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SUNSPOTS, ANIMAL SPIRITS, AND ECONOMIC FLUCTUATIONS

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Multiple-equilibria macroeconomic models suggest that consumers' and investors' perceptions about the state of the economy may be important independent factors for business cycles. In this paper, we verify empirically the interrelations between waves of optimism and pessimism and subsequent economic fluctuations. We focus on the behavior of nonfundamental movements in the consumer sentiment index, as a proxy for consumers' sunspots, and in the business formation index, representing investors' animal spirits, around economic turning points. We find that bearish consumers and entrepreneurs were present before the onset of some U.S. economic downturns, sometimes even when the fundamentals were all very strong. In particular, our analysis shows that self-fulfilling pessimism may have played a nontrivial role in the 1969–1970, the 1973–1975, and the 1981–1982 recessions. The results are robust to a range of alternative linear and nonlinear specifications. Our evidence provides some empirical support for the role of nonfundamental rational expectations in economic fluctuations.

Keywords: Multiple Equilibria, Sunspots, Animal Spirits, Economic Fluctuations, Markov Switching Models

1. INTRODUCTION

Recently, there has been growing interest in dynamic general equilibrium models that exhibit indeterminacy and a continuum of stationary rational expectations equilibria.[1] In contrast to standard frameworks with a unique equilibrium, these models provide a theoretical justification of how shocks to agents' self-fulfilling beliefs can be an independent source of business-cycle fluctuations.[2] However, most of the research in this area is theoretical or quantitative in nature, leaving the empirical relevance of sunspots largely unexplored. This paper attempts to fill this gap by studying the role of sunspots empirically in the U.S. economy. Specifically, we examine the interrelations between waves of optimism and pessimism and subsequent aggregate fluctuations around economic turning points.

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The basic intuition for indeterminacy and sunspot equilibria to occur in this class of models can be understood as a coordination problem. Consider starting with a specific equilibrium trajectory of consumption or investment, and inquire whether a faster rate of accumulation can also be justified as an equilibrium. Suppose that a subset of agents becomes optimistic about the rate of return of an asset and decides to invest more in it. If there exist sufficiently strong strategic complementarities in the economy, then it is in the other agents' best interest to invest more in this asset as well [see Cooper and John (1988)].[3] As a result, agents' expectations of a higher rate of return are validated, which in turn causes an investment spurt without any change in economic fundamentals. We can repeat this argument to construct infinitely many equilibrium paths and, therefore, the original equilibrium is said to be indeterminate. Moreover, it is well known that there are many other mechanisms that can generate multiple equilibria in dynamic general equilibrium models, such as strong income effects, incomplete market participation, external increasing returns, and monopolistic competition, among others.

In this paper, we take an agnostic view on the exact channel through which agents' beliefs may affect economic activity. Instead, we focus on the fact that nonfundamental shifts in agents' expectations are self-fulfilling in these sunspot models, and examine the empirical importance of fluctuations in nonfundamental variables around the beginning and end of NBER-dated recessions and slowdowns.

The analysis begins by empirically modeling consumers' and investors' expectations. To measure consumers' expectations, we use the University of Michigan's Index of Consumer Sentiment, which is constructed on the basis of consumers' responses to survey questions regarding current and expected economic conditions. Figure 1 plots this index against NBER-dated recessions and slowdowns between

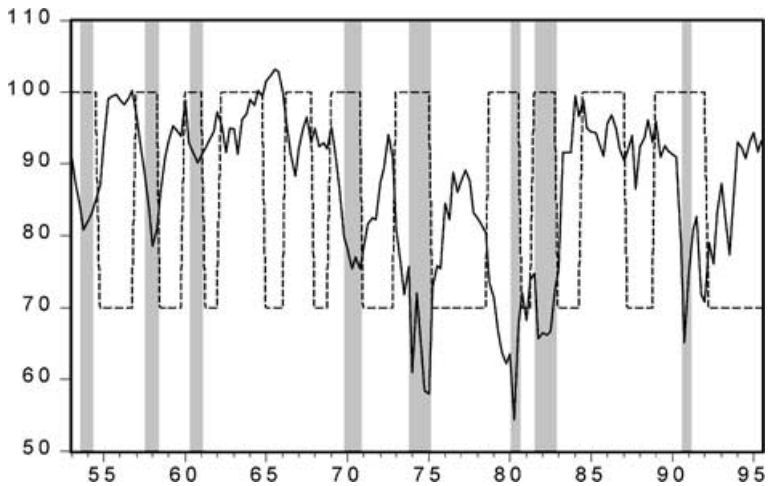


Figure 1. Consumer sentiment (—), NBER recessions (shaded areas) and slowdowns (- - -).

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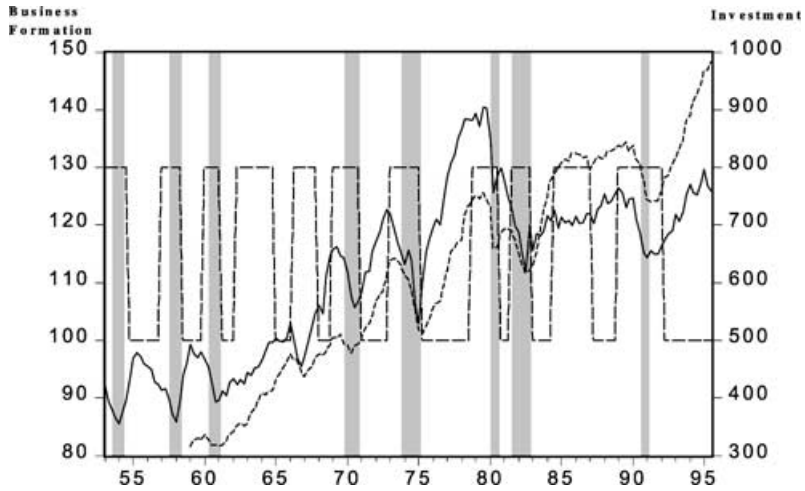


FIGURE 2. Business formation index (—), fixed investment (– – –), NBER recessions (shaded areas) and slowdowns (- - -).

1953:1 and 1995:3.[4] Notice that all recessions and many slowdowns are preceded by a decline in consumer sentiment. The Index of Net Business Formation is used to measure investors' expectations. Figure 2 illustrates that falling business formation precedes decreases in gross fixed investment in almost every economic downturn over the sample period. These two figures suggest that changes in consumer and investor confidence are related to subsequent business- and growth-cycle turning points.[5]

The next step is to extract nonfundamental idiosyncratic variations in consumer and investor expectations. One way found in the literature to formalize this is by estimating vector autoregressions (VAR's) including GDP, consumer sentiment index, and variables that reflect information on economic fundamentals.[6] For example, Fuhrer (1993) and Matsusaka and Sbordone (1995) model fundamentals using VAR systems with money supply, government spending, oil prices, sensitive material prices, interest rates, leading economic indicators and their components, among others, and interpret the residuals obtained from the consumer sentiment equation as sunspots. The idea underlying these studies is to verify whether consumer sentiment Granger-causes output, as measured by GDP or industrial production. Their findings are that consumer sentiment plays a nontrivial role in affecting current and future variations in aggregate activity even after controlling for economic fundamentals.[7]

In this paper, we use a similar approach. However, our analysis differs from the previous literature in two important respects. First, in addition to examining the effects of consumer sentiment, we also investigate nonfundamental shifts in investor expectations represented by the innovations to the business formation index. Second, and most important, the previous literature has concentrated on the average

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linear effect of consumer sentiment innovations on output. Nevertheless, variables that exhibit low power in explaining the linear long-run variance of output may be highly important in specific situations. Katona (1975) and Throop (1992) show that unusually large and unpredictable changes in consumer sentiment at particular historical episodes are important independent factors in determining consumption spending. Moreover, Fuhrer (1993) finds the largest errors in predicting sentiment around the NBER-dated turning points.[8] These results suggest that agents may react differently to changes in economic or financial variables, depending on their perceptions about the state of the economy. For example, agents may consider increases in interest rates as positive news if this occurs when expected inflation is high. On the other hand, if the economy is in a low-growth phase, high interest rates may have a negative effect on consumer sentiment.

Based on these considerations, our analysis focuses on cyclical variations in innovations to consumer sentiment and business formation around the beginning and end of each economic recession and slowdown in the post-Korean War U.S. economy. The idea behind this analysis is to capture potential asymmetric behavior across business-cycle phases, whose effects could be averaged out in a linear analysis of the whole sample data. Hence, this study sheds light on the role of sunspots in causing, intensifying, or not affecting specific historical economic downturns as dated by the NBER, in addition to their average linear effect on the economy.

To formally examine the role of self-fulfilling prophecies around economic turning points, we too obtain the residuals from the consumer sentiment and business formation equations combined with variables reflecting economic fundamentals in a VAR. However, we model consumer sentiment and business formation as following two-state Markov switching processes. The Markov states can be interpreted as consumers' or investors' perceptions about the economy, either pessimistic or optimistic. This is in the same line as the switching autoregressive conditional heteroskedastic (SWARCH) model proposed by Hamilton and Susmel (1994), and extensions of Hamilton (1989) to Markov switching VAR (MS-VAR).

