the equation implies that the expected change in next period consumption is a function of the current change in consumption and of the present discounted value of a stream of real interest rates. Finally, when the structural variable is investment, equation (1) says that investment depends

[1] For example, in the present-value relationship for consumption, ε can be interpreted as a shock to tastes (a preference shifter that affects the marginal utility of consumption vis-à-vis labor) or as a shock to intertemporal preferences (a shock to the value of current consumption vis-à-vis future consumption for a given stream of expected real interest rates).

on past investment and on the present discounted value of the return to investment.

Taking expectations at time *t-1* and assuming that $E_{t-1}\varepsilon = 0$, equation (1) can be rewritten as follows:

$$E_{t-1}y_t - \gamma y_{t-1} = \lambda \sum_{i=0}^{\infty} \zeta^i E_{t-1} x_{t+i} \ . \qquad (2)$$

Equation (2) says that expected movements in y_t given y_{t-1} are perfectly correlated with the present discounted value of future expected movements in x.

We test the prediction of a perfect correlation between expected movements in the structural variable and expected movements in the present discounted value of the driving process on actual data. Our findings indicate that the empirical correlation of inflation, consumption, and investment with their respective driving processes in close to zero. Only the correlation of the real wage with its driving process is estimated to be high and close to the unit correlation implied by the theory.

Given these findings, it is appropriate to ask whether the test we are performing has sufficient power to reject some of the model's predictions. In this regard, small sample bias will drive the estimated correlations away from unity even if the model is the true underlying process generating the data. The larger the noise in equation (1), the more difficult it is to detect a relationship between y and the present discounted value of x in small samples. For this reason, we construct a Monte Carlo experiment where the data are generated by the model and assess the extent to which the estimated correlation between the left-

hand side and the right-hand side of equation (2) is biased away from unity in a small sample.

We find that the small sample bias is indeed important, but not sufficient to explain some of the low correlations found in the data. For the model to generate correlations close to zero, the variance of the error term ε must explain most of the variation in y. This is akin to saying that y is mainly driven by something other than the present discounted value of the driving process x.

Our findings are robust to a variant of the test that, instead of focusing on expected movements in y and x, relies on innovations in y and x. Define the time t innovation in a variable z as the difference between its expected value at time t and its expected value as of $t - 1$: $\hat{z}_{t+k} \equiv E_t z_{t+k} - E_{t-1} z_{t+k}$, for any $k \geq 0$. Then equation (1) can be written in terms of innovations as follows:

$$\hat{y}_t = \lambda \sum_{i=0}^{\infty} \zeta^i \hat{x}_{t+i} + \varepsilon_t \text{ .}^2 \tag{3}$$

This specification of the test has the advantage of removing the backward-looking component of y from the tested relationship. However, it has the drawback that the covariance between the innovation in x and ε is not necessarily zero. In particular, a low correlation between $\hat{y}$ and the present discounted value of $\hat{x}$ could be the result of a negative covariance between $\hat{x}$ and ε, and not the consequence of the model being counterfactual. Thus, to better gauge the validity of the present value relationship in

[2] We make use of the fact that $y_{t-1} - E_{t-1} y_{t-1} = 0$.

terms of innovations, one should consider the correlation between the part of innovation in y and the part of innovation in the present discounted value of x that are orthogonal to ε. From equation (3) it follows that :

$$\hat{y}_{\perp\varepsilon,t} = \lambda \sum_{i=0}^{\infty} \zeta^i \hat{x}_{\perp\varepsilon,t+i} \tag{4}$$

where the subscript $\perp\varepsilon$ denotes that the variable is orthogonal to ε.

Finding the portion of $\hat{y}$ and $\hat{x}$ that is orthogonal ε requires to identify the shock ε. We identify structural shocks in equation (3) by assuming that empirical and model responses to shocks are identical on impact. Because of this strong identifying assumption, our estimates of the correlation between innovations in the structural variables and innovations in the present discounted value of the driving processes should be interpreted with caution. Still, it is interesting that the results from this exercise largely mirror the findings for the version of the test that relies on expected changes in the structural variables and the driving processes. Specifically, the estimated correlations are low except for the wage equation. We again assess the power of the test in the context of a Monte Carlo exercise.

