Spotting sunspots: Some evidence in support of models with self-fulfilling prophecies

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Abstract

This paper adds financial assets to Roger Farmer’s business cycle model with increasing returns and self-fulfilling beliefs. By using information from the financial markets in conjunction with the structure of the model, we can uncover from financial data the belief shocks that drive the model. Specifically, we assume that belief shocks drive both economic fluctuations and asset returns. The financial market information allows us to identify these shocks. We use our methods to generate dynamic simulations of the model and show that it has incremental predictive power for key US time series. © 1998 Elsevier Science B.V. All rights reserved.

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Keywords: Real business cycles; Sunspots

1. Introduction

There has always been a fascination in economics with the possibility of self-fulfilling prophecies; that is, swings of optimism and pessimism that translate into corresponding movements in economic activity. Traditional Keynesian economics had such a mechanism: fluctuations in ‘animal spirits’, often reflected in the capital markets and, particularly, investment, which could cause booms or busts through changes in aggregate demand.

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In recent work, Roger Farmer (1993) and R. Farmer and Jang-Ting Guo (1994a) have developed a formal rational expectations model of the business cycle that features self-fulfilling prophecies. In their model, an arbitrary sequence of non-fundamental (i.e. extrinsic) shocks can cause fluctuations in economic activity that mirror economic fluctuations in modern economies. In this paper, we incorporate a financial market into the Farmer framework. We show how this permits random shocks to be identified through realized asset returns, thereby providing an observable counterpart to the non-fundamental shock that impinges on the economy. This leads to some simple tests which provides support, albeit limited, for the Farmer model.

In Farmer’s work, the non-fundamental shock is postulated to be identical to a shock to consumption and is essentially a residual in the model. In our work, we add a simple financial market to Farmer’s calibrated model. Using the traditional consumption-based asset pricing model, we can compute the ex-ante and ex-post returns on assets implied by the model. Using data on actual asset prices, we can identify the belief shock and then solve for the entire set of endogenous variables in the model. We can then test whether the predictions of the increasing returns model, identified through additional financial market information, provides incremental predictive power for U.S. output, consumption, investment, and labor. We find that it indeed has incremental power and contains more information than is present in the financial markets themselves.

2. The Farmer model with a financial market

The model which we study is similar to that developed in Farmer and Guo (1994); hence, expository comments will be brief. The critical assumption is that the aggregate production is characterized by increasing returns to scale:

\[
y_t = z_t k_t^\mu h_t^\gamma,
\]

where \( y_t \) denotes output, \( k_t \) denotes the capital stock, \( h_t \) is labor, and \( z_t \) represents an exogenous productivity shock which follows the \( AR(1) \) process given in Eq. (2.2).\(^1\) The innovation to the technology shock, \( w_t \), is assumed to be i.i.d.

\[z_t = z_{t-1}^\theta w_t; \quad w_t \in [w_1, w_2]) \forall t \text{ with } 0 < w_1 < w_2 < \infty ,\]

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\(^1\) We depart from Farmer (1993) and Farmer and Guo (1994a) by including technology shocks along with belief shocks. Recently, Farmer and Guo (1994b) also incorporated productivity shocks (as well as taste shocks) into a version of their increasing returns model. However, they did not use the model to generate artificial data but, instead, studied the econometric implications of the model.
with bounded support. The assumption of increasing returns is reflected in the assumption that \((\mu + \nu) > 1\). In addition to technology shocks, the economy will be affected by belief shocks; the characteristics of these shocks will be specified below.