We find that there is a "bad" state, which displays a low or negative mean, high volatility, and a shorter average duration. By contrast, the "good" state is characterized by a high or positive mean, low volatility, and a longer average duration. As we will see later, the bad state reflects agents' pessimism and high uncertainty associated with recessions and economic slowdowns, whereas the good state corresponds to periods of relative calmness and agents' optimism, which prevail mostly during economic expansions.[9]

The model yields estimated probabilities of the Markov states, which can be used to examine cyclical variations in the consumer sentiment and business formation innovations around turning points of recessions and slowdowns, as dated by the NBER. In particular, the lead–lag relationships between the estimated probabilities and business-cycle turning points indicate whether nonfundamental variations in consumers' and investors' perceptions of the economy were present before the onset of specific recessions or expansions, or if they just acted as a catalyst for other shocks. This analysis is corroborated by linear Granger causality tests.

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We study individually each of the slowdowns and recessions that were preceded by a substantial increase in the probabilities of consumers' and investors' pessimism, and examine the economic environment in which agents' perceptions about the economy were formed. Specifically, we study the behavior of variables such as sales, employment, personal income, and interest rates. Moreover, we contrast the probabilities of pessimism with subsequent changes in consumption and investment growth since these are the channels through which pessimism could have affected specific economic downturns. Our results suggest that even after controlling for the behavior of many variables reflecting economic fundamentals, self-fulfilling pessimism may have played an important independent role in the 1969–1970, the 1973–1975, and the 1981–1982 recessions.

We examine the robustness of this evidence by estimating alternative linear and nonlinear models, with different lag structures, and using many different additional variables capturing fundamental information. We find that the innovations to consumer sentiment and business formation continue to show the same cyclical patterns around economic turning points. Therefore, our results provide some empirical support for the class of macroeconomic models with multiple equilibria whereby consumers' sunspots and investors' animal spirits exert important independent influences on aggregate fluctuations.

The remainder of this paper is organized as follows. Section 2 describes the econometric model and Section 3 the estimation procedure. Section 4 presents the empirical results and Section 5 concludes.

2. MODEL

Many dynamic economic models postulate expectational relationships between currently observable variables and future variables. Given a mechanism that describes the expectation formation, the rational expectations (RE) hypothesis implies some restrictions on the statistical model. Let $\boldsymbol{y}_t$ be a $n \times 1$ vector containing the variables of interest, and $\boldsymbol{y}_t^*$ be the expectation of $\boldsymbol{y}_t$, which is formed using the information set I_{t-1}. Thus, we have

$$\boldsymbol{y}_t = \boldsymbol{y}_t^* + \boldsymbol{\varepsilon}_t, \tag{1}$$

where $\boldsymbol{\varepsilon}_t$ is the forecast error. Taking conditional expectations on both sides of (1), we obtain

$$\boldsymbol{y}_t^* = E[\boldsymbol{y}_t \mid I_{t-1}]. \tag{2}$$

The left-hand side of (2) can be interpreted as the subjective beliefs of economic agents, whereas the right-hand side is the objective expectation conditional on data available when the expectation was formed. Now, consider the following VAR:

$$\boldsymbol{y}_t = \boldsymbol{\mu} + \sum_{h=1}^{p} A_h \boldsymbol{y}_{t-h} + \boldsymbol{\varepsilon}_t, \tag{3}$$

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where A_h is the $n \times n$ parameter matrix for the hth lag of $\boldsymbol{y}_t$, and $\boldsymbol{\mu}$ is the $n \times 1$ vector of drift terms. In this framework, the RE hypothesis postulates that agents use past p-period observations of $\boldsymbol{y}_t$ to formulate their conditional expectations:

$$\boldsymbol{y}_t^* = \boldsymbol{\mu} + \sum_{h=1}^{p} A_h \boldsymbol{y}_{t-h}, \tag{4}$$

and it requires that the $n \times 1$ error terms $\boldsymbol{\varepsilon}_t$ satisfy three important properties.[10] First, they should have no systematic component, $E[\boldsymbol{\varepsilon}_t] = 0$. Second, the errors should be uncorrelated with the entire information available at the time the prediction is made; that is, $\boldsymbol{y}_t^*$ should completely summarize the information in I_{t-1}. Finally, since agents have full information, the VAR model should explain much of the variations in the variables with no significant serial correlation remaining in the estimated residuals, $E[\boldsymbol{\varepsilon}_t \boldsymbol{\varepsilon}_{t-h}] = 0, \forall\, h \neq 0$. The residuals from the estimated VAR then provide an approximation to the "innovations" in variables.

In the existing literature, consumers' expectations have been modeled as a VAR system including the consumer sentiment index and variables that reflect comprehensive information on economic fundamentals. The innovations to consumer sentiment have been interpreted as sunspots since they correspond to the part that cannot be explained by the information on fundamentals utilized. Most of these empirical studies assume a stable linear relationship relating sentiment to this set of publicly available information. Hence, the possibility that agents may react differently to a piece of economic information, depending on their perceptions about the stage of business cycles, is not taken into account.

To capture these potential asymmetric reactions, we specify agents' expectations as following Markov-switching processes.[11] Consider the following general formulation of the Markov-switching vector autoregressive (MS-VAR) model:

$$\boldsymbol{y}_t = \boldsymbol{\mu}_{s_t} + \sum_{h=1}^{p} A_h \boldsymbol{y}_{t-h} + \boldsymbol{\varepsilon}_t, \qquad \boldsymbol{\varepsilon}_t \mid s_t \sim N\left(0, \Omega_{s_t}\right), \qquad s_t = 0, 1, \tag{5}$$

where s_t is an unobservable first-order two-state Markov chain, μ_{s_t} is the state-dependent drift term, and Ω_{s_t} is the state-dependent covariance matrix. The drift term and the variance switch between two regimes representing changes in agents' expectations as functions of the state of the economy. These switches are governed by the transition probability matrix P with elements $p_{ij} = \text{pr}[s_t = j \mid s_{t-1} = i]$, where i denotes the ith column and j the jth row. Each column of P sums to one, so that $\mathbf{1}_2' P = \mathbf{1}_2'$, where $\mathbf{1}_2$ is a column vector of ones. The transition probability matrix is ergodic and irreducible, and unless each column of the transition matrix is equal to the egordic probabilities π, with $P\pi = \pi$, the Markov chain is serially correlated.

We assume that $\varepsilon_t \mid s_t$ is heteroskedastic as its conditional variance Ω_{s_t} switches between the two Markov regimes. Although ε_t is assumed to be serially uncorrelated, the conditional squared residual (Ω_{s_t}) can be serially correlated since the

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Markov variable s_t itself is serially correlated. This is in the same line as the autoregressive conditional heteroskedasticity (ARCH) model proposed by Engle (1982) and generalized by Engle and Bollerslev (1986), and the switching ARCH (SWARCH) model of Hamilton and Susmel (1994).

The first-order assumption of the Markov chain implies that all the relevant information for predicting future states is included in the current state, i.e., $\text{pr}[s_t \mid I_{t-1}, s_{t-1}, s_{t-2}, \ldots] = \text{pr}[s_t \mid s_{t-1}]$. In this case, agents use all information available at time $t-1$ to form expectations about future economic conditions and to make inferences about the unobserved state of the economy. Here again, the innovations in the MS-VAR correspond to the part that cannot be predicted using available information about fundamentals, and are consistent with the postulates of rational expectations. We use this formulation to capture potential asymmetric behavior across business-cycle phases, whose effects could be averaged out in a linear analysis of the entire sample. The advantage of this modeling approach over some of the alternatives is that its estimation yields filtered probabilities of the Markov states, which can be used to analyze the dynamics of agents' expectations around economic turning points.

3. EMPIRICAL PROCEDURE

The analysis starts by measuring consumers' and investors' expectations. We use, respectively, the Index of Consumer Sentiment from the Survey Research Center at the University of Michigan, and the Index of Net Business Formation at the quarterly frequency, from 1953:1 to 1995:3.[12] The next step is to extract nonfundamental idiosyncratic variations in consumers' and investors' expectations using the MS-VAR framework. The information set comprises forward-looking variables that reflect consumers' and investors' perceptions about economic fundamentals and the state of the economy, as well as variables that have been shown in the literature to be good predictors of GDP, consumer sentiment, and business formation.

The initial list of candidates includes over 50 series. At first, these variables are ranked according to their bivariate cross correlation with output, consumer sentiment, and business formation, and their ability to Granger-cause each of these three series. The top variables are[13]: the 3-month, 1-year, and 10-year T-Bill rates, interest-rate spread, misery index,[14] inflation rate (CPI and PPI growth), hours worked and number of employees in nonagricultural payrolls, manufacturing and trade sales, unemployment rate, average weekly insured unemployment rate, average duration of unemployment in weeks, sales of retail stores, personal income, consumer installment credit outstanding, net change in consumer installment credit, money supply (M2), government spending, stock prices (S&P500), commercial and industrial loans outstanding, net change in business loans, corporate domestic profits after tax to income, price to unit labor cost, corporate net cash flow, Stock and Watson's (1989, 1991) leading economic indicator (SW); and some of the components of the Composite Leading Indicator constructed by the

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Conference Board—manufacturer's new orders, housing permits, manufacturer's unfilled orders, vendor performance, unemployment insurance initial claims, and index of sensitive material prices.[15] Notice that variables such as the leading economic indicators, interest-rate spreads, or stock prices encompass the effects of a number of different predictors, and have been found in the literature to be good predictors of business-cycle turning points.[16]

The underlying goal of the subsequent analysis is twofold. First, we want to obtain the best forecasting model for output, sentiment, and business formation. This would simultaneously yield residuals that are the closest approximations to innovations. Second, we want to test the robustness of the results to a range of different combination of variables, and to alternative linear and nonlinear model specifications. For that, we examine over 500 linear and MS-VAR systems to assess the marginal predictive content of the above variables and to rank the best forecasting models.