Relationship with previous literature

This is not the first study to assess the empirical fit of models with nominal rigidities using present value relationships. In particular, the present value relationship has been exploited (in different ways) in studies on the empirical relevance of the

"New-Keynesian" Phillips curve (see Ruud and Whelan, 2006, Kurmann, 2005, and Sbordone, 2002). Still, the uncertainty surrounding the test has not been fully explored. Kurmann is an exception, though his exercise is not cast in terms of a Monte Carlo experiment of the kind we perform here. In addition, we provide a test not just of the inflation equation, but also of other key structural equations in the dynamic stochastic general equilibrium setup of Christiano, Eichenbaum, and Evans.

Methodology

We construct empirical processes for structural and driving variables according to an unrestricted VAR which, in first-order form, can be written as follows:

$$\mathbf{Y}_t = \mathbf{A}\mathbf{Y}_{t-1} + \mathbf{u}_t \,, \tag{5}$$

where $\mathbf{Y}$ is a vector that includes both structural and driving variables, $\mathbf{A}$ is a vector of coefficients, and $\mathbf{u}$ is a vector of reduced-form residuals. Each of the equations in the VAR is estimated by OLS, and we denote by $\hat{\mathbf{A}}$ the matrix of estimated coefficients. The test of relationship in (2) between the expected value of a structural variable and the expected present discounted value of its driving process is then performed by computing the following correlation on the estimated reduced-form VAR:

$$corr(\mathbf{e}_y(\hat{\mathbf{A}} - \gamma I)\mathbf{Y}_{t-1} \;,\; \lambda \mathbf{e}_x (I - \zeta \hat{\mathbf{A}})^{-1} \hat{\mathbf{A}} \mathbf{Y}_{t-1}) \,, \tag{6}$$

where $\mathbf{e}_y$ is a row vector that has the value of one in the same position where y is located in $\mathbf{Y}$ and zero elsewhere, $\mathbf{e}_x$ is a row vector with the value of one where x is located in $\mathbf{Y}$ and zero

elsewhere, and I is an identity matrix conformable with $\mathbf{A}$. In order to evaluate this correlation, we need an estimate of the magnitude of the parameters γ and ζ. We rely on parameter values estimated or calibrated in Christiano, Eichenbaum, and Evans. While we do not need to calibrate λ for the purpose of our exercise, it is important to note that the driving process x is often a linear combination of several variables, and the specific linear combination is a function of deep model structural parameters. Again, we take the linear combination implied by the model with parameters estimated or calibrated in Christiano, Eichenbaum, and Evans.

The dynamic general equilibrium model we are testing has an approximate reduced form solution of the form:

$$\mathbf{Y}_t = \mathbf{A}^{\mathbf{R}}\mathbf{Y}_{t-1} + \mathbf{B}^{\mathbf{0}}\boldsymbol{\varepsilon}_t \,, \tag{7}$$

where $\mathbf{A}^{\mathbf{R}}$ and $\mathbf{B}^{\mathbf{0}}$ are matrices of structural parameters that impose the restrictions implied by the model, and $\boldsymbol{\varepsilon}$ is a vector of structural shocks. In terms of the structural model, equation (2) is then given by:

$$\mathbf{e}_y(\mathbf{A}^{\mathbf{R}} - \gamma I)\mathbf{Y}_{t-1} = \lambda \mathbf{e}_x (I - \zeta \mathbf{A}^{\mathbf{R}})^{-1}\mathbf{A}^{\mathbf{R}}\mathbf{Y}_{t-1} \,. \tag{8}$$

It is apparent that the only difference in the construction of the variables in (6) and (8) is given by the matrix of coefficients $\mathbf{A}$. As long as the model is a good approximation of actual data, the reduced form VAR should recover a matrix $\hat{\mathbf{A}}$ close enough to $\mathbf{A}^{\mathbf{R}}$ to deliver a positive correlation between expected movements in the structural variables and expected movements in the present discounted value of their driving processes. Because of finite sample bias, however, we do not

expect the estimated correlation to be unity even if the model is the true data generating process.

The test we are performing differs from the present-value test developed by Campbell (1987). The reduced form solution (7) to the dynamic general equilibrium model implies that the evolution of the variables in $\mathbf{Y}$ is such that equation (7) holds at any point in time. The model, however, does *not* impose a restriction of the form

$$\mathbf{e}_y(\mathbf{A}^{\mathbf{R}} - \gamma\mathbf{I}) = \lambda\mathbf{e}_x(\mathbf{I} - \zeta\mathbf{A}^{\mathbf{R}})^{-1}\mathbf{A}^{\mathbf{R}}$$

on the model parameters. [...]