Aggregate increasing returns is justified by assuming that there exist two sectors in the economy: an intermediate and final goods sector. In the intermediate sector, firms have monopoly power due to increasing returns in the production of this intermediate good. However, the final goods sector is competitive. Under the assumption that the downward sloping demand curves faced by intermediate firms offsets the non-convexity in their technology, an interior solution will exist. In addition, the final goods sector produces a single good so that the aggregate concepts of GNP, investment, and consumption are well-defined. Farmer shows that this scenario implies that factor shares and factor output elasticities will be proportional. That is, letting \(m\) and \(n\) denote the capital and labor factor shares respectively, we have the following restriction:

\[
m = \lambda \mu, \quad n = \lambda \nu. \tag{2.3}
\]

As Farmer and Guo (1994) demonstrate, a competitive equilibrium in this model is characterized by the following necessary conditions:

\[
\frac{1}{c_t} = \beta E_t \left[ \frac{1}{c_{t+1}} \left( 1 - \delta + m \frac{y_{t+1}}{k_{t+1}} \right) \right]. \tag{2.4}
\]

\[
n \left( \frac{y_t}{h_t} \right) = c_t, \tag{2.5}
\]

\[
k_{t+1} = y_t + (1 - \delta)k_t - c_t. \tag{2.6}
\]

In the above equations \(c_t\) denotes consumption in period \(t\) and \(\delta\) is the depreciation rate of capital. The first expression is the intertemporal efficiency condition while Eq. (2.5) reflects the necessary condition for intratemporal efficiency. The last equation depicts the economy wide resource constraint as reflected in the law of motion for the aggregate capital stock.

Randomness in this economy is due to intrinsic uncertainty as represented by the technology shocks, \(z_t\), and extrinsic (non-fundamental) uncertainty which is characterized by a probability distribution for agents’ ‘belief shocks’. Belief shocks can be elements of a stationary sunspot equilibrium in an approximate (linearized) version of the economy described above. To incorporate belief shocks requires several steps: (1) Solve for the steady-state (i.e. non-stochastic) equilibrium implied by the above necessary conditions. The imposed parameter restrictions imply the existence and uniqueness of steady-state equilibrium. (2) Take first-order approximations to the dynamic system described by Eqs. (2.4), (2.5) and (2.6) and demonstrate that, for the parameter values given in footnote 2 (the same as used by Farmer and Guo, 1994a), there are multiple paths
converging to the steady state. (3) Introduce a probability distribution over the possible convergence paths. The shock which moves the economy from one path to another is defined as the belief shock. Given that the distribution for this belief shock is assumed to be stationary (as is the distribution for the technology shock), there will exist a stationary rational expectations equilibrium within this economy. This equilibrium is described by a set of linear equations for the endogenous variables. The results of the three steps described above are the following equilibrium laws of motion:

\[
\hat{c}_{t+1} = 0.89\hat{c}_t + 0.045\hat{y}_t + 0.11\hat{z}_t + \hat{\epsilon}_{t+1},
\]

\[
\hat{y}_{t+1} = -0.24\hat{c}_t + 0.94\hat{y}_t + 5.30\hat{z}_t - 4.76\hat{z}_{t+1} + 5.76\hat{\epsilon}_{t+1}.
\]

The circumflex denotes that all variables are expressed as percentage deviations from steady-state values. The belief shock at time \(t\) is denoted by \(\hat{\epsilon}_t\). It is assumed that it is independently and identically distributed over time. Given the behavior of output and consumption, the remaining endogenous variables are implied by the (linearized) intratemporal efficiency conditions and the resource constraint. For the parameter values used, these are, respectively,

\[
\hat{h}_t = \hat{y}_t - \hat{c}_t,
\]

\[
\hat{i}_t = 6.12\hat{y}_t - 5.19\hat{c}_t.
\]

There are several different empirical approaches that can be taken to analyze the model. First, it would be possible to make some additional identification assumptions on the errors in Eqs. (2.7) and (2.8) and estimate a VAR. Cochrane (1994) discusses a variety of alternative approaches to identification, such as characterizing shocks as permanent or transitory. Alternatively, Farmer and Guo (1994a) use Monte Carlo methods to generate belief shocks and then compute model statistics. In this paper, we take a third approach which uses additional model information to pin down the shocks. In particular, we use estimates of the Solow residual to isolate the technology shock and the equity market to isolate the belief shock. This is the novel feature of our approach – we

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2 The following parameter values were used: \(n = 0.7, \, \nu = 1.21, \, m = 0.23, \, \mu = 0.4, \, \beta = 0.99, \, \delta = 0.025, \, \rho = 0.95, \, A = 1\).