The VAR system allows us to analyze the role of sentiment and business formation in causing subsequent fluctuations in GDP. In particular, if sentiment and business formation forecast output fluctuations even after controlling for fundamentals and other good predictors of output, then there is a possibility that nonfundamental variations in these variables cause output fluctuations. To verify this, we introduce into the VAR model a sequence of the above-mentioned candidate variables that might have been used by consumers and investors to form their expectations about future economic conditions. The procedure is as follows: We first construct a baseline unrestricted VAR—a three-variable system with consumer sentiment, business formation, and GDP. Then we add one variable at a time and examine its marginal predictive content at lags 1 to 5 in these four-variable VAR's, using Akaike Information Criterion, Schwartz Criterion, likelihood ratio tests, F-statistics, t-statistics, and adjusted coefficient of determinations. We repeat the exercise for five-variable VAR systems at lags 1 to 4, keeping in mind the trade-off between the optimal number of lags and a reasonable degree of freedom.[17] Finally, each of these resulting VAR's is reestimated, but now allowing the equations for consumer sentiment and business formation to switch regimes according to two-state Markov processes.[18]

Next, we classify the models that best forecast GDP, consumer sentiment, and business formation using these frameworks. Most important, we rank the models in which the residuals from the consumer sentiment and business formation equations display the lowest offset correlations with GDP, sentiment, and business formation. It turns out that the top two specifications are a four-variable four-lag system, composed of consumer sentiment, business formation, GDP, and either the interest rate (3-month Treasury Bill) or the SW leading economic indicator. Serial correlation of the residuals is verified using the Lagrange multiplier test and Ljung–Box Q-statistics. These tests fail to reject the null of no serial correlation, indicating that the system is an adequate approximation of the dynamics of the variables being modeled.

Finally, we study whether idiosyncratic variations in sentiment and business formation are correlated with current or subsequent recessions and slowdowns,

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as dated by the NBER. In particular, the top two models are estimated, allowing the drift terms and conditional variances of the consumer sentiment and business formation equations to switch regimes following two independent Markov processes[19]:

$$y_t^c = \mu_{s_t}^c + a_k^c(L)\boldsymbol{y_t} + \varepsilon_t^c, \qquad \varepsilon_t^c \mid s_t \sim N\left(0, \Omega_{s_t}^c\right), \qquad s_t = 0, 1, \tag{6}$$

$$y_t^b = \mu_{s_t^*}^b + a_k^b(L)\boldsymbol{y_t} + \varepsilon_t^b, \qquad \varepsilon_t^b \mid s_t^* \sim N\left(0, \Omega_{s_t^*}^b\right), \qquad s_t^* = 0, 1, \tag{7}$$

where $\boldsymbol{y_t}$ is the vector of all four endogenous variables in the model, y_t^c is the consumer sentiment index, y_t^b is the business formation index, and $a_k^c(L)$ and $a_k^b(L)$ are lag polynomials for the kth variable in the sentiment and business formation equations, respectively. The drift terms for consumer sentiment and business formation, $\mu_{s_t}^c$ and $\mu_{s_t^*}^b$, as well as the volatility of the innovations, Ω_{s_t} and $\Omega_{s_t^*}$, switch between the Markov states, representing agents' pessimism or optimism.[20] We assume that consumer sentiment follows a Markov process s_t, while business formation follows a distinct Markov process s_t^*. This specification allows consumers' and investors' expectations to switch nonsynchronously over time, although it does not preclude them from switching simultaneously. Hence, it can provide more insight into the analysis of the idiosyncratic factors that may lead to waves of pessimism among consumers and entrepreneurs.[21]

The MS-VAR is estimated using a combination of the Dempster et al. (1977) expectation maximization (EM) algorithm with Hamilton's filter. At each iteration, the EM algorithm estimates the probabilities of the unobserved states (expectation step), and an estimate of the model parameters is obtained as the solution to the first-order conditions of the likelihood function (maximization step). These parameters are then used to update the filtered probabilities of the states. The estimation procedure and derivation of the likelihood function are described by Hamilton (1994).

The model estimation yields inferences about the probabilities of the Markov states, which are used to examine the linkages between consumers' and investors' perceptions about the state of the economy and the NBER-dated turning points. Notice that the Markov switching terms, after estimating the MS-VAR model, can be collected into

$$\omega_t^c = \mu_{s_t}^c + \varepsilon_t^c, \qquad \omega_t^c \mid s_t \sim N\left(\mu_{s_t}^c, \Psi_{s_t}^c\right), \qquad s_t = 0, 1, \tag{8}$$

$$\omega_t^b = \mu_{s_t^*}^b + \varepsilon_t^b, \qquad \omega_t^b \mid s_t^* \sim N\left(\mu_{s_t^*}^b, \Psi_{s_t^*}^b\right), \qquad s_t^* = 0, 1. \tag{9}$$

The estimated Markov probabilities of sentiment and business formation refer, respectively, to the dynamics of the disturbance terms, ω_t^c and ω_t^b. If these probabilities are not related to different stages of the business cycle, then this supports the hypothesis that agents' self-fulfilling beliefs, based on nonfundamentals, do not affect economic activity.

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4. EMPIRICAL RESULTS

We obtain sentiment and business formation innovations from the two selected MS-VAR(4) models, and find that they yield highly correlated residuals—around 92% for sentiment and 90% for business formation. These innovations are plotted in Figure 3. In addition, we find that the filtered probabilities of the Markov states are very similar in both specifications, especially around economic turning points (Figure 4). Hence, we focus our empirical analysis on the MS-VAR model with interest rate as the fourth variable because it has a longer sample than the SW leading indicator, thereby including two additional recessions and two slowdowns.[22]

The maximum log likelihood estimates of the chosen MS-VAR are shown in Table 1. For both consumer sentiment and business formation, the Markov state 0

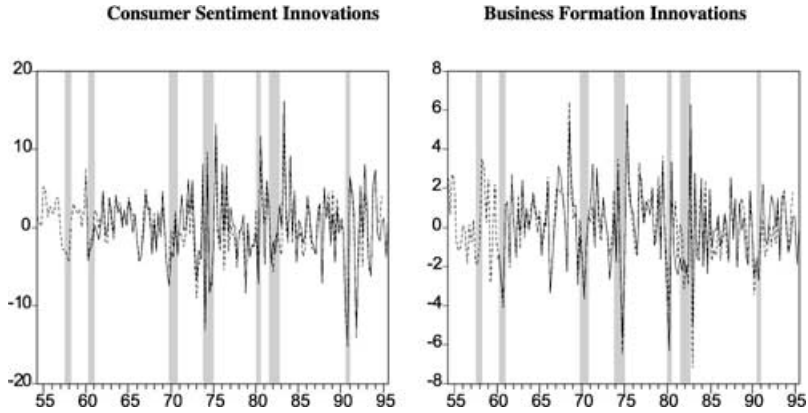


FIGURE 3. Consumer sentiment and business formation innovations from top two MS-VAR(4) models and NBER recessions (shaded areas).

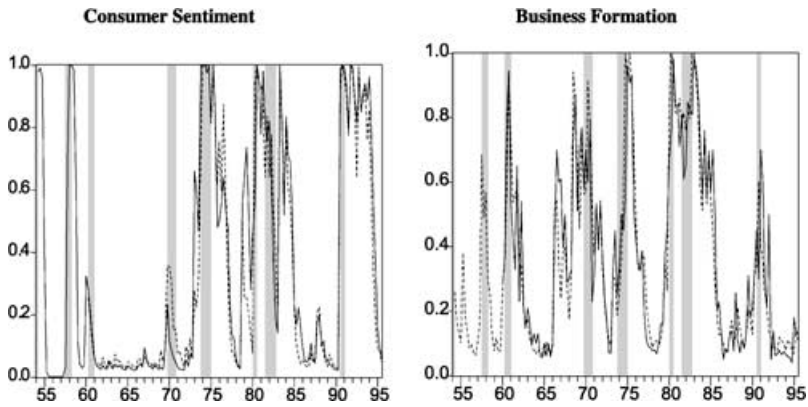


FIGURE 4. Filtered probabilities of pessimistic state from top two MS-VAR(4) models and NBER recessions (shaded areas).

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Table 1. Maximum likelihood estimates[a]

Variable	μ_0	μ_1	σ_0^2	σ_1^2	p_{00}	p_{11}	Sum of the autoregressive coefficients
Sentiment	78.28	92.12	23.21	3.88	0.89	0.94	
(level)	(2.96)	(1.93)	(3.17)	(1.06)	(0.07)	(0.03)	−2.16
Business formation	−0.38	0.23	7.66	2.10	0.90	0.94	
(log first difference)	(0.23)	(0.16)	(2.31)	(0.62)	(0.07)	(0.04)	−0.98
GDP	0.68	—	0.87	—	—	—	
(log first difference)	(0.65)		(0.24)				−0.63
3-Month T-Bill rate	0.06	—	0.48	—	—	—	
(changes)	(0.55)		(0.11)				0.86

[a]Asymptotic standard errors in parentheses.

exhibits a low or negative intercept, high volatility, and a shorter average duration, whereas state 1 has a high or positive intercept, low volatility, and a longer average duration. These results suggest that periods of falling business formation and consumer confidence (pessimistic state) are associated with high volatility or greater uncertainty, whereas periods of rising business formation and consumer confidence (optimistic state) are associated with lower volatility.