The variant of the test that relies on innovations – equation (3) – can be written in terms of the reduced form VAR and of the structural shocks as follows:

$$\mathbf{e}_y\mathbf{u}_t = \lambda\mathbf{e}_x(\mathbf{I} - \zeta\hat{\mathbf{A}})^{-1}\mathbf{u}_t + \mathbf{e}_y\boldsymbol{\varepsilon}_{\mathbf{t}} \ . \tag{9}$$

As already mentioned, the estimated correlation between the left-hand side and the first term on the right-hand side of (9) can be biased because of a nonzero covariance between $\mathbf{u}$ and $\boldsymbol{\varepsilon}$. To correct for this bias, we identify the structural shocks in the data as

$$\mathbf{B}^{\mathbf{0}^{-1}}\mathbf{u}_t = \boldsymbol{\varepsilon}_{\mathbf{t}} \ , \tag{10}$$

where $\mathbf{B}^{\mathbf{0}}$ is the matrix of model structural parameters that determines the contemporaneous effect of $\boldsymbol{\varepsilon}$ on $\mathbf{Y}$ in the model. In other terms, our identification procedure assumes that the impact responses to shocks in the empirical VAR are identical to the model responses. We evaluate the matrix $\mathbf{B}^{\mathbf{0}}$ according to the parameters estimated or calibrated in Christiano, Eichenbaum, and

Evans. With this identification assumption, we then compute the following correlation:

$$corr(\mathbf{e}_y \mathbf{u}_{\perp\varepsilon,t} \ , \ \lambda \mathbf{e}_x (\mathbf{I} - \zeta \hat{\mathbf{A}})^{-1} \mathbf{u}_{\perp\varepsilon,t}), \tag{11}$$

where the subscript $\perp\varepsilon$ indicates that we are taking the portion of the reduced form shocks $\mathbf{u}$ orthogonal to $\mathbf{e}_y \boldsymbol{\varepsilon}$.

The relationship between innovations in the structural variable and in the present discounted value of the driving process can be written in terms of the structural model as

$$\mathbf{e}_y \mathbf{B}^{\mathbf{0}} \boldsymbol{\varepsilon}_{\perp\varepsilon,t} = \lambda \mathbf{e}_x (\mathbf{I} - \zeta \mathbf{A}^{\mathbf{R}})^{-1} \mathbf{B}^{\mathbf{0}} \boldsymbol{\varepsilon}_{\perp\varepsilon,t}. \tag{12}$$

Because of the identifying assumption in equation (10) for the structural shocks, the only difference in the construction of the variables between (11) and (12) is again given by the matrix of coefficients $\mathbf{A}$. Insofar as the model is a good approximation to actual data, the estimated matrix $\mathbf{A}$ from the reduced form VAR will deliver a positive correlation between innovation in the structural variables and innovations in the present discounted value of their driving processes.

Model Equations

We now describe the set of relationships that we test on actual data. These relationships are derived by Christiano, Eichenbaum and Evans (2005) in a dynamic stochastic general equilibrium framework with wage and price stickiness and capital accumulation, and we refer the interested reader to their work for a more detailed analysis.

The equation for inflation takes the form

$$\pi_t - \pi_{t-1} = \phi \sum_{j=0}^{\infty} E_t \beta^j s_{t+j} \ , \tag{13}$$

where π is inflation (the log difference of the price level) and s is (the log of) real marginal costs, defined as

$$s_t = w_t + h_t - y_t + R_t \ ,$$

with w denoting the log real wage, h the log of per capita hours, y the log of per capita GDP, and R the log of the gross nominal rate of interest. The inflation equation is derived in the context of a Calvo-style setp where firms that do not re-optimize in a given period change prices according to the most recent rate of inflation (hence the presence of lagged inflation in the equation). As is well known, because in this setup firms cannot adjust prices optimally every period, inflation is a function not only of current marginal costs, but of the expected present discounted value of current and future marginal costs.