3 For a discussion of the solution method, see Farmer (1993). The fact that the steady state in this economy is a sink rather than a saddle-path implies that shocks can be introduced into the equilibrium laws of motion for the economy. In this model, these shocks are assumed to be the innovations to technology \((w_t)\) and the shocks to consumption \((\epsilon_t)\).

4 Note that we are using output rather than, as is typical, capital as a state variable. The reason for doing this is the measurement problems associated with capital, especially on a quarterly basis. Of course, the model implies that capital, hours, and output (all measured as deviations from steady state) are linearly related through the production function. For our parameter values, this is \(\hat{y}_t = \hat{z}_t + 0.40\hat{h}_{t-1} + 1.21\hat{h}_t\).
can compare predictions of the model to the data without relying on a priori identifying assumptions on the shocks.

It is worth emphasizing that adding a financial market to the model is part of a general strategy of placing more theoretical structure on a model and using the implied observational implications to identify shocks in actual time series. It is analogous to using the structure of a production function to generate a Solow residual as a technology shock. This strategy allows a researcher to analyze historical time series instead of using artificially generated shocks to explore only correlations or moments. While it might be possible to use markets other than financial to identify the belief shock, these particular markets are natural for this purpose since they fundamentally involve expectations.

For the technology shock, we construct the Solow residual implied by the production function and then linearly detrend this series. The detrended series is used as the technology shock, $\hat{z}_t$. Specifically,

$$Z_t = \ln y_t - 0.40 \ln k_t - 1.21 \ln h_t.$$  \hspace{1cm} (2.11)

Then $\hat{z}_t$ is measured as the residuals from regressing $Z_t$ on a constant and time trend.

Measuring the belief shock is more problematic. Note that the solution to the model suggests that the belief shock can be measured by using actual time series for output, consumption, and the technology shock in Eq. (2.7) and identifying the belief shock as the residual in the consumption equation. While this approach was used in Salyer (1995) to compare the increasing returns model to a standard real business cycle model, it is not altogether satisfactory since it reduces the dimensions by which the predictive content of the model can be studied. That is, using this technique to measure the belief shock implies that model and actual consumption data will, because of the construction of the belief shock, be highly correlated. In order to avoid this problem, we attempt to identify the belief shock by introducing an additional market, in particular, an equity market, into this economy and use the equilibrium characteristics of realized returns to uncover the time series for the belief shock.\footnote{In an earlier version of this paper, we also introduced a bond market and used realized bond returns to identify the belief shock. This model was not successful and, hence, those results are not reported.}

Since the model being studied is a representative agent economy, the introduction of asset markets will not disturb the equilibrium characteristics of any of the endogenous variables but, instead, result in sustaining or autarky equilibrium asset prices. Consequently, the equilibrium price of equity will be determined by evaluating the agents’ necessary condition associated with the purchase of this asset at the equilibrium levels of consumption and dividends. Denoting the price of equity as $q_t$ and the dividends from equity ownership as $d_t$,
the necessary condition is the familiar intertemporal condition:

\[ q_t U' = \beta E_t[U_{t+1}(q_{t+1} + d_{t+1})] \]  
(2.12)

Using the assumption that utility is logarithmic and letting \( R_t \) denote the (gross) return on equity Eq. (2.12) can be written as

\[ 1 = \beta E_t\left[ \frac{c_t}{c_{t+1}} R_{t+1} \right]. \]  
(2.13)

In a stationary rational expectations equilibrium, equity prices will be a stationary function of the relevant aggregate state variables. Moreover, in the linearized version of the economy, these functions will also be linear and must satisfy Eq. (2.13) when expanded around the steady state.