The analysis focuses on the probabilities of pessimism (state 0) around economic turning points.[23] However, we are interested in studying not only recessions and expansions, but also periods of low and high growth in output, as dated by the NBER. The analysis of both economic contractions and slowdowns should encompass all phases in which the economy exhibits "weak" fundamentals. The dynamics of the probabilities of pessimism around business- and growth-cycle turning points may shed light on the role of self-fulfilling prophecies in subsequent economic fluctuations.

In the sample used, there are 10 slowdowns and 7 recessions. Empirical observation indicates that economic slowdowns are generally more frequent and precede contractions. Sometimes the economy enters a low-growth phase, but no recession follows, as in 1951–1952, 1962–1964, 1966–1967, and 1984–1986. However, with the exception of the 1981–1982 recession, each of the other six recessions was preceded by a low-growth phase. As discussed later, we find interesting correlations between waves of pessimism from consumers and entrepreneurs and the unusual 1981 recession.

Figures 5 and 6 show the filtered probabilities of the pessimistic state for consumers and investors, and NBER-dated recessions and slowdowns. The economic fluctuation pattern underlying these probabilities is remarkable. Probabilities of consumer pessimism generally rise right before or at the beginning of economic slowdowns and recessions, although during the latter the increases are more abrupt. The same feature is also found in business formation, with the pessimistic state occurring around recessions and slowdowns.

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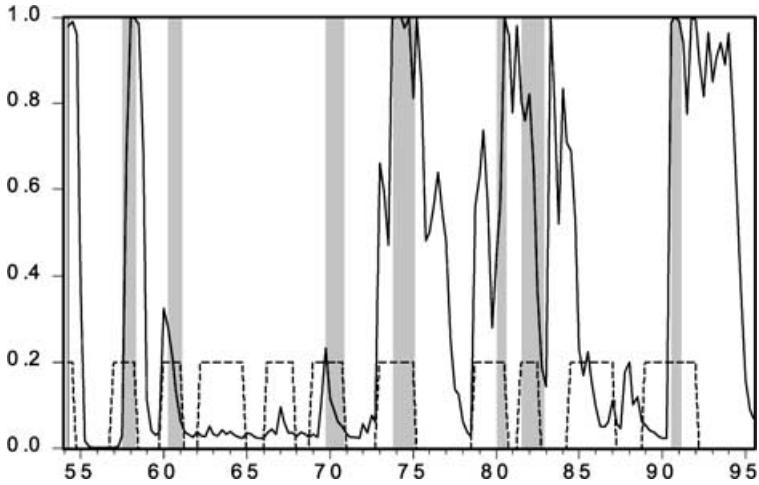


FIGURE 5. Filtered probabilities of consumers' pessimism (—), NBER recessions (shaded areas), and slowdowns (- - -).

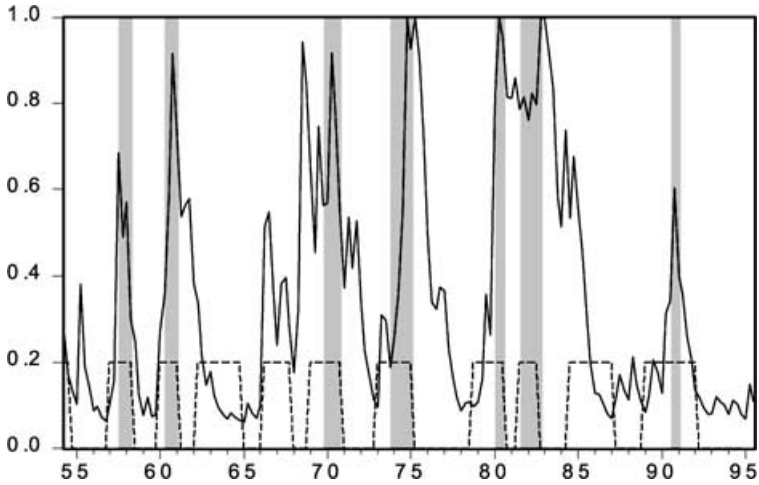


FIGURE 6. Filtered probabilities of investors' pessimism (—), NBER recessions (shaded areas), and slowdowns (- - -).

As seen in Figure 5, increases in the probabilities of consumers' pessimism were less persistent and less responsive to economic recessions and slowdowns in the first half of the sample. In fact, a general optimism seemed to have prevailed in the 1950s and 1960s. During the oil crisis in 1973 and thereafter, however, consumer sentiment was much more reactive to uncertainty about the future of the economy. In particular, some slowdowns and all recessions subsequently were

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associated with higher probabilities of the pessimistic state. Furthermore, waves of pessimism prevailed for a while even after the end of economic downturns.

Tables 2 and 3 summarize the lead–lag relationships between filtered probabilities of waves of consumers' pessimism with recession and slowdown turning points (peaks and highs).[24] The probabilities of pessimism preceded the 1973–1975 and the 1981–1982 recessions, were coincident with the 1957 and 1990 recessions, and lagged the 1980 recession (Table 2). With respect to low-growth phases, these probabilities lagged the 1956–1958 and 1989–1992 slowdowns, were coincident with the 1973–1975 and 1978–1980 slowdowns, and preceded the 1984–1987 low-growth phase (Table 3). The interesting economic downturns for our analysis seem to be the 1973–1975 and the 1981–1982 recessions, and the 1984–1987 slowdown because they were preceded by an increase in the probabilities of pessimism three, four, and two quarters before their turning points, respectively. That is, since

Table 2. Peak turning-point signals of business cycles (NBER)[a]

Turning point	Consumer pessimism	Investor pessimism	Low consumption state	Low investment state
1957:3	0	0	—	—
1960:2	—	+1	+1	**−1**
1969:4	—	**−5**	—	0
1973:4	**−3**	+3	0	+1
1980:1	+2	0	0	+1
1981:3	**−4**	**−6**	**−6**	+1
1990:3	0	0	**−6**	**−1**

Source: First column, Survey of Current Business, December 1995.
[a]The (+) and (−) signs refer to lags and leads, respectively.

Table 3. High turning-point signals of growth cycles (NBER)[a]

Turning point	Consumer pessimism	Investor pessimism	Low consumption state	Low investment state
1957:1	+2	+2	—	—
1960:1	—	0	+2	0
1962:2	—	**−2**	—	—
1966:2	—	0	—	0
1969:1	—	−2	—	+3
1973:1	0	+6	+3	+4
1978:4	0	+5	+5	+5
1984:3	**−2**	**−1**	—	—
1989:1	+6	+6	0	+4

Source: First column, NBER.
[a]The (+) and (−) signs refer to lags and leads, respectively.

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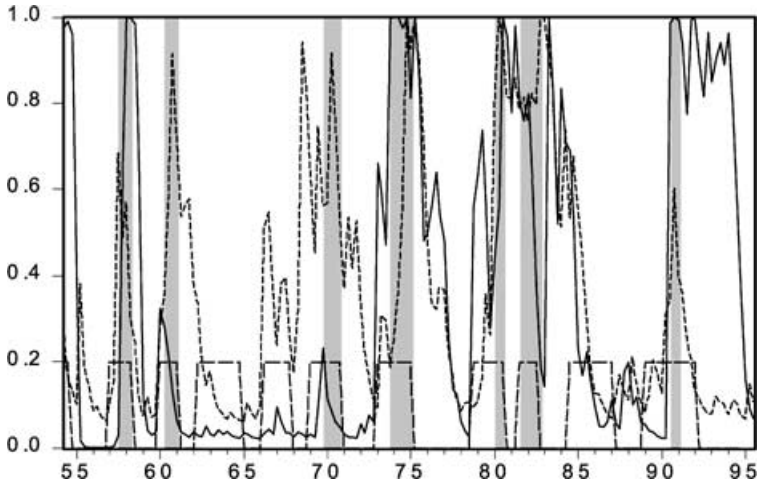


FIGURE 7. Filtered probabilities of consumers' (—) and investors' pessimism (– – –), NBER recessions (shaded areas), and slowdowns (- - -).

consumer pessimism was present before the onset of these events, this is at least one potential causal factor of these economic downturns.

Figure 6 shows the filtered probabilities of the pessimistic state for business formation against NBER-dated recessions and slowdowns. The probabilities of pessimism for entrepreneurs, which can be interpreted as animal spirits, are more reactive to both slowdowns and recessions than the probabilities of consumer pessimism. They responded to all 7 recessions and 9 out of 10 slowdowns in the economy. As reported in Tables 2 and 3, the probabilities of pessimism for entrepreneurs preceded the 1962–1965 slowdown, the 1969–1970 slowdown and recession, the 1981–1982 recession, and the 1984–1987 slowdown. Again, these are the economic downturns that could have been caused by entrepreneurs' pessimism.

Figure 7 contrasts the probabilities of consumers' and investors' pessimism. These probabilities are highly correlated, although investors' pessimism rises in both recessions and slowdowns, whereas consumers' pessimism is more related to economic recessions.

4.1. Economic Downturns

The estimated probabilities from the MS-VAR model can be used as filtering rules to analyze the role of nonfundamental variations in consumer sentiment and business formation around economic turning points.[25] In particular, we can argue that

(a) If the peak of the probabilities of pessimism lagged or coincided with the onset of a recession or slowdown, it is possible that waves of pessimism may have intensified

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or extended the economic downturn. However, they could not have been an original cause since they did not anticipate it.