The equation for the real wage is given by

$$w_t - \omega_2^{-1} w_{t-1} = \beta \omega_2^{-1} \sum_{j=0}^{\infty} \omega_1^j E_t [\beta(\pi_{t+j+1} - \pi_{t+j}) - (\pi_{t+j} - \pi_{t+j-1}) + \zeta(\psi_{t+j} - h_{t+j})] , \tag{14}$$

where ψ defines the marginal utility of a monetary unit, which is equal to

$$\psi_t = \sum_{i=0}^{\infty} E_t (R_{t+1+i} - \pi_{t+1+i}) \ .$$

As with the price-setting equation, the wage equation is derived from a Calvo-style setup where workers face a constant probability of re-optimizing their nominal wage every period. The set of workers that in each period are not able to re-optimize their wage are assumed to adjust their nominal wage according to the most recent rate of inflation. As a consequence of this

setup, when workers have the ability to re-optimize their nominal wage, they will take into account expected changes in future inflation and the evolution of current and future marginal rates of substitutions between consumption and leisure. The dynamic wage-updating scheme for workers that cannot re-optimize in a given period accounts for the presence of the lagged real wage in equation (14). As in the case of inflation, this feature helps the model account for the slow, persistent movement in prices and nominal wages after a policy shock.

The model equation for consumption is derived under the assumption of habit formation in consumption preferences. Habit persistence effectively replaces the level of consumption with its growth rate in the utility function. As a result, the equation for consumption takes the form

$$E_t(\Delta c_{t+1}) - b\Delta c_t = \sigma_c^{-1} \sum_{j=0}^{\infty} (b\beta)^i E_t(R_{t+1+i} - \pi_{t+1+i}), \qquad (15)$$

where c is (the log of) consumption per capita, and b is the habit persistence parameter. According to the equation, the expected change in next period consumption depends on the current change in consumption and on a present discounted stream of expected real interest rates.

The specification for investment incorporates adjustment costs. The motivation for having adjustment costs to investment is largely empirical. Several authors have noted that the response of investment to monetary policy shocks is counterfactually large without some mechanism that penalizes changes in investment. As a result, the present value relation for investment takes the form

$$\Delta i_t = \frac{1}{s}\sum_{j=0}^{\infty} E_t \beta^j P_{k,t+j} \ , \qquad (16)$$

where i is (the log of) per capita investment and $P_{k,t}$ is the hypothetical spot price of a unit of capital stock installed at time t. In turn, the price of capital is determined according to a familiar asset pricing equation whereby the price of capital at time t depends on the price of capital next period plus its period t dividend, equal to the rental rate of capital $r_t^k = w_t + R_t + h_t - k_t$, with k denoting the log of the capital stock. Forward iteration of the equation for the price of capital yields the following relationship:

$$P_{k,t} = (1-\beta(1-\delta))\sum_{j=0}^{\infty}(\beta(1-\delta))^j E_t r_{t+1+j}^k - \sum_{j=0}^{\infty}(\beta(1-\delta))^j E_t (R_{t+1+j} - \pi_{t+1+j})$$

This relationship can be substituted into (16) to obtain an expression for the change in investment in terms of a present discounted value of the rental rate of capital and of the real interest rate.

The four present value relationships for inflation, the real wage, consumption, and investment – equations (13) to (16) – are the subject of our empirical test. We compute the correlation between the right-hand side and the left-hand side of each of the equations, where the variables are either expressed as expected values as of t-1, or as period t innovations. In the appendix, we define the expressions for the left-hand side and the right-hand side of each of the four relationships in terms of the reduced-form VAR used in our empirical analysis. Some of these expressions – notably the driving process for the real wage and the driving process for investment – are tedious, but they are a

straightforward application of the formulas (6) and (11) outlined in the previous section.

Data and Empirical Specification

We estimate a reduced form VAR in the following variables:

$$\mathbf{Y}_t = \begin{pmatrix} \Delta y_t - \Delta h_t \\ \pi_t \\ h_t \\ w_t + h - y_t \\ c_t - y_t \\ i_t - y_t \\ R_t \end{pmatrix},$$

where all variables have been defined already in the previous section. A similar VAR (with three additional variables) is used in Altig, Christiano, Eichenbaum, and Linde (2004). These seven variables are sufficient to characterize the Christiano Eichenbaum and Evans model when the monetary policy reaction function takes the form of a Taylor rule.

Hours h are defined as total hours in the non-farm business sector. Inflation π is the quarterly log difference in the GDP deflator, and y is real GDP. The real wage w is compensation in the non-farm business sector deflated by the GDP deflator. Consumption c is consumption of nondurable goods, services, and government consumption deflated by the GDP deflator, while investment is total private investment plus durable consumption deflated by the GDP deflator. The nominal interest rate R is the Federal Funds rate. Hours, output, consumption, and investment are expressed in per-capita terms.

The VAR is estimated on quarterly U.S. data over the period 1966:Q1 to 1995:Q4. The number of lags in the estimated VAR is four. Our results do not depend on the specific sample we use. However, we focus on this particular sample because the VAR estimated over this period is very stable, with the largest root of the estimated matrix of coefficients $\mathbf{A}$ only slightly above .97. Given that we are computing present discounted values, stability of the estimated VAR is crucial.