To use equity returns to uncover the belief shock note that the linearized structure of the economy implies that realized (ex-post) equity returns will be a linear function of last period’s state variables, i.e. output, consumption, and the technology shock, and the current belief and technology shocks:

\[ R_{K_{t+1}} = a_0 c_t + a_1 y_t + a_2 \hat{z}_t + a_3 \hat{e}_{t+1} + a_4 \hat{w}_{t+1}. \]  
(2.14)

This function must satisfy the linearized version of Eq. (2.13):

\[ \hat{c}_t = E_t(\hat{c}_{t+1} - \hat{R}_{t+1}). \]  
(2.15)

The equilibrium function for consumption (see Eq. (2.7)) imposes restrictions on the parameters in Eq. (2.14) so that the necessary conditions for equity returns are satisfied. In particular, \( a_0 = -0.11, a_1 = 0.045, a_2 + \rho a_4 = 0.11 \) (where the last equality uses the fact that \( \hat{z}_{t+1} = \rho \hat{z}_t + \hat{w}_{t+1} \)). As a consequence, the realized returns on equity implies that the belief shock can be observed by calculating:

\[ (a_3 - 1) \hat{e}_{t+1} = \hat{c}_t + \hat{R}_{t+1} - \hat{c}_{t+1} - 1 - a_4 \hat{w}_{t+1}. \]  
(2.16)

Since \( a_3 \) cannot be identified, the variance of the shock is undetermined.\(^6\) However, since we engage in a regression analysis in the next section, this scaling factor is not important. We assume that the coefficient on the belief shock in Eq. (2.16) is equal to unity. The other scaling factor, \( a_4 \), will determine the correlation between the belief shock and the technology shock innovation. In general, belief or sunspot shocks could be correlated with observables. For example, technology shocks could trigger further belief shocks. However, a natural normalization is to make the belief shock uncorrelated with any

\(^6\)The parameter \( a_3 \) cannot be identified since the dividend process has not been specified.
fundamentals. Specifically, let \( \hat{\gamma}_t = \hat{\gamma}_{t-1} + \hat{R}_t - \hat{c}_t \), then

\[
\text{Cov}(\varepsilon_t, w_t) = \text{Cov}(\gamma_t - \alpha_4 w_t, w_t) = \text{Cov}(\gamma_t, w_t) - \alpha_4 \text{Var}(w_t). \tag{2.17}
\]

We choose \( \alpha_4 \) so that the above covariance is zero; i.e. \( \alpha_4 \) is determined by the regression of \( \gamma_t \) on \( w_t \). Over the sample period 61.1–90.4, this regression implied \( \alpha_4 = 0.51 \). Therefore, Eq. (2.16) implies that using realized equity returns in conjunction with Eqs. (2.7), (2.8), (2.9), (2.10) and (2.11), it is possible to uncover the belief shock and solve for the remaining endogenous variables.

Before proceeding to a study of the empirical implications of the model, a few comments on the limitations of the model are in order. First, in this paper we take as given that the economy is characterized by increasing returns which are sufficient to generate sunspot equilibria. As noted by Rotemberg and Woodford (1994), the degree of increasing returns necessary to produce self-fulfilling equilibria is at the upper range of empirical observation. Second, our use of the consumption-based capital asset pricing model (CCAPM) to identify the belief shock introduces another hypothesis into our analysis; namely, that the CCAPM is an accurate description of the data. Numerous studies (e.g. Hansen and Singleton, 1982; Mehra and Prescott, 1985) have established that the empirical implications of the CCAPM are not fully consistent with the data. In particular, as the two cited papers made clear, the model cannot explain jointly the returns on (risky) equity and (riskless) bonds. Since we examine the implications of adding one of these markets to the increasing returns model, i.e. the equity market, the empirical failure of the CCAPM along these dimensions is lessened somewhat. Another apparent failure of the CCAPM is the inability to produce mean-reversion of asset returns. Our empirical focus, as discussed in the next section, is exclusively on the cyclical implications of the model; consequently, these long-run issues are not studied.