(b) If the peak of the probabilities of pessimism preceded a recession or slowdown, there is a possibility that self-fulfilling pessimism was a source of the economic downturn as long as the fundamentals were strong. On the other hand, if pessimism was associated with weak fundamentals such as falling income, higher unemployment, or lower borrowing power, then pessimism may have been a natural consequence and not an independent cause. This is generally the case during slowdowns that turned into recessions. In this case, if the probabilities of pessimism rose after the beginning of the slowdown, pessimism may have triggered the subsequent recession, but not the low-growth phase.

We study individually each of the slowdowns and recessions that was preceded by substantial increases in the filtered probabilities of consumers' and investors' pessimism, that is, the cases described in item (b). We analyze the economic environment in which consumers' and entrepreneurs' perceptions about the economy were formed. Specifically, we examine the behavior of variables such as sales, employment, interest rates, and personal income.

In addition, we contrast the probabilities of pessimism with subsequent changes in consumption and investment growth since these are the channels through which pessimism could have affected these economic downturns.[26] For that, we fit a univariate AR(1) two-state Markov-switching model individually for consumption growth and investment growth.[27] The two Markov states for consumption and investment refer to low- and high-growth phases. The filtered probabilities of low consumption or investment growth are then compared to the probabilities of consumer and investor pessimism (Figures 8 and 9). The transmission mechanism to

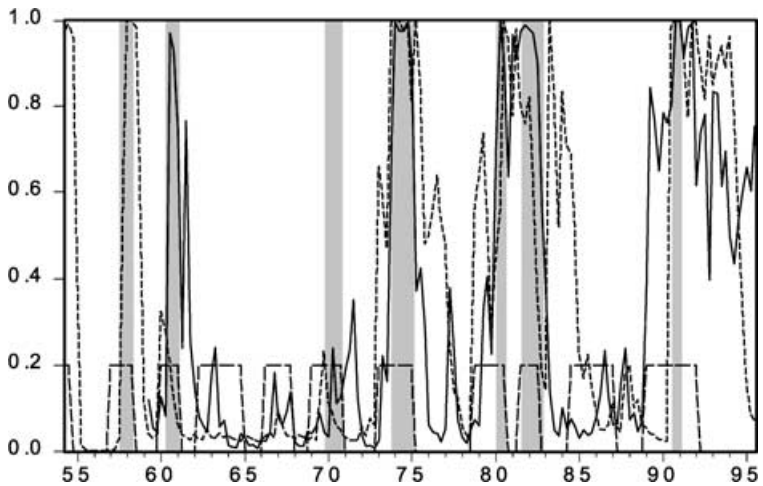


Figure 8. Filtered probabilities of low-consumption growth state (—): MS-AR(1) on consumer growth, filtered probabilities of consumers' pessimism (– – –), NBER recessions (shaded areas), and slowdowns (- - -).

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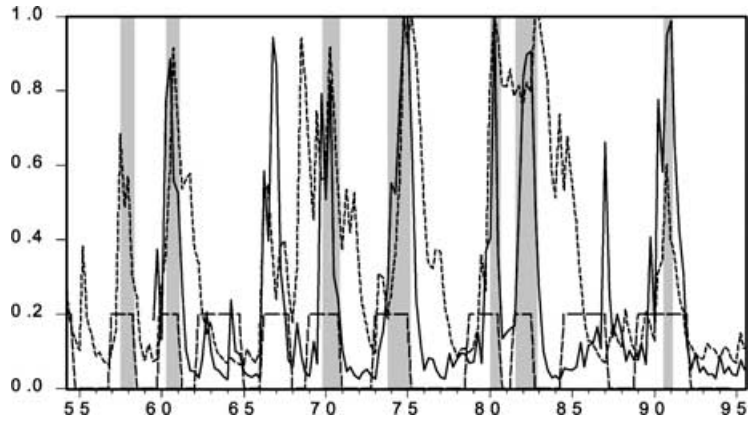


FIGURE 9. Filtered probabilities of low investment growth state (—): MS-AR(1) on investment growth, filtered probabilities of investors' pessimism (– – –), NBER recessions (shaded areas), and slowdowns (- - -).

consumption and investment is further investigated using Granger causality tests for the whole sample and for subperiods around economic turning points. Tables 4 to 6 report whether (a) consumers' sentiment (the index itself) or consumers' pessimism [the residuals from equation (6)] does not Granger-cause consumption growth; (b) business formation (the index itself) or investors' pessimism [the residuals from equation (7)] does not Granger-cause investment growth.[28] It is worth mentioning that when the entire sample is examined, agents' pessimism does not Granger-cause consumption or investment growth. However, analysis of particular economic downturns using subperiods yields statistically significant results for this test, uncovering important relationships around turning points.

In our sample, five economic downturns were preceded by agents' pessimism. The 1973 recession was anteceded by consumers' pessimism, while the 1962 slowdown and the 1969 slowdown and recession were preceded by investors' pessimism. The two most intriguing economic downturns were the 1981 recession and the 1984 slowdown since waves of pessimism from both consumers and investors were present before their onset. In addition to these economic downturns, we also study the role of consumer sentiment in the 1990 recession in order to verify the popular claim that sentiment played an important role in causing it.

4.2. Consumer Sentiment

4.2.1. The 1973 recession. This recession started in the last quarter of 1973, three quarters after the beginning of a low-growth phase associated with the hike of oil prices. The probabilities of pessimism rose in the beginning of the 1973 slowdown, and remained high during and after the subsequent recession in 1973–1975. This may indicate that the unprecedented pessimism and uncertainty that consumers were facing during this low-growth period could have intensified and

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Table 4. Transmission channels: Granger causality—full sample and around turning points (*P*-value %)—1973 recession[a]

Time period	Consumers' sentiment ⇒ consumption growth	Consumers' pessimism ⇒ consumption growth	Business formation ⇒ investment growth	Investors' pessimism ⇒ investment growth
1959:2–1995:4	36.72	**68.68**		
Lag 4	0.03	**42.26**	0.25	**1.79**
1972:1–1977:3	95.72	**5.70**		
Lag 4	5.16	**1.21**	30.35	**14.29**

[a]The second and third rows of columns 2 and 3 in this and Tables 5 and 6 have two entries: The top one refers to the test applied to consumption of nondurables and services, while the bottom one to consumption of durable goods. Tables 4–6 report *p*-values in percentage terms of Granger causality tests using full sample and around turning points of some U.S. economic downturns. For example, the second row, second column of this table indicates that the test rejects the null that consumers' pessimism [the residuals from equation (6)] does not Granger-cause consumption of nondurables and services at the 5.7% significance level (top entry), and consumption of durable goods at the 1.21% significance level (bottom entry), with four lags.

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Table 5. Transmission channels: Granger causality–full sample and around turning points (P-value %)—1969 slowdown and recession[a]

Time period	Consumers' sentiment ⇒ consumption growth	Consumers' pessimism ⇒ consumption growth	Business formation ⇒ investment growth	Investors' pessimism ⇒ investment growth
1959:2–1995:4	0.75	**59.21**		
Lag 1	1.21	**11.85**	0.001	**2.50**
1967:2–1972:1	34.10	**11.27**		
Lag 1	92.12	**56.26**	2.89	**5.49**

[a] See note in Table 4.

Table 6. Transmission channels: Granger causality—full sample and around turning points (P-value %)—1981 recession[a]

Time period	Consumers' sentiment ⇒ consumption growth	Consumers' pessimism ⇒ consumption growth	Business formation ⇒ investment growth	Investors' pessimism ⇒ investment growth
1959:2–1995:4	9.32	**68.49**		
Lag 2	0.44	**22.45**	0.01	**4.39**
1980:4–1986:1	46.44	**2.97**		
Lag 2	14.79	**24.73**	45.95	**63.18**

[a] See note in Table 4.

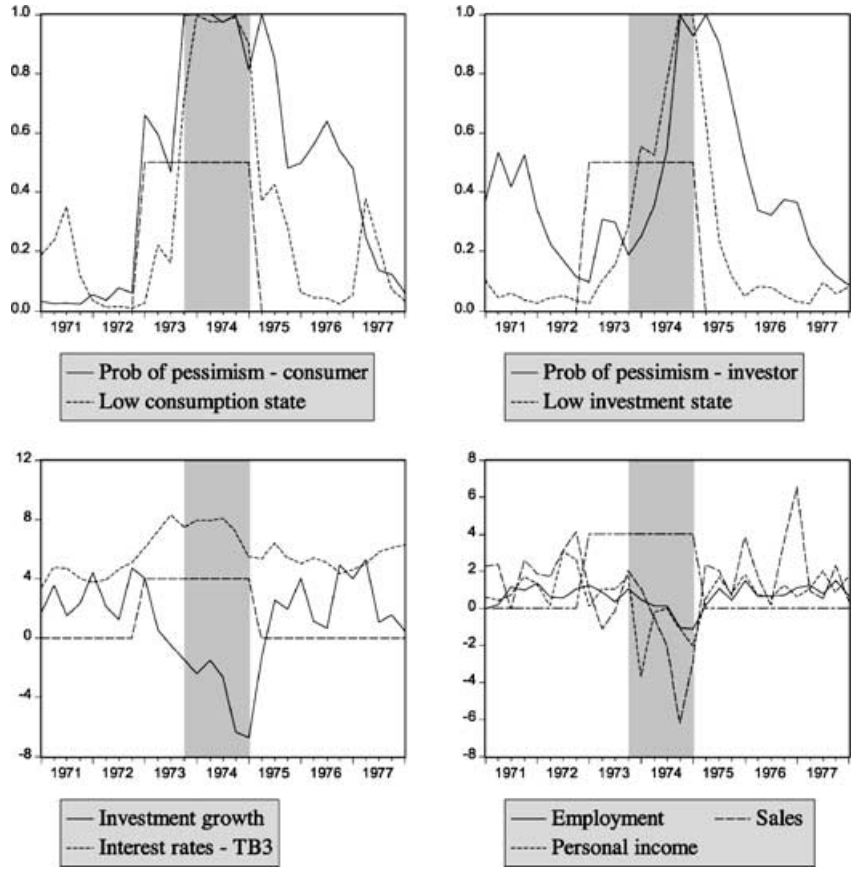


Figure 10. The 1973 recession: Probabilities of consumers' and investors' pessimism, low consumption and investment growth states, investment growth, 3-month T-Bill rate, growth rates of employment, personal income, and sales—NBER recessions (shaded areas) and slowdowns (- - -).