Empirical Findings

The estimated reduced form VAR described in the previous section is used to compute the correlation of the structural variables with their respective driving processes. When estimating these correlations, we need to calibrate several model parameters. The calibrated values, taken from Christiano, Eichenbaum, and Evans, are reported in the appendix. The appendix also describes how the estimated correlations can be written in terms of the estimated reduced form VAR.

Table 1 reports the estimated correlations for inflation, the real wage, consumption, and investment. Standard errors are computed by bootstrapping the residuals of the estimated reduced form VAR.[3] Panel A considers the estimated correlations in terms of equation (6) – that is, when variables are expressed in terms of expectations as of *t-1*. The estimates are low except for the real wage, whose correlation with the expected evolution of the driving process is close to .90, though estimated imprecisely.

[3] At each draw, we generate a new data set and compute a new estimated value for the correlations. This procedure is repeated 1000 times to obtain a bootstrap standard deviation.

Figure 1A plots the actual relationships between the expected value of the structural variables and the expected value of the present discounted value of their driving processes over the sample period we consider.

Panel B of the table reports the estimated correlations in terms of equation (11) – that is, when variables are expressed in terms of time *t* innovations. As mentioned in the methodology section, we take the portion of the innovations that is orthogonal to the structural shocks, which are identified from the reduced-from residuals by means of equation (10). The estimated correlations essentially mirror the estimates for the predictable component of the variables reported in the previous panel. Figure 1B plots of the actual relationship between innovations in the structural variables and innovations in their driving processes over the sample period we consider.

Overall, our findings do not lend strong support for some key predictions of the model, with the notable exception of the wage equation. Whether the findings are significantly at odds with the model, however, is still an open issue. We address this issue in the next section in the context of a Monte Carlo exercise.

Monte Carlo Simulation

We now evaluate the magnitude of the empirical correlations under the assumption that the model is the true data generating process. To do so, we generate model-consistent artificial data, estimate a reduced form VAR on these artificial data, and evaluate the correlation between the structural variables and their driving processes. This exercise is repeated 1000 times to generate a distribution of the estimated correlations when the

model is the true data generating process. Because we are interested in evaluating the small sample properties of the estimated correlations, at each repetition the reduced form VAR is estimated on 150 artificial data – about the same sample size used in actual data.

The Christiano, Eichenbaum, and Evans (2005) dynamic stochastic general equilibrium model can be summarized by seven equations in seven variables when monetary policy is defined by means of a Taylor rule. Four of these equations are the structural relationships (13)-(16) for inflation, the real wage, consumption, and investment. When generating the artificial data, we append a shock to each of these four equations. The disturbances can be interpreted as misspecification in the relationships or as fundamental shocks, depending on the relationship in question. We label these shocks generically as structural shocks to inflation, the real wage, consumption, and investment. We consider also three additional structural shocks: a shock to the nominal interest rate, a shock to the price of capital, and a shock to hours. We draw from these seven shocks to generate model consistent artificial data.

We run different Monte Carlo simulations for each of the structural variables we are interested in. Let y be any of these four variables. Then, in terms of equation (7), the variance of an innovation to y is given by

$$\mathbf{e}_{\mathbf{y}}\mathbf{B}^{\mathbf{0}}\Sigma_{\varepsilon}\mathbf{B}^{\mathbf{0}'}\mathbf{e}_{\mathbf{y}}', \qquad (17)$$

where Σ_{ε} is the covariance matrix of the structural shocks. We assume that the structural shocks are uncorrelated with each other, so that Σ_{ε} is a diagonal matrix. To generate the data, we

keep (17) constant but vary the weight of the variance of the structural shock to y relative to the variance of the other structural shocks. Specifically, we assess the distribution of correlations for variable y with its driving process when the structural shock to that variable accounts for 25 percent, 50 percent, 75 percent, or 90 percent of the innovation to y. As a result, for each variable y we consider four different model-consistent data generating processes, where the difference lies in the importance of the structural shock y relative to the other shocks.

A low variance of the structural shock to y means that movements in y are mainly driven by movements in the driving process. Conversely, a high variance of the structural shock to y means that the driving process is relatively unimportant in explaining the behavior of y. We cast the Monte Carlo simulation within this framework because the relative weight of the variance of the structural shock to y can influence the estimated correlation between y and its driving process in small samples.