3. Empirical results

Our empirical analysis of the equity cum increasing returns model consisted of the following steps. First we computed the empirical analogs to the equity returns described above. Then these series (along with the measured technology shocks) were used as the driving processes in each model economy and the

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7 For consistency, this regression coefficient should be determined using model consumption (in \( \gamma_t \)) rather than actual consumption. As noted in the next section (see footnote 10), the model produces almost the same value.

8 The CCAPM can produce equity returns with characteristics similar to mean reversion when the income process follows a Markov switching model. For a discussion of these issues, see Cecchetti et al. (1990).
remaining endogenous variables were constructed by dynamically solving the models. Second, we then examined whether the implied belief shocks were white noise as assumed in our analysis. Third, we then fit univariate time-series models for actual consumption, output, labor, and investment. To each of these time series representations, the model’s current forecast for the relevant variable was added as an additional regressor. If the coefficient on the sunspot economy’s prediction was significant, we interpreted this as providing evidence in support of the model. To examine whether the forecasting ability of the model was caused not by the inherent properties of the model but, instead, by the driving process, the same forecasting exercise was conducted with equity returns. Our estimate of the belief shock incorporates \( \hat{\epsilon}_{t+1} \) which is a function of the realized equity return in period \( t + 1 \) as well as information dated time \( t \). By comparing the predictions of the model with predictions based on the realized equity return itself, we insure that the model does not have an unfair information advantage in the empirical comparisons. Both the relevant model variables and equity returns were included together as regressors in the time-series models in order to directly compare the information content of each. Therefore, while we use contemporaneous information in our tests we do so only in the context of the theoretical restrictions imposed by the model. Empirical support for the model will be provided to the extent that it has additional explanatory power relative to that contained in the realized contemporaneous equity returns.

In order to construct the return on equity, the quarterly dividend return and capital gains on the Standard and Poor’s 500 stock index was used. Since all returns in the model are real, nominal capital gains were converted to a real return by using the implied price deflator for consumption of non-durables and services.\(^9\)

Using the real returns for each asset as the driving process, the models was dynamically solved over the sample period 1960.1–1990.4.\(^10\) (All remaining variables were initially set to zero.)

In order to study more closely the implications of the equity model, we pursue the incremental forecasting exercise described above. However, since the model variables are defined as percentage deviations from steady state, it was first

\(^9\) The data for output, consumption, investment, and labor were taken from Citibase while the capital stock is from Musgrave. More information on the construction of the data is available from the authors.

\(^10\) Recall from the previous section that the scaling factor \( z_4 \) in Eq. (2.16) was determined so that the covariance of the innovations to technology and the belief shock was equal to zero. However, the value used in the model was determined by using actual consumption when it is model consumption that is appropriate. Regressing \( \gamma_t = \hat{\epsilon}_{t-1} - \hat{\epsilon}_t + \hat{R}_t \) (constructed from model consumption) on \( w_t \) generated virtually the same value for \( z_4 \).
necessary to construct empirical analogs to this concept. For this, we used the deviations from a linear trend estimated separately for all series. The H–P filter was not used to construct the trend due to the serial correlation properties this method imparts to the detrended series (see Cogley and Nason, 1995). For each detrended series, a univariate autoregressive model was constructed in which the number of lags was chosen so that the residuals appeared to be white noise using the Breusch–Godfrey test for fourth-order serial correlation. This resulted in the modeling of output, consumption, investment and hours as $AR(2)$, $AR(3)$, $AR(2)$, and $AR(5)$ respectively. Note that these are not, in general, the autoregressive structure implied by the Farmer model but were chosen to capture the dynamics of actual, detrended US series. This approach ensures that the predictions from the Farmer model or from equity returns do not appear to be significant because we failed to model US time series adequately.

Table 1 contains the results of adding the model prediction (all model series are denoted with an M) and equity returns for each time series. For example, for output, the first equation is the $AR$ model, the second equation adds the model prediction by itself, the third equation adds the equity return by itself, and the fourth equation adds both the model prediction and equity returns. Only for investment did we find that lagged values of the model prediction or equity returns contained incremental information or improved the fit of the regression using tests for serially correlated residuals.