even caused the recession. Figure 10 shows that a low-consumption-growth phase followed the probabilities of pessimism three quarters later (Table 2), with its peak coinciding with the beginning of the recession. At the same time, growth in personal income and employment were both rising before the recession. Therefore, the decrease in consumption growth cannot be attributed to falling income and high unemployment. In fact, since waves of pessimism were present before the 1973–1975 recession, they could have turned the economic slowdown into this more intense recession. This evidence is further examined using linear Granger causality tests, as shown in Table 4. The test rejects the null that consumers' pessimism did not Granger-cause consumption growth of nondurables and services at the 5.7% significance level. Notice that although this is true for the period around

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this economic recession, the null hypothesis cannot be rejected at the 68.68% significance level when the test is applied to the entire sample. This result illustrates how linear analysis of the full sample can average out the dynamics of the economy around economic turning points.

4.3. Business Formation

4.3.1. The 1962 slowdown. According to the NBER dating, the 1962–1965 slowdown started in the second quarter of 1962. The probabilities of pessimism from entrepreneurs rose during the previous recession in 1960 and fell very slowly, overlapping with the following slowdown in 1962. However, investment growth was not affected by this persistence in entrepreneurs' pessimism, as shown by the filtered probabilities of low investment growth in Figure 11 and Table 3. Therefore,

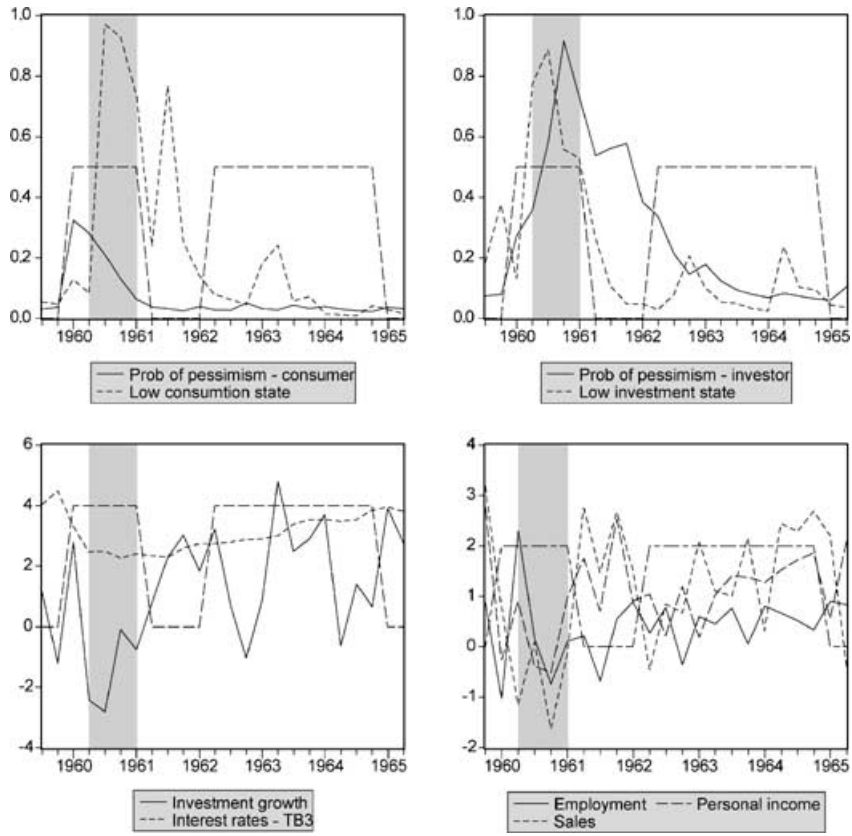


Figure 11. The 1962 slowdown: Probabilities of consumers' and investors' pessimism, low consumption and investment growth states, investment growth, 3-month T-Bill rate, growth rates of employment, personal income, and sales—NBER recessions (shaded areas) and slowdowns (- - -).

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the channel through which investors' pessimism could have affected the economy was not present in this economic downturn.

4.3.2. The 1969 slowdown and recession. The economy entered a low-growth phase in the first quarter of 1969, which turned into a recession in the fourth quarter of that year. In 1968, the economy was functioning at a normal pace, with sales, personal income, and industrial production all growing above average. In addition, interest rates were considerably lower, and investment growth was higher. The probabilities of entrepreneurs' pessimism started rising in 1968 and peaked two quarters before the onset of this economic slowdown and, therefore, five quarters before the beginning of the 1969 recession (Figure 12 and Tables 2 and 3). The probabilities of low investment growth followed the probabilities of investors' pessimism, peaking at the beginning of the subsequent recession (Table 3). As

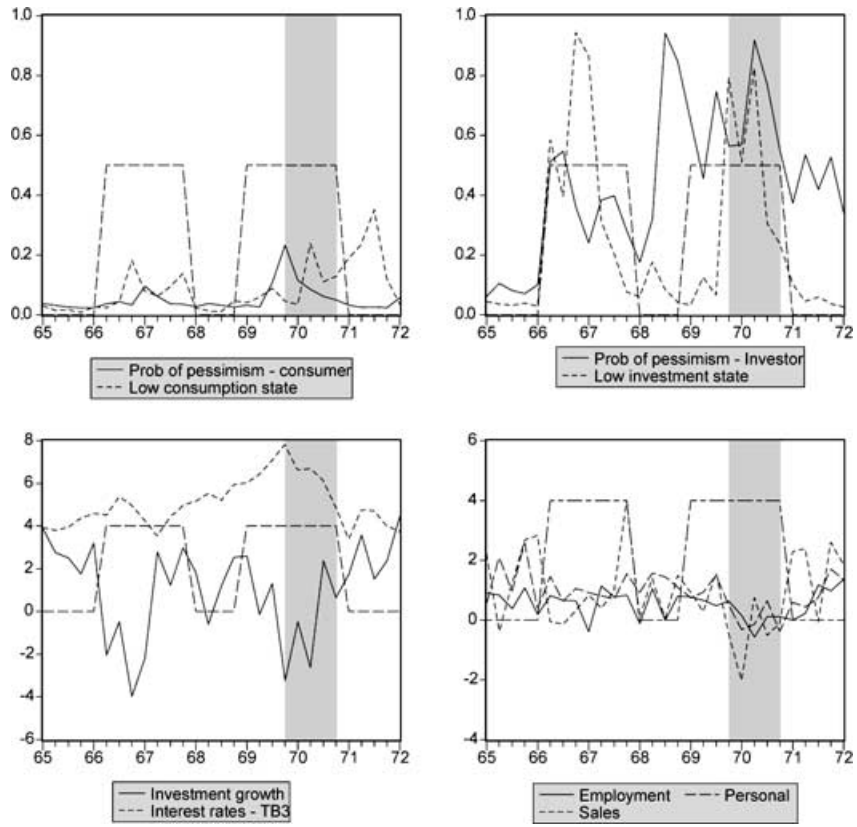


Figure 12. The 1969 slowdown and recession: Probabilities of consumers' and investors' pessimism, low consumption and investment growth states, investment growth, 3-month T-Bill rate, growth rates of employment, personal income, and sales—NBER recessions (shaded areas) and slowdowns (- - -).

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shown by the probabilities of pessimism, entrepreneurs were uncertain about the state of the economy and were not prone to open new businesses in spite of positive signals from fundamental variables. Hence, although entrepreneurs' pessimism may not have caused the economic slowdown in 1969, it may have triggered the following 1969 recession. Table 5 shows that, for the period around this economic downturn, the null that investors' pessimism did not Granger-cause investment growth is rejected at the 5.49% significance level.

4.4. Consumer Sentiment and Business Formation

4.4.1. The 1981 recession. This recession is the only one that was not preceded by an economic slowdown, as discussed earlier. However, the three years before this recession were marked by a slowdown and a short subsequent recession. In fact, the 1978–1980 slowdown culminated in a recession, which the NBER declared to have ended in the third quarter of 1980. After that, the economy was then in a recovery pace, with a steep growth in personal income and employment (Figure 13). Furthermore, interest rates dropped rapidly during 1981, after having reached their highest level in the whole sample at the end of the 1980 recession.