Table 2A shows the result of the Monte Carlo exercise for the predictable component of the structural variables – that is, the estimated correlations in terms of equation (6). For each variable, the table reports the median correlation, the standard deviation of the correlation, and the 10th and 90th percentile correlation from 1000 replications under the four different assumptions about the relative importance of the variable's structural shock.

The estimates in the table show that a small sample biases the estimated correlations away from unity. The standard

deviation of the estimates is also fairly large. In addition, the larger the relative variance of the structural shock to y, the lower the estimated median correlation between y and its driving process. Still, the 10th percentile estimated correlation is safely into positive territory unless the relative variance of the structural shock becomes very large.

Overall, we interpret the findings as indicating that the estimated correlations on actual data reported in panel A of Table 1 are unlikely to have been generated by the model. Of course, it's possible that *some* of the estimated correlations are low because of the presence of large structural shocks. However, in the model at hand a structural shock to variable y is often a shock to the driving process of some other structural variable. For example, large structural shocks to consumption can explain the low empirical correlation of consumption with its driving process. But these large structural shocks to consumption affect, among other things, the driving process for investment. Results from our Monte Carlo exercise (not reported) indicate that when the variance of the structural shock to consumption is large, the median correlation of investment with its driving process is .75. Thus, it is difficult to reconcile the contemporaneous presence of low correlations for inflation, consumption, and investment with their respective driving processes in light of the model.

Table 1

A. CORRELATIONS FOR PREDICTABLE COMPONENT			
Inflation	**Consumption**	**Real Wage**	**Investment**
0.06147 (0.06423)	-0.00326 (0.16331)	0.87142 (0.49563)	0.11928 (0.07086)

Bootstrap standard errors in parenthesis.

B. CORRELATIONS FOR INNOVATIONS			
Inflation	**Consumption**	**Real Wage**	**Investment**
0.32165 (0.23989)	-0.18616 (0.29024)	0.83343 (0.16494)	0.13724 (0.24914)

Bootstrap standard errors in parenthesis.

Table 2A
Estimated Correlations from Monte Carlo Simulations: Predictable Component

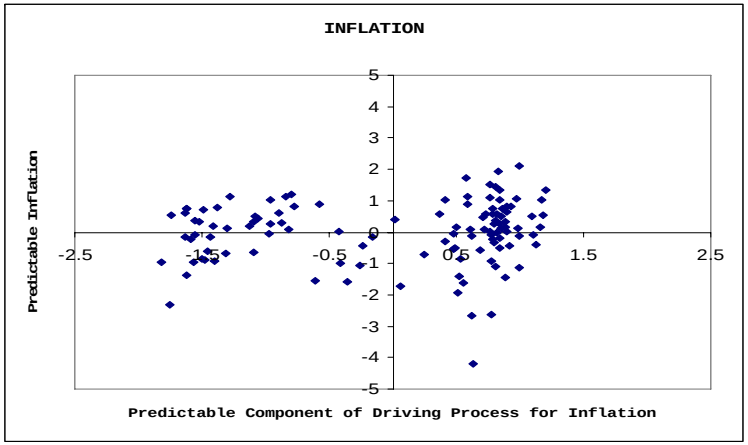
Inflation				
Relative weight of own variance	25%	50%	75%	90%
median	0.58	0.53	0.44	0.33
std	0.19	0.19	0.19	0.19
10th percentile	0.29	0.26	0.17	0.07
90th percentile	0.79	0.73	0.67	0.57

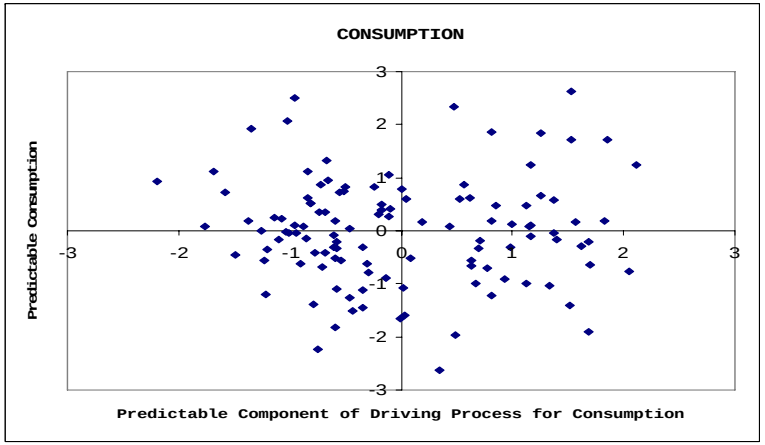
Consumption				
Relative weight of own variance	25%	50%	75%	90%
median	0.57	0.49	0.35	0.24
std	0.11	0.12	0.12	0.12
10th percentile	0.40	0.33	0.19	0.09
90th percentile	0.70	0.64	0.52	0.39