The regressions in Table 1 employ some generated regressors. To calculate appropriate test statistics, we used a bootstrap method to calculate $p$-values for our null hypotheses. Following Beran (1988), we bootstrapped the $t$-statistic (a pivotal statistic) to provide the most reliable asymptotics. (Each $t$-statistic was bootstrapped 1000 times. Sample empirical distributions for the $t$-statistics reported for the output equations, lines 2–4 in Table 1, appear in Fig. 1. The empirical distributions generated by the other equations had the same fairly symmetric characteristics.) The $p$-values reported in Table 1 are two-tailed tests based on the empirical distribution for the $t$-statistic; i.e. the percentage of bootstrapped $t$-statistics which exceed the absolute value of the $t$-statistic in the original regression.

Starting with GNP, the results reported in line 2 indicate that the artificial economy’s output does provide additional information for the behavior of actual GNP. Moreover, this result is in stark contrast to equity returns (see line 3) which are highly insignificant. The predictive power of equity returns is increased somewhat when both the model prediction and equity returns are included as regressors; nonetheless, the model prediction is more significant. This suggests that the increasing returns model captures some but not all of the information contained in equity returns.

We observe a similar pattern with respect to hours. The prediction of the model for hours alone has a significant effect but equity returns do not. Including both variables leads to the best fitting equation.
Table 1
Regression results

<table>
<thead>
<tr>
<th>Variable</th>
<th>Equation</th>
<th>Regressors</th>
<th>Coefficient (p-values in parentheses)</th>
<th>$R^2$</th>
<th>Serial correlation$^a$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>AR(4)</td>
<td>—</td>
<td>0.960</td>
<td>0.11 (0.98)</td>
<td>0.48 (0.97)</td>
</tr>
<tr>
<td><strong>Output</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>$YM_t$</td>
<td>0.006 (0.004)</td>
<td>0.962</td>
<td>1.78 (0.14)</td>
<td>7.31 (0.12)</td>
</tr>
<tr>
<td>3</td>
<td>$\bar{R}_t$</td>
<td>0.0001 (0.99)</td>
<td>0.959</td>
<td>0.11 (0.98)</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>$YM_t$</td>
<td>0.009 (0.000)</td>
<td>0.963</td>
<td>1.76 (0.14)</td>
<td>7.32 (0.12)</td>
</tr>
<tr>
<td></td>
<td>$\bar{R}_t$</td>
<td>-0.023 (0.035)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>AR(4)</td>
<td>—</td>
<td>0.985</td>
<td>1.03 (0.40)</td>
<td>4.28 (0.37)</td>
</tr>
<tr>
<td><strong>Consumption</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>$CM_t$</td>
<td>0.005 (0.084)</td>
<td>0.986</td>
<td>0.63 (0.64)</td>
<td>2.70 (0.61)</td>
</tr>
<tr>
<td>7</td>
<td>$\bar{R}_t$</td>
<td>0.009 (0.063)</td>
<td>0.986</td>
<td>1.69 (0.16)</td>
<td>6.95 (0.14)</td>
</tr>
<tr>
<td>8</td>
<td>$CM_t$</td>
<td>0.004 (0.16)</td>
<td>0.986</td>
<td>1.16 (0.33)</td>
<td>4.90 (0.30)</td>
</tr>
<tr>
<td></td>
<td>$\bar{R}_t$</td>
<td>0.008 (0.12)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>AR(4)</td>
<td>—</td>
<td>0.822</td>
<td>0.46 (0.77)</td>
<td>1.95 (0.74)</td>
</tr>
<tr>
<td><strong>Investment</strong></td>
<td></td>
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<td></td>
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<td></td>
</tr>
<tr>
<td>10</td>
<td>$IM_t$</td>
<td>-0.003 (0.20)</td>
<td>0.848</td>
<td>1.54 (0.19)</td>
<td>6.44 (0.17)</td>
</tr>
<tr>
<td></td>
<td>$IM_{t-1}$</td>
<td>0.009 (0.002)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>$\bar{R}_t$</td>
<td>-0.038 (0.29)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>11</td>
<td>$\bar{R}_{t-1}$</td>
<td>0.085 (0.018)</td>
<td>0.849</td>
<td>5.12 (0.27)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$\bar{R}_{t-2}$</td>
<td>0.135 (0.005)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>12</td>
<td>$IM_t$</td>
<td>0.009 (0.00)</td>
<td>0.848</td>
<td>1.52 (0.20)</td>
<td>6.38 (0.17)</td>
</tr>
<tr>
<td></td>
<td>$\bar{R}_{t-2}$</td>
<td>-0.181 (0.00)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>13</td>
<td>AR(5)</td>
<td>—</td>
<td>0.915</td>
<td>0.69 (0.60)</td>
<td>2.92 (0.57)</td>
</tr>
<tr>
<td><strong>Hours</strong></td>
<td></td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>14</td>
<td>$HM_t$</td>
<td>0.006 (0.02)</td>
<td>0.919</td>
<td>0.33 (0.85)</td>
<td>1.46 (0.83)</td>
</tr>
<tr>
<td>15</td>
<td>$\bar{R}_t$</td>
<td>-0.004 (0.62)</td>
<td>0.915</td>
<td>0.82 (0.51)</td>
<td>3.52 (0.47)</td>
</tr>
<tr>
<td>16</td>
<td>$HM_t$</td>
<td>0.012 (0.003)</td>
<td>0.924</td>
<td>1.53 (0.20)</td>
<td>6.38 (0.17)</td>
</tr>
<tr>
<td></td>
<td>$\bar{R}_t$</td>
<td>-0.033 (0.005)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