Even though the fundamentals were giving positive signals, both consumers and entrepreneurs were still very uncertain about the economic recovery. Consumer confidence did not rise during this economic recovery (Figure 1), perhaps as a lingering effect of the recent bad times. Moreover, the probabilities of consumer pessimism based on nonfundamentals remained at high levels after the end of the 1980 recession (Figure 13). During that period, consumption growth closely followed the probabilities of pessimism; that is, increases in the probabilities of pessimism were associated with subsequent increases in the probabilities of low consumption growth a couple of months later (Table 2). The same pattern was observed in entrepreneurs' pessimism between the 1980–1981 recession and the 1981–1982 recession. However, investment switched to a high-growth phase in the period before the 1981 recession. This indicates that there is a possibility of occurrence of self-fulfilling prophecies from the consumers' side—but not from the investors' side—as a cause of the 1981 recession, which started just one year after the end of the 1980 recession.

Linear Granger causality tests support this evidence. Table 6 reports that, for the period between the end of the 1980 recession and the 1984 slowdown, the null that consumers' pessimism did not Granger-cause consumption growth of nondurables and services is rejected at the 2.97% significance level. Here again, if the full sample is used, this behavior around turning points is average out, and the test cannot reject the null at the 68.49% significance level. Finally, notice that the null that investors' pessimism did not Granger-cause investment growth during the subperiod cannot be rejected at the 63.18% significance level.

4.4.2. The 1984 slowdown. The 1984 slowdown was preceded by a period of great uncertainty and pessimism from both consumers and entrepreneurs not

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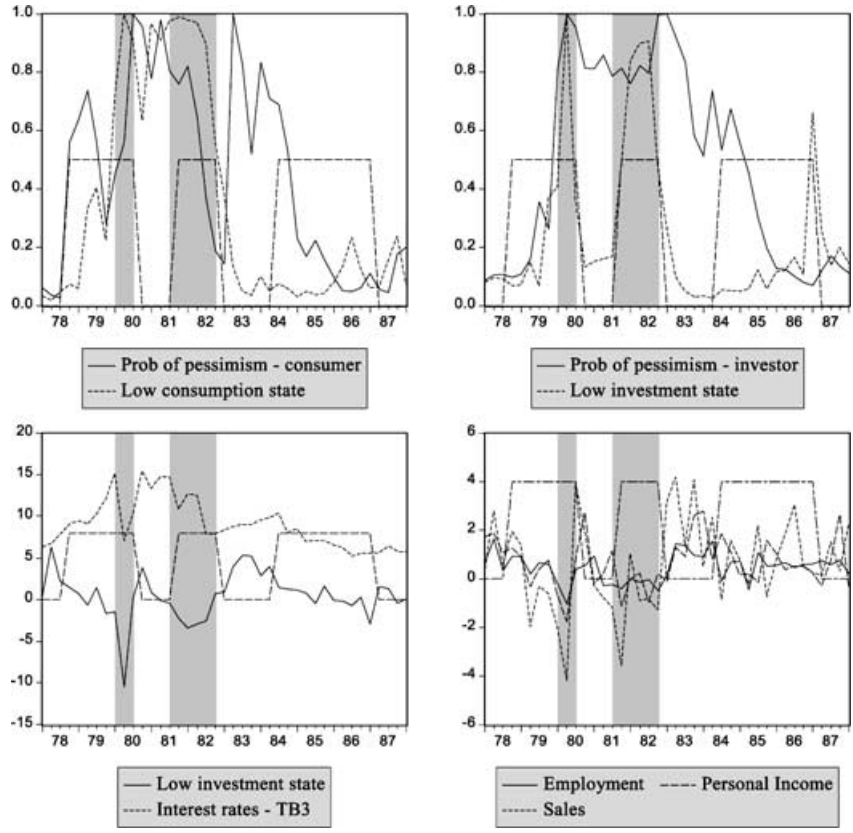


Figure 13. The 1981 recession and the 1984 slowdown: Probabilities of consumers' and investors' pessimism, low consumption and investment growth states, investment growth, 3-month T-Bill rate, growth rates of employment, personal income, and sales—NBER recessions (shaded areas) and slowdowns (- - -).

accounted for by fundamentals. After consecutive periods of weak economic performance, comprising the 1979–1980 slowdown, the 1980–1981 recession and again another recession in 1981–1982, the probabilities of pessimism indicate that agents were skeptical about the ensuing recovery (Figure 13). In fact, the probabilities of waves of pessimism from entrepreneurs dipped at the end of the 1981 recession, only to immediately rose to high levels and remained there until the middle of the 1984 slowdown. This pessimism persisted even though personal income and employment were in a positive growth phase and interest rates were low. A close examination of the data, however, shows that increases in the pessimism probabilities were not followed by a subsequent decline in investment or consumption growth (Figure 13). Hence, this suggests that consumers or investors' pessimism may not have caused the 1984 economic slowdown.

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4.4.3. The 1990 recession. It is a popular belief, which was widely spread by the press, that a fall in consumer confidence was the main cause of the 1990 recession.[29] In particular, the minutes of the Federal Open Market Committee meeting in December 1990 pointed to consumer sentiment as one of the principal contributing factors for this recession. Blanchard (1993) and Hall (1993) both attribute the 1990 recession to a big drop in consumption, and speculate that consumer sentiment may have had something to do with it. Leeper (1992) and Fuhrer (1993), on the other hand, do not find any strong evidence supporting this argument.

Our results confirm the two latter studies. We find that consumption growth did switch to a low-growth state at the beginning of the 1989 slowdown (Figure 14). Consumer confidence also fell during the slowdown, as observed in all the previous low-growth phases and recessions (Figure 1). However, the probabilities of pessimism based on nonfundamentals rose only in July 1990, coinciding with the

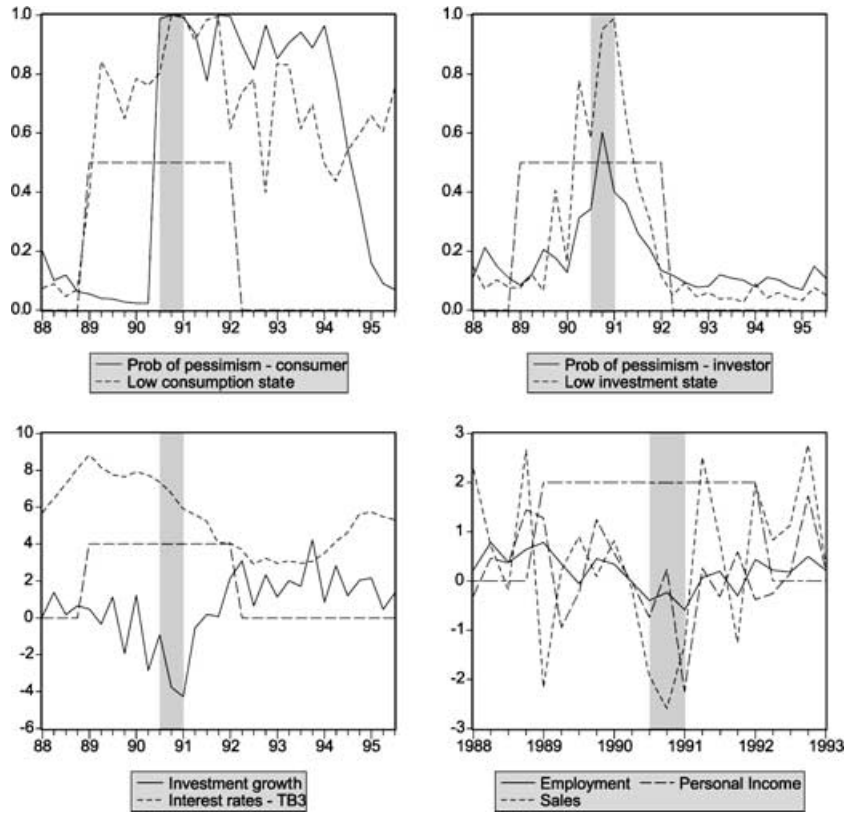


FIGURE 14. The 1990 recession: Probabilities of consumers' and investors' pessimism, low consumption and investment growth states, investment growth, 3-month T-Bill rate, growth rates of employment, personal income, and sales—NBER recessions (shaded areas) and slowdowns (- - -).

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onset of this recession (Figure 14). The same pattern was observed for growth in personal income, manufacturing trade and sales, and employment, whose falls coincided with the beginning of this recession. Therefore, consumers' pessimism did not seem to be a source of this recession.

However, consumers' pessimism may have been an important factor in intensifying and extending the 1989–1992 slowdown. Officially, the recession ended in the first quarter of 1991, and the low-growth phase in the first quarter of 1992. This was the only time in the sample that an economic slowdown outlived the end of a recession. The probabilities of consumers' pessimism remained high until the end of 1994. The low consumption growth phase lagged consumers' pessimism, and lasted until the end of the sample in 1995. Thus, consumers' attitudes toward the economy after the official end of the 1990 economic recession could have been a cause of the unprecedented extended slowdown.

With respect to entrepreneurs, the probabilities of pessimism started increasing slowly before the recession, but their peak coincided with the beginning of the economic contraction. However, even though interest rates were kept at low levels, investment growth was very low during the preceding slowdown. Hence, decreases in fundamental variables such as consumption and investment growth, rather than sunspots, could have been possible causes of the 1990 recession.