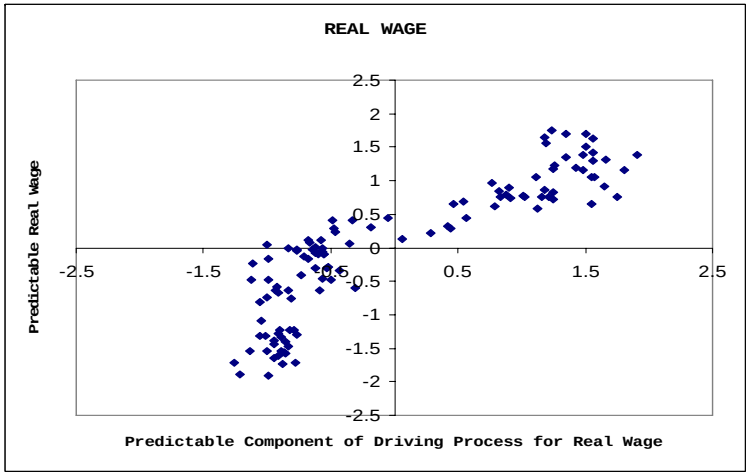
Real Wage				
Relative weight of own variance	25%	50%	75%	90%
median	0.68	0.57	0.50	0.46
std	0.19	0.20	0.20	0.19
10th percentile	0.37	0.26	0.21	0.19
90th percentile	0.85	0.75	0.69	0.66

Investment				
Relative weight of own variance	25%	50%	75%	90%
median	0.67	0.65	0.62	0.56
std	0.17	0.17	0.18	0.18
10th percentile	0.39	0.37	0.34	0.28
90th percentile	0.83	0.81	0.78	0.73

Figure 1A


INFLATION
Predictable Inflation
Predictable Component of Driving Process for Inflation


CONSUMPTION
Predictable Consumption
Predictable Component of Driving Process for Consumption


REAL WAGE
Predictable Real Wage
Predictable Component of Driving Process for Real Wage

