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DOES FEAR LEAD TO RECESSIONS?

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This paper investigates the link between consumer pessimism and U.S. economic recessions empirically. First we use structural vector autoregressive models to identify negative structural shocks to consumer confidence, which are used as a proxy for recession fear. We then apply probit models and time-varying-transition-probability Markov-switching autoregressive models to investigate how the lack of consumer confidence affects the probability of recession. We find that recession fear leads to a higher probability of economic downturns. Furthermore, strong evidence exists that an increase in market pessimism may push the economy from an expansion state to a recession state. We also find weaker evidence suggesting that a lack of consumer confidence may trap the economy in the depressed regime longer. We conclude that a lack of confidence can push the economy into recession.

Keywords: Market Pessimism, Fear of Recession, Shock to Consumer Confidence, Business Cycles

1. INTRODUCTION

The persistent lack of consumer confidence since the 2008 U.S. subprime crisis has attracted the attention of the press, policy makers, and macroeconomists alike and has led to great concern about the impact of market pessimism on the economy. For instance, in a recently published book, Akerlof and Shiller (2009) argued for the necessity of an active macroeconomic policy to restore the confidence of consumers and businesses in order to extricate the economy from the recession. John Maynard Keynes popularized the phrase "animal spirits" in economics to describe emotions that affect human behavior and can be measured in terms of consumer confidence. The exogenous shift in pessimism or optimism may have a causal effect on aggregate output. Using negative shocks to consumer confidence as a proxy of recession fear, this paper aims to examine whether increased fear of recession leads to economic downturns.

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In general, the existing literature suggests that sentiment is correlated highly with real economic activity [see, for instance, Ludvigson (2004)]. In particular, consumer sentiment may play an important role in business cycle fluctuations. For example, Oh and Waldman (1990) use revisions of the series of leading indicators to measure expectation shocks, and then show that expectation shocks are able to explain over 20% of the fluctuation in the quarterly growth rate of industrial production for the time period 1976–88. Blanchard (1993) shows that the 1990–91 recession was associated with large negative consumption shocks, which may have been caused by a decline in confidence. After controlling for standard macroeconomic variables, Matsusaka and Sbordone (1995) find evidence that changes in consumer sentiment have a statistically significant impact on output fluctuations, using tests of Granger causality. Similarly, Howrey (2001) finds that consumer confidence is a statistically significant predictor of future real GDP growth rates and the probability of recession. Finally, Chauvet and Guo (2003) find that bearish consumers and entrepreneurs were present before some of the U.S. economic downturns, even when the fundamentals were all very strong.

Theoretical studies suggest that the channel through which changes in consumer sentiment may cause economic fluctuations is changes in the purchases of consumer durable goods. That is, people will spend more on durable goods when consumer confidence is high, and spend less when consumer confidence is low [see Weder (1998)]. Furthermore, it is also argued in the literature that the impact of consumer sentiment on business cycles is simply a self-fulfilling prophecy [see Matsusaka and Sbordone (1995) and Harrison and Weder (2006)]. Aggregate output may fluctuate simply because people expect it to. Finally, Lorenzoni (2009) provides a model where technology determines long-run equilibrium output level and consumers can receive only noisy signals about permanent productivity in the short run. The noisy signals produce expectation errors (noise shocks), which generate a sizable fraction of observed demand-side volatility and economic fluctuations. See Lorenzoni (2011) for a thorough review of the literature on news as a source of economic fluctuations.

This paper aims to answer the following questions empirically. First, does recession fear lead to a higher probability of recession? Second, if it does, how does the fear of recession affect the probability of recession? Does the pessimism cause a higher probability of switching from an expansion to a recession and/or a higher probability of trapping the economy in a recession state?

Measuring the current fear of recession is not a straightforward task. One popular proxy for the degree of recession fear is the consumer confidence index. For instance, see Blanchard (1993) and Carroll et al. (1994). However, if we wish to examine the effect of a contemporary exogenous sentiment shock on the probability of recession, simply using changes in the consumer confidence index may be subject to an endogeneity problem because the state of the economy (recession or expansion) may also affect consumer confidence. In this paper, we account for the endogeneity of the fear measure by using structural VAR models to estimate the structural shocks to consumer confidence, and then using negative versions of these shocks as proxies of contemporary recession fear. After obtaining this proxy of recession fear, we use probit models and time-varying-transition-probability Markov-switching autoregressive (TVTP-MS-AR) models to examine the link between recession fear and the probability of recession.

The rest of the paper is structured as follows. Section 2 presents the empirical framework. Section 3 describes the data and preliminary test results, and Section 4 reports the key empirical results. Robustness checks are provided in Section 5. Finally, concluding remarks are offered in Section 6.

2. ECONOMETRIC FRAMEWORK

In this section, we first show how we measure recession fear. We then present the empirical framework used to examine the link between recession fear and the probability of recession.

2.1. Measuring Recession Fear

To estimate shocks to consumer confidence, we consider a structural VAR model, $Y_t = [\mathrm{CCI}_t \quad \pi_t \quad x_t]'$, where CCI_t is (log) consumer confidence, $\pi_t = 100 \times (\log p_t - \log p_{t-1})$ is consumer price inflation rate, and $x_t = 100 \times (\log y_t - \log y_{t-1})$ is the growth rate of aggregate output. The structural VAR representation is

$$D(L)Y_t = e_t, \tag{1}$$

where $D(L) = I - D_0 - D_1 L - \cdots - D_k L^k$ is a lag polynomial, and e_t are the structural innovations. Letting ε_t denote the vector of reduced-form VAR innovations, the identification condition is

$$\begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \end{bmatrix} = (I - D_0)^{-1} e_t = \begin{bmatrix} a_{11} & 0 & 0 \\ a_{12} & a_{22} & 0 \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \begin{bmatrix} e_t^c \\ e_t^m \\ e_t^a \end{bmatrix}, \tag{2}$$

where e_t^c, e_t^m, and e_t^a represent confidence shocks, nominal shocks, and real shocks, respectively. One possible interpretation of the nominal and real shocks could be as monetary and productivity shocks, respectively. The restrictions on $(I - D_0)^{-1}$ may be motivated as follows. Consumer confidence is assumed not to respond to both nominal and real shocks within the same month. That exclusion restriction is plausible because, in practice, the cutoff date for the preliminary results of the consumer confidence survey conducted for The Conference Board by Nielsen is in the middle of each month. For instance, the Conference Board Consumer Confidence Index was released on April 30, 2013, but the cutoff date for the preliminary results was April 18, 2013. We further assume that the inflation will be slow to respond to a productivity shock because a transitory change in the level of productivity is unlikely to have immediate effects on business pricing behavior.

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Although this identification assumption can be well justified, we will consider different orderings to check the robustness of our empirical results later.

Finally, we proxy recession fear (negative confidence) using a negative value of the structural shock:

$$f_t = -\hat{e}_t^c. \tag{3}$$

Hence, a higher value of f_t implies greater market pessimism.

2.2. Market Pessimism and Business Cycle Dynamics

One well-known way of predicting future turning points in economic activity is to utilize a probit framework. For example, Estrella and Mishkin (1998) use a probit model and forecast the recession probability of the U.S. economy. Since then this approach has been employed in a number of studies, including Filardo (1999), Chauvet and Potter (2005), and Wright (2006). In particular, Negro (2001) has shown the predictive superiority of probit models compared with the usual econometric models or leading indicators.

Following Estrella and Mishkin (1998), we consider the probit model

$$P(d_t = 1) = \Phi\left(\alpha + \beta'\mathbf{f}_t + \delta'\mathbf{z}_{t-1}\right), \tag{4}$$

where $\Phi(\cdot)$ is the cumulative standard normal distribution function, d_t is the recession indicator, $\mathbf{f}_t = \{f_t, f_{t-1}, \ldots, f_{t-k}\}$, f_t is the proxy of recession fear, $\beta' = [\beta_0, \quad \beta_1, \quad \beta_2, \cdots, \beta_k]$, and $\mathbf{z}_{t-1}$ contains other (lagged) control variables that may affect the probability of recession, including the yield curve spread (the difference between the 10-year treasury constant maturity rate and the 3-month treasury bill rate, spread$_t$), the rate of consumer price inflation (π_t), and stock returns (return$_t$).

A popular recession indicator is obtained from the standard National Bureau of Economic Research (NBER) recession dates:

$$d_t = \begin{cases} 1 & \text{if the economy is in recession,} \\ 0 & \text{otherwise.} \end{cases}$$

Using equation (4), we will examine how recession fear affects the probability of recession. If market pessimism induces a higher probability of recession, we expect $\beta_j > 0$, $j = 0, 1, \ldots, k$.

Furthermore, since the seminal work by Hamilton (1989), Markov-switching autoregressive (MS-AR) models have been applied successfully to studies of real output fluctuations. These models have been employed as an independent objective algorithm for generating business cycle dating and applied widely in the literature on business cycle analysis. In particular, a two-state MS-AR model characterizes well the switching of economic fluctuations between expansions and contractions. For instance, see Hamilton and Perez-Quiros (1996), Raymond and Rich (1997), Filardo and Gordon (1998), McConnell and Perez-Quiros (2000), Garcia and Schaller (2002), Clements and Krolzig (2003), Lam (2004), and Layton and Smith

(2007). We will thus use this popular alternative approach to treat the question of whether the economy is experiencing a recession. Moreover, to examine whether a lack of consumer confidence affects the probability of recession, we further adopt a modified version of the original Hamilton (1989) MS-AR model by allowing the transition probability to vary depending on recession fear.

Following Durland and McCurdy (1994) and Filardo (1994), we use a time-varying-transition-probability (TVTP) MS-AR(q) model to investigate the impact of recession fear on economic fluctuations. Consider the following TVTP-MS-AR(q) model of output growth, x_t:

$$\varphi(L)(x_t - \mu_{S_t}) = \epsilon_t, \quad \epsilon_t \sim \mathcal{N}\left(0, \sigma_{S_t}^2\right), \tag{5}$$

where $\varphi(L) = 1 - \varphi_1 L - \varphi_2 L^2 - \cdots - \varphi_q L^q$ is a polynomial in the lag operator, L. The terms μ_{S_t} and $\sigma_{S_t}^2$ are the state-dependent mean and variance of x_t, respectively. The unobserved state variable S_t is a latent dummy variable equal to either 0 or 1, indicating recession or expansion, respectively. It is assumed to follow a Markov process with a TVTP matrix,

$$P(t) = \begin{bmatrix} p_t^{00}(\mathbf{w}_t) & 1 - p_t^{11}(\mathbf{w}_t) \\ 1 - p_t^{00}(\mathbf{w}_t) & p_t^{11}(\mathbf{w}_t) \end{bmatrix}, \tag{6}$$

where $p_t^{jl}(\mathbf{w}_t) = P(s_t = l | s_{t-1} = j, \mathbf{w}_t)$, and $\mathbf{w}_t$ represents variables that may affect the transition probabilities. The TVTP matrix in equation (6) guides the shifts between the two different regimes over time. The probability of a switch in regime, from either recession to expansion or expansion to recession, is assumed to vary with the evolution of recession fears and other macroeconomic variables. Furthermore, the transition probability function is specified as follows:

$$p_t^{00}(\mathbf{w}_t) = \frac{\exp\{\gamma_0 + \theta_0 f_t + \eta_0 z_{t-1}\}}{1 + \exp\{\gamma_0 + \theta_0 f_t + \eta_0 z_{t-1}\}}, \tag{7}$$

$$p_t^{11}(\mathbf{w}_t) = \frac{\exp\{\gamma_1 + \theta_1 f_t + \eta_1 z_{t-1}\}}{1 + \exp\{\gamma_1 + \theta_1 f_t + \eta_1 z_{t-1}\}}. \tag{8}$$

Notice that $p_t^{10}(\mathbf{w}_t) = 1 - p_t^{11}(\mathbf{w}_t)$ is the probability of switching from an expansion to a recession. If greater market pessimism sends the economy into downturns, we may expect to obtain $\hat{\theta}_1 < 0$. On the other hand, $\hat{\theta}_0 > 0$ suggests that a greater lack of confidence raises the probability of remaining in the recession state. It is worth noting that the TVTP-MS-AR(q) model can be transformed into a fixed transition probability Markov-switching autoregressive model (FTP-MS-AR(q)) when the recession fears are not informative about the evolution of the business cycle dynamics: $\theta_0 = \theta_1 = \eta_0 = \eta_1 = 0$. Furthermore, if we follow Hamilton (1989) and assume that regime switches only shift the mean growth rate ($\sigma_0 = \sigma_1 = \sigma$), the model degenerates to a TVTP-MS-AR model with constant variance, and is denoted by TVTP-MS-CV-AR(q).

3. DATA AND PRELIMINARY TESTS

We use the monthly Conference Board Consumer Confidence Index (CBCCI) provided by the Conference Board Survey as a measure of consumer confidence. The sample span is from 1967:M2 to 2010:M10 because the data are available at monthly frequency. The CBCCI data are obtained from Datastream. We use monthly growth in industrial production as a proxy for the growth rate in aggregate output. Data on industrial production, consumer price index, the 3-month treasury bill rate, the 10-year treasury constant maturity rate, and the S&P 500 stock price index are from Federal Reserve Economic Data (FRED) provided by the Federal Reserve Bank of St. Louis.

Unit root tests are used to examine whether the series for real output growth, consumer confidence, and inflation are stationary. We apply conventional unit root tests, including the augmented Dickey–Fuller (ADF) test, the Phillips–Perron (PP) test, and the Elliott–Rothenberg–Stock DF-GLS test. The results of the unit root tests suggest that a unit root process is rejected for each series for all tests.[1]

4. EMPIRICAL RESULTS

4.1. A Measure of Recession Fear

The optimal lag in equation (1) is chosen to be nine by the Akaike information criterion. The impulse response functions are plotted in Figure 1. The 95% confidence intervals are constructed by bootstrapping with 10,000 replications. Each column shows the effect of one-standard-deviation structural shocks on consumer confidence, inflation rate, and output growth. It is worth noting that an unexpected positive confidence shock causes a significant increase in output growth. At the same time, a shock to confidence triggers a small and insignificant decrease in inflation, followed by a partial reversal of the decline. The effects of monetary shocks on consumer confidence and output growth are somewhat weak and insignificant. Finally, an unanticipated productivity shock has a significant and persistent effect on consumer confidence.

The forecast error variance decompositions of each variable suggest considerable interaction between these variables.[2] Perhaps the most striking result is the fact that the shock to consumer confidence is able to explain a sizable portion of the total variance in the forecast error of output growth. At horizons longer than six months, about 20% of the error variance in forecasting output growth is a result of confidence shocks. This preliminary result suggests that consumer psychology may play an important role in determining the business cycle dynamics, which is in line with the results of Matsusaka and Sbordone (1995).

4.2. Results from Probit Models

We showed in the preceding section that shocks to consumer confidence are able to account for changes in output growth substantially. Now we turn to the main

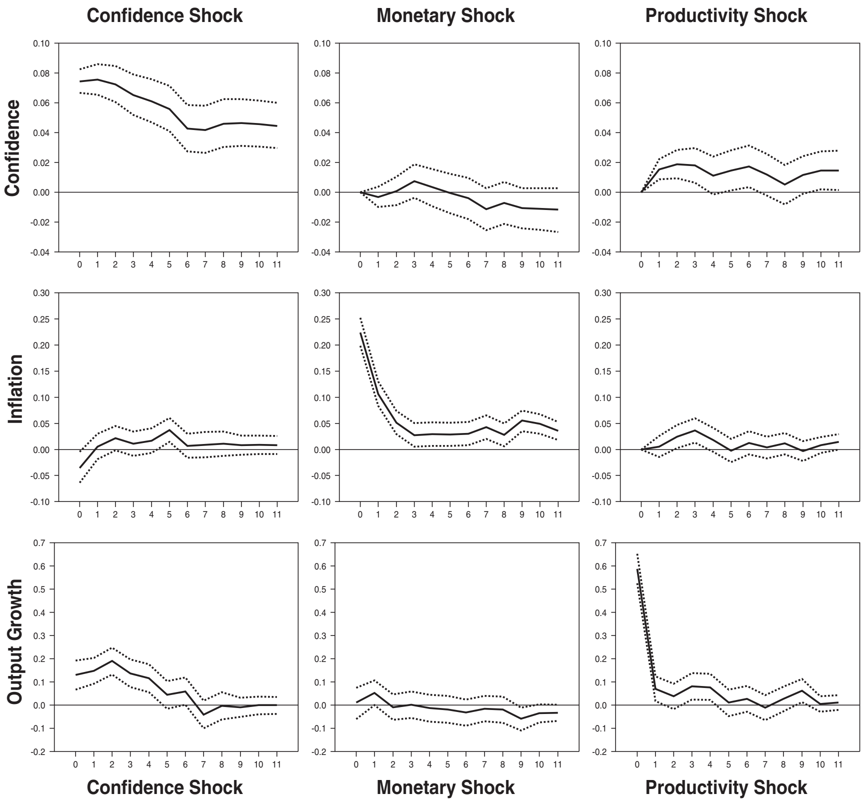

FIGURE 1. Impulse response functions for baseline SVAR model.

question of whether greater recession fear f_t leads to a higher probability of a recession using probit models. To measure the model's fit, we follow Estrella and Mishkin (1998) in computing the pseudo-R^2 developed by Estrella (1998). Let L_u denote the value of the maximized probit likelihood, and let L_c denote the value of the maximized likelihood under the constraint that all coefficients are zero except for the constant. Then the measure of fit is defined by

$$\text{pseudo-}R^2 = 1 - \left(\frac{\log L_u}{\log L_c}\right)^{-(2/T)\log L_c}. \quad \textbf{(9)}$$

A low value of the pseudo-R^2 suggests "no fit," whereas pseudo-$R^2 = 1$ represents "perfect fit."

Table 1 shows the empirical results for several model specifications. First of all, it is worth noting that all the estimates are statistically significant at the 5% level. In column (1), the contemporary fear of recession has a significantly positive effect on the probability. That is, the greater the market pessimism, the higher the

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TABLE 1. Probit models of U.S. recessions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
f_t	**0.21**	**0.21**	**0.23**	**0.24**	**0.25**	**0.26**	**0.17**	**0.23**
	(0.08)	(0.08)	(0.07)	(0.08)	(0.07)	(0.07)	(0.08)	(0.07)
f_{t-1}		**0.27**	**0.27**	**0.29**	**0.29**	**0.31**		**0.25**
		(0.08)	(0.09)	(0.08)	(0.08)	(0.07)		(0.08)
f_{t-2}			**0.34**	**0.35**	**0.35**	**0.34**		**0.42**
			(0.09)	(0.09)	(0.08)	(0.08)		(0.09)
f_{t-3}				**0.37**	**0.37**	**0.36**		**0.46**
				(0.10)	(0.10)	(0.09)		(0.10)
f_{t-4}					**0.28**	**0.28**		**0.37**
					(0.09)	(0.09)		(0.10)
f_{t-5}						**0.24**		**0.33**
						(0.09)		(0.09)
spread$_{t-1}$							**−0.09**	**−0.24**
							(0.05)	(0.07)
π_{t-1}							**0.57**	**0.58**
							(0.27)	(0.24)
return$_{t-1}$							**−0.05**	**−0.05**
							(0.02)	(0.02)
Constant	**−0.97**	**−0.99**	**−1.03**	**−1.09**	**−1.11**	**−1.13**	**−1.04**	**−1.05**
	(0.07)	(0.07)	(0.08)	(0.08)	(0.08)	(0.08)	(0.17)	(0.16)
Pseudo-R^2	0.02	0.06	0.11	0.17	0.20	0.23	0.08	0.31

Note: The entries in parentheses are the standard errors. Bold entries indicate significance at the 10% level or less. The Probit model is $P(d_t = 1) = \Phi(\alpha + \beta'\mathbf{f}_t + \delta'\mathbf{z}_{t-1})$, where $\Phi(\cdot)$ represents the cumulative standard normal distribution function, d_t denotes the recession indicator identified by the NBER, and $\mathbf{f}_t = [f_t, f_{t-1}, \ldots, f_{t-k}]$ is the measure of recession fears. The vector $\mathbf{z}_{t-1} = [\text{spread}_{t-1}\ \ \pi_{t-1}\ \ \text{return}_{t-1}]$, where spread$_t$ is the yield curve spread spread, π_t is the rate of consumer prices inflation, and return$_t$ is the stock return.

recession probability. The average marginal effect $\frac{\partial\Phi(\bar{f})}{\partial f_t}\hat{\beta}_0 = 0.05226$ implies that the likelihood of recession increases by 5% in response to a one-unit fear shock.

Columns (2) to (6) show that the main result regarding the effect of recession fear on the probability of economic downturns is unchanged when various lags of f_t are included. We also consider other possible factors that may affect the recession probability in columns (7) and (8). It is clear that our major finding of recession fear having a significant impact still exists. Furthermore, higher inflation is associated positively with the probability of recession, as expected. Higher stock returns are associated negatively with the probability of recession because the stock market usually begins to decline before the economy declines and improves before the economy begins to pull out of a recession. Finally, as reported in a number of empirical studies [for instance, see Estrella and Mishkin (1998)], the term spread (long-term yields less short-term rates) is an important leading indicator of future recessions in real activity. Here, we show that the term spread is associated negatively with future recession probability. A possible explanation comes from the expectation theory of the term structure of interest rates. It can be shown

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that long-term interest rates equal the average of the expected values of short-term interest rates into the future, plus a term premium. If people expected a recession in the future, the expected short-term rate would decrease, because a loose monetary policy would be expected in the future. Hence the long-term rate would be lower, so that the term spread decreases.

4.3. Results from Markov-Switching Models

The evidence shown in the preceding suggests that greater recession fear leads to a higher probability of economic downturns. In this section, we use Markov-switching models to investigate further whether an increase in unexpected negative sentiment raises the probability of switching from an expansion to a recession. Furthermore, we examine whether greater market pessimism also increases the probability of becoming trapped in a recession regime.

Table 2 presents the empirical results. Columns (1) and (2) provide the estimates for the linear AR(1) and FTP-MS-AR(1) models. To start with, the Markov-switching model yields a higher value of the likelihood function than the linear model. The likelihood ratio (LR) statistic is 98.11. Therefore, although the conventional LR test is not applicable, because of the nuisance parameter problem, Garcia (1998) tabulates critical values for the FTP-MS-AR(1) model. The LR statistic is much larger than the 1%-critical value of 11.92 tabulated by Garcia (1998, Table 3). This finding may suggest that with output growth in the model, the Markov-switching model performs better than the linear AR model.

The Markov-switching model, where the process is allowed to switch between regimes, identifies a regime with a positive mean growth rate ($\mu_1 = 0.26$) and low variance ($\sigma_1 = 0.50$) and a regime with a negative mean growth rate ($\mu_0 = -0.15$) and higher variance ($\sigma_0 = 1.27$). The high-mean stable and low-mean volatile states of output growth are labeled conventionally as expansions and recessions, respectively. Obviously, the Markov-switching model has identified well the fluctuations in the economy. Finally, the transition probabilities, $p^{00} = \frac{\exp(1.15)}{\exp(1+1.15)} = 0.76$ and $p^{11} = \frac{\exp(2.94)}{\exp(1+2.94)} = 0.95$, show that the expansion state is far more persistent than the recession state. The expansion regime persists, on average, for $1/(1 - p^{11}) = 1/(1 - 0.95) \approx 20$ months, whereas it is expected that the recession regime will persist for $1/(1 - p^{00}) = 1/(1 - 0.76) \approx 4$ months.

Column (3) in Table 2 reports the estimates from the TVTP-MS-AR(1) model. The result is in general similar to the result obtained from the FTP-MS-AR(1) model. However, the LR test statistic comparing the FTP model with the TVTP model is 12.41, which has a p-value of less than 0.01, according to the χ^2 distribution with two degrees of freedom. We are able to reject the first-order Markov-switching model with constant transition probabilities in favor of the first-order Markov-switching model with time-varying transition probabilities that are dependent on recession fear. Figure 2 plots the smoothed probabilities of state 0 (the low-mean/high-volatility state labeled as recession) from the TVTP model. When close to one, the smoothed probability shows strong evidence that the economy

TABLE 2. Markov-switching models of U.S. economic fluctuations

	Linear AR(1)	FTP MS-AR(1)	TVTP MS-AR(1)	TVTP MS-CV-AR(1)	TVTP-MS-AR(1)		
					z_{t-1}		
			$\eta_0 = \eta_1 = 0$		spread$_{t-1}$	π_{t-1}	return$_{t-1}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
μ	**0.19**						
	(0.05)						
μ_0		−0.15	**−0.65**	**−1.08**	**−0.61**	**−0.66**	**−0.66**
		(0.19)	(0.19)	(0.10)	(0.15)	(0.18)	(0.18)
μ_1		**0.26**	**0.32**	**0.32**	**0.35**	**0.33**	**0.33**
		(0.04)	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)
σ	**0.71**			**0.62**			
	(0.01)			(0.02)			
σ_1		**1.27**	**1.10**		**1.02**	**1.08**	**1.09**
		(0.14)	(0.07)		(0.06)	(0.07)	(0.07)
σ_2		**0.50**	**0.56**		**0.55**	**0.56**	**0.56**
		(0.02)	(0.02)		(0.02)	(0.02)	(0.02)
φ_1	**0.35**	**0.29**	**0.18**	**0.18**	**0.16**	**0.17**	**0.17**
	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
γ_0		**1.15**	**2.50**	**1.17**	**2.11**	**2.71**	**2.39**
		(0.51)	(1.22)	(0.46)	(1.14)	(1.41)	(1.15)
γ_1		**2.94**	**5.36**	**5.72**	**4.27**	**6.84**	**5.23**
		(0.42)	(1.02)	(1.15)	(1.27)	(2.09)	(1.07)
θ_0			**1.17**	−0.13	**1.50**	**1.19**	0.89
			(0.69)	(0.31)	(0.59)	(0.64)	(0.69)
θ_1			**−1.83**	**−2.16**	**−2.53**	**−1.65**	**−1.45**
			(0.55)	(0.58)	(1.05)	(0.64)	(0.56)
η_0					0.43	−0.43	−0.08
					(0.69)	(1.76)	(0.22)
η_1					**−1.67**	−3.61	0.18
					(0.90)	(2.74)	(0.18)
LogLik	−559.44	−510.38	−504.18	−522.21	−498.70	−501.36	−503.30

Note: The entries in parentheses are the standard errors. Bold entries indicate significance at the 10% level or less. The Markov-switching autoregressive model is $\varphi(L)(x_t - \mu_{S_t}) = \epsilon_t$, $\epsilon_t \sim$ i.i.d.$\mathcal{N}(0, \sigma^2_{S_t})$, $S_t = \{0, 1\}$. The transition probabilities for TVTP are specified as $p_t^{00}(f_t) = \frac{\exp\{\gamma_0+\theta_0 f_t+\eta_0 z_{t-1}\}}{1+\exp\{\gamma_0+\theta_0 f_t+\eta_0 z_{t-1}\}}$ and $p_t^{11}(f_t) = \frac{\exp\{\gamma_1+\theta_1 f_t+\eta_1 z_{t-1}\}}{1+\exp\{\gamma_1+\theta_1 f_t+\eta_1 z_{t-1}\}}$. It is assumed that $\theta_0 = \theta_1 = \eta_0 = \eta_1 = 0$ for FTP-MS-AR(q) models. TVTP-MS-CV-AR(1) represents the TVTP Markov-switching autoregressive model with constant variance. LogLik represents the value of the log-likelihood function.

was in the recession regime. As a comparison, the plots also contain shaded areas that represent the recession periods identified by the NBER. Clearly, the TVTP model provides a good match to the NBER expansions and contractions.[3]

We now move to the final focus of the study: does greater market pessimism push the economy into recession? As discussed in Section 2, if the rising negative

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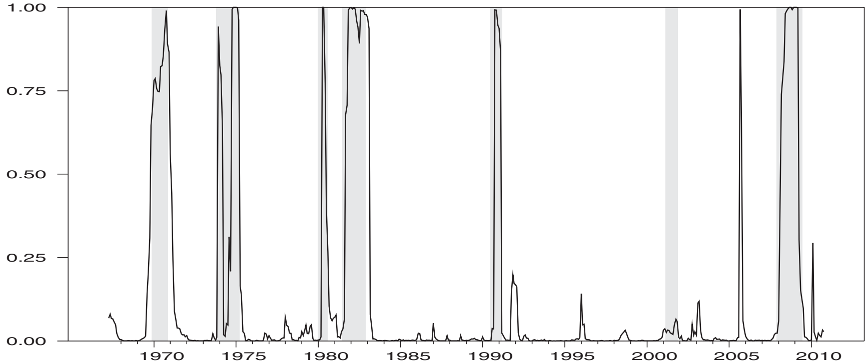

FIGURE 2. Smoothed probabilities in state 0 (recession), TVTP-MS-AR(1) model.

sentiment sends the economy into a downturn, we can expect to obtain $\hat{\theta}_1 < 0$ in equation (8). Furthermore, we find that $\hat{\theta}_0 > 0$ in equation (7) if an increase in pessimism increases the probability of remaining in the recession regime. According to column (3) in Table 2, the estimate of θ_1 is negative and statistically significant at the 1% level. This result provides strong evidence that an increase in negative sentiment increases the probability of switching from an expansion to a recession. That is, lack of confidence definitely sends the economy into a downturn phase. In contrast, greater market pessimism also increases the probability of becoming trapped in a bearish regime, as suggested by $\hat{\theta}_0 > 0$, which is marginally significant at the 10% significance level. Column (4) reports the estimation results from the TVTP-MS-CV-AR(1) model with constant variance ($\sigma_0 = \sigma_1 = \sigma$) as assumed in Hamilton (1989). Similarly to column (3), the results show that $\hat{\theta}_1 < 0$ at the 1% significance level. However, the estimate of θ_0 is statistically insignificant, although negative. Finally, columns (5)–(7) present the empirical results when including other control variables at a one-period lag: the term spread (spread_{t-1}), inflation rate (π_{t-1}), or stock returns (return_{t-1}). For all of these specifications, the estimates are similar qualitatively and quantitatively to the results in column (3).

To sum up, the TVTP-MS-AR models present strong evidence that a greater fear of recession raises the probability of switching from an expansion to a recession. On the other hand, the evidence that market pessimism affects the probability of becoming trapped in the recession regime is somewhat weaker.

5. ROBUSTNESS

To check the robustness of the empirical results, we consider the following modifications. First, we assess whether the main results are robust to different measures of confidence. We also consider different structural VAR models to extract the structural shocks to consumer confidence. Finally, we consider different specifications of the Markov-switching models, to complete our empirical analysis.

5.1. An Alternative Measure of Consumer Confidence

As a robustness check, we use the monthly University of Michigan Consumer Sentiment Index (UMCSI) as an alternative measure of consumer confidence. The sample is from 1978:M1 to 2009:M5. The results are shown in columns (1)–(2) of Table 3 and the first column of Table 4.[4] We again find that recession fear raises the probability of recession in the probit models and leads to a