5. CONCLUSION

This paper examines the behavior of nonfundamental shifts in agents' expectations around economic downturns. In particular, we focus on the relationships between waves of pessimism—as represented by movements in consumer sentiment and business formation that cannot be explained by a list of economic fundamental variables—and subsequent turning points of NBER-dated recessions and slowdowns. Our analysis shows that bearish consumers and entrepreneurs were present before the onset of specific economic downturns, even when the fundamentals were all very strong. We then study individually each of the slowdowns and recessions that were preceded by substantial increases in the probabilities of consumers' and investors' pessimism, and examine the economic environment in which agents' perceptions were formed. In addition, we investigate the transmission channels through which agents' self-fulfilling beliefs may have affected the economy, that is, the relationships between consumers' and investors' pessimism with subsequent fluctuations in consumption and investment growth.

The empirical results suggest that, even after controlling for fundamental variables, negative shocks to nonfundamental rational expectations may have played an important role in the 1969–1970, the 1973–1975, and the 1981–1982 recessions. Our evidence is robust across a range of alternative linear and nonlinear specifications, which include many different additional variables as proxies for economic fundamentals and different lag structures. This indicates that specific U.S. recessions and slowdowns could have been responses not to shifts in economic

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fundamentals, but to agents' self-fulfilling pessimism. Hence, our results provide some empirical support for the class of macroeconomic models with multiple equilibria—such as coordination failure or self-fulfilling prophecies—whereby consumers' sunspots and investors' animal spirits have important independent influence on economic fluctuations.

NOTES

1. Notable examples within the overlapping generations paradigm include Azariadis (1981), Cass and Shell (1983), and Farmer and Woodford (1997), among many others. For real-business-cycle models with multiple equilibria, see Benhabib and Farmer (1994), Farmer and Guo (1994), and a recent survey by Benhabib and Farmer (1999).

2. As is common in the literature, we use the terms "animal spirits," "sunspots," "self-fulfilling prophecies," and "waves of optimism and pessimism" interchangeably in the paper. All of them refer to innovations that are not related to economic fundamentals such as technology, preferences, and endowments.

3. The term "strategic complementarity" means that one agent's optimal action is positively correlated with the actions of others. For the existence of multiple equilibria, the slope of one agent's reaction function must be greater than 1 over some range.

4. The shaded areas and dotted bars in this and all remaining figures correspond to 0/1 dummy variables that take the value of zero for expansions or high-growth phases, and one for contractions or low-growth phases, as dated by the NBER. The NBER Business Cycle Committee dates recessions on the basis of variables that move simultaneously with the business cycle, such as manufacturing and trade sales, personal income, industrial production, and employment. The NBER also dates growth cycles using the same procedures and variables. Whereas business-cycle dates are decided on the basis of a consensus about turning points of some coincident economic variables in levels, growth-cycle dates are obtained from the concurrence of cyclical variations in the deviations from the long-term trend of these same coincident series.

5. The null hypothesis that the business formation index does not Granger-cause gross fixed investment growth or GDP growth is rejected at the 0.001% and 0.000% significance levels, respectively. On the other hand, the null that the consumer sentiment index does not Granger-cause consumption growth of nondurables and services or GDP growth is rejected at the 0.75% and 0.28% significance levels, respectively (some of these results are reported in Tables 4–6).

6. Hamilton and Whiteman (1985), Imrohoroglu (1993), Dagsvik and Jovanovic (1994), Farmer and Guo (1995), Salyer and Sheffrin (1998), Carton (1998), and Farmer and Ohanian (1998) take a different approach. Each of these papers presents parameter estimates based on a particular theoretical model and investigates the empirical plausibility of multiple equilibria.

7. A different approach is pursued by Oh and Waldman (1990), where revisions of the Conference Board's Index of Leading Indicators are used to measure expectational shocks. They find that these revisions have marginal linear predictive power in forecasting industrial production.

8. Potter (1999) shows that rational fluctuations in investors' confidence can explain the business-cycle asymmetries observed in the U.S. economy. Specifically, in the prewar period, the reaction to large negative shocks such as the Great Depression was a prolonged slump in the economic activity. By contrast, negative shocks during recessions appear to have less persistent effects in postwar U.S. output.

9. This evidence is consistent with the kind of "growth cycles" described by Evans et al. (1998).

10. See Baillie (1989) for a survey of rational expectations using VAR's and applications.

11. See Hamilton (1995) for a discussion of rational expectations with Markov regime switching and applications.

12. This is the common sample of these data available from the 1999 DRI Database. The University of Michigan also constructs an Index of Consumer Expectation using a subset of the questions in the

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survey for the consumer sentiment index. We choose the consumer sentiment index because it has a longer sample period, starting in 1953:1.

13. Although this list is not exhaustive, it contains all the variables found in recent literature to be the best forecasters of output, consumer sentiment, and business formation.

14. Interest-rate spread is the difference between the 10-year and the 3-month T-Bill rates; the misery index is the sum of unemployment and inflation rates.

15. Some of these variables are transformed to achieve stationarity, based on the augmented Dickey–Fuller (1979) and Phillips–Perron (1988) tests. With the exception of consumer sentiment, inflation rate, interest rates, misery index, SW leading indicator, and unemployment claims, we consider the log first differences of the other variables. The Conference Board's Composite Leading Indicator itself should not be used because one of its components is the consumer sentiment index. See Rogers (1994) for a detailed description of the Composite Leading Indicator and its components. The components of the SW leading indicator are the index of new housing authorized, manufacturers' unfilled orders, trade-weighted nominal exchange rate (U.S., U.K., West Germany, France, Italy, and Japan), part-time work in nonagricultural industries, yield on 10-year T-bonds, spread between interest rate on 6-month corporate paper and the interest rate on 6-month U.S. Treasury bills, spread between the yield on constant-maturity portfolio of 10-year U.S. T-bonds and the yield on 1-year U.S. T-bonds.

16. See, for example, Stock and Watson (1991, 1993), Hamilton and Lin (1996), Hamilton and Perez-Quiros (1996), Perez-Quiros and Timmermann (1996), Estrella and Mishkin (1998), Chauvet (1998/1999), and Chauvet and Potter (2001).

17. An unrestricted VAR will approximate well the dynamics of a vector stochastic process with arbitrarily large number of variables and lag lengths. In practice, however, finite-order VAR models are used because of the limited number of observations available. In fact, there is a trade-off between having a sufficient number of lags and a sufficient number of free parameters. In our analysis, we want lags long enough to fully capture the dynamics of the system so that the estimated residuals are serially uncorrelated. On the other hand, the number of parameters to be estimated increases rapidly with the number of lags, resulting in an overparameterized model with poor and inefficient estimates.

18. We find that the residuals from the sentiment and business formation equations obtained from these exercises are very similar to those from the baseline model. In particular, the correlation ranges between 0.710 and 0.919 for the consumer sentiment residuals, and between 0.829 and 0.944 for the business formation residuals. Moreover, the cyclical economic patterns underlying these VAR residuals as depicted by the filtered probabilities of the Markov states are robust across these different model specifications [see Chauvet and Guo (1999)].

19. If we were to model each of the endogenous variables and each of the autoregressive parameters as functions of independent Markov chains, this would result in an explosive number of regimes and parameters to be estimated. In addition, given the sample size available, this would lead to overparameterization of the model.

20. Chauvet and Guo (1999) estimate a model in which only the volatility of each of the innovations switches, and find very similar results to the ones reported here. The likelihood ratio test favors the mean-variance switching specification.

21. We have also estimated a model in which the volatility of both innovations switches synchronously as a function of only one Markov variable. The resulting probabilities under this restriction strongly resemble the probabilities obtained from the univariate Markov switching on the consumer sentiment innovations, masking the independent dynamics of business formation.

22. In its current version, the SW leading indicator starts in 1959:1.

23. The probabilities of the optimistic state are simply 1 minus the probabilities of pessimism.

24. The last two columns of these tables are discussed later.

25. The frequency distribution of the estimated probabilities can be used to define turning points: a "peak" occurs if the probabilities are greater than their mean plus their standard deviation. This criterion is flexible across different probabilities since it is based on their specific distribution. Moreover, since most of the regime switches in the estimated probabilities occur abruptly with changes close to 0/1, turning-point calls are not very ambiguous.

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26. The existing econometric evidence is mixed regarding whether consumer sentiment affects consumption expenditures. For example, Batchelor and Dua (1992), Throop (1992), Fuhrer (1993), Carroll et al. (1994), and Wilcox (1999) show that the index of consumer sentiment helps predict future personal consumption expenditures. By contrast, Garner (1991) and Bram and Ludvigson (1998) do not find a statistically significant relationship between consumer confidence and consumption spending.

27. We use personal consumption expenditures of nondurables and services, consumption of durable goods, and gross fixed investment in billions of 1992 dollars. In the 1999 DRI Database, these series start in 1959:2. The MS-AR(1) specification is the best among alternative MS lag structures, using the likelihood ratio test.

28. These tables report the p-values in percentage terms, that is, the significance level at which the null hypothesis that the series does not Granger-cause consumption or investment growth is rejected.

29. For example, *The New York Times* on April 3, 1991, reported a quote by Roger Brinner, director of research at DRI/McGraw-Hill, that "If consumers hadn't panicked, there wouldn't have been a recession." In addition, the lead story in *The Wall Street Journal* on November 4, 1991, was entitled "Economy in the U.S. Isn't Nearly as Sour as the Country's Mood. But Pessimism Could Become Self-Fulfilling Prophecy Further Stalling Recovery. Can Attitude Be Everything?"

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