$^a$Breusch–Godfrey tests for serial correlation. The top pair of numbers is the F-form. The bottom pair is the (number of observations) X $R^2$ form which is distributed asymptotically as Chi-square. $P$-values are given in parentheses.

The results for investment and consumption do not provide quite as much support for the model. With regard to investment, lagged values of both model predictions and equity returns (each the sole additional regressor) had roughly the same predictive content. When current values of both variables were added,
Fig. 1. Empirical distribution of bootstrapped $t$-statistics.
both were significant. Thus, both the model and equity returns provide incremental information but neither dominated the other. In the consumption series, the same basic pattern emerges: model predictions and equity returns have similar explanatory power by themselves but both have incremental information.

Finally, it is worth noting that we also explored the behavior of an equity model without technology shocks. The implied belief shocks as well as the other endogenous variables were very similar to the two-shock model studied above. Regression results using these series were qualitatively similar. There is a straightforward explanation why the two models produce similar belief shocks and, subsequently, similar output. In the absence of technology shocks, belief shocks are determined by consumption growth and equity returns (see Eq. (2.16)). The variance of equity returns is large relative to the variance of consumption changes. Although adding technology shocks does influence the change in consumption and does add an additional term (the innovation to technology shocks) to the solution equations, the behavior of belief shocks is still determined by the high-variance equity returns.

4. Conclusion

The key idea in this paper is to use information from financial markets to identify the shocks in a model with self-fulfilling prophecies. In our framework, prices in financial markets and the behavior of the real variables in the economy jointly reflect the underlying belief shocks. Using actual returns from the financial markets and an estimate of the technology shock, we show how to determine the belief shock and the remaining variables in the model.

To test the model, we compare the predictions of the model to actual U.S. data. Specifically, we look at the incremental predictive power of the series over the past history of the variables. In all cases, the predictions from the model had explanatory power for U.S. time series over and above information contained in equity returns by themselves. Moreover, in some cases, the performance of the model predictions by themselves were clearly superior to the equity returns by themselves.

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11 A discussion of these results is available from the authors.
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