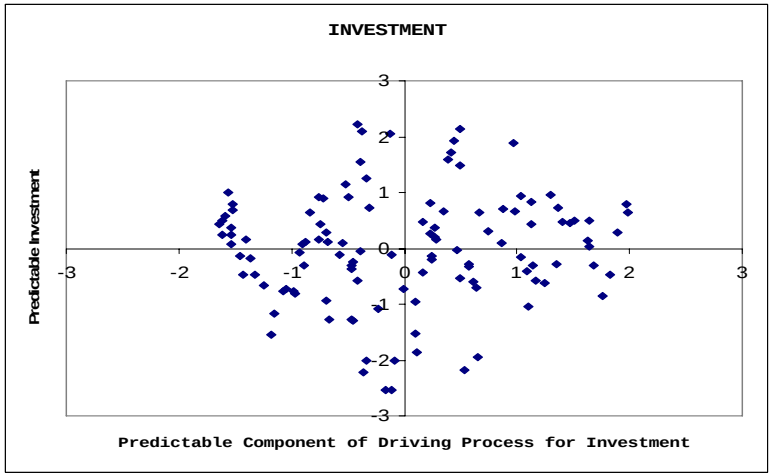
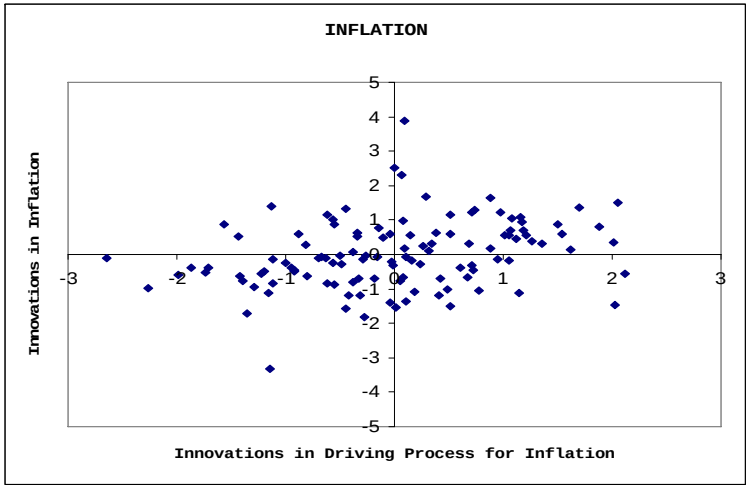
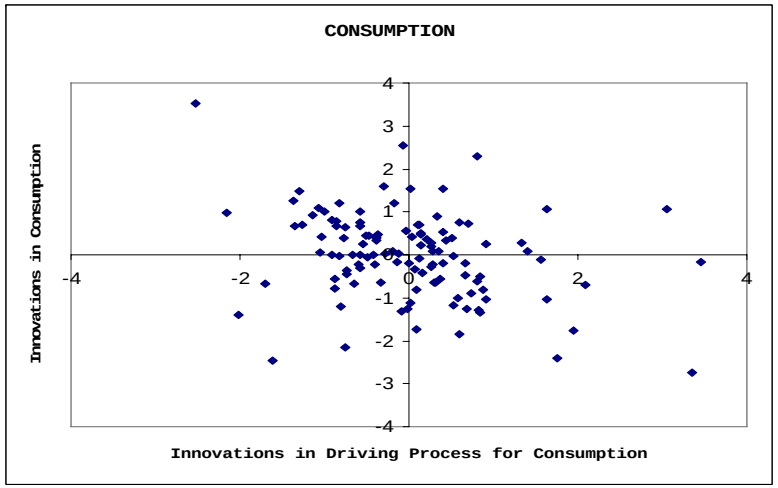
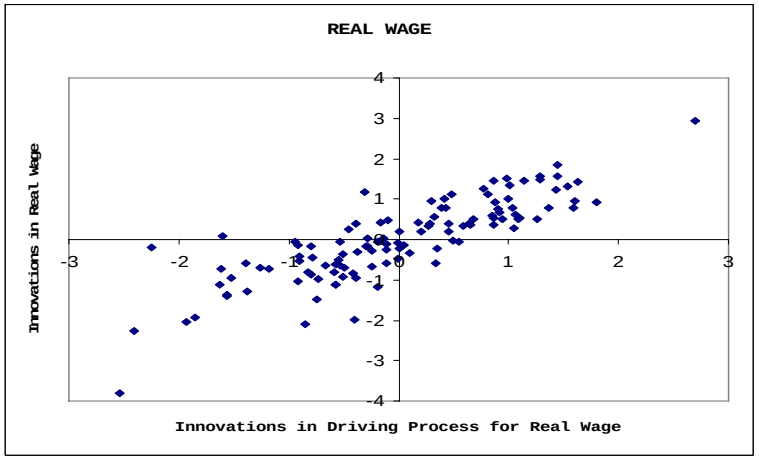
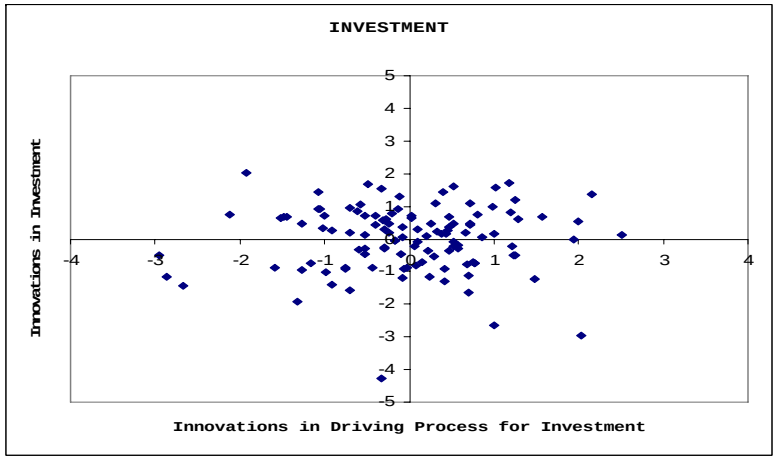

INVESTMENT
Predictable Investment
Predictable Component of Driving Process for Investment

Figure 1B


INFLATION
Innovations in Inflation
Innovations in Driving Process for Inflation


CONSUMPTION
Innovations in Consumption
Innovations in Driving Process for Consumption


REAL WAGE
Innovations in Real Wage
Innovations in Driving Process for Real Wage


INVESTMENT
Innovations in Investment
Innovations in Driving Process for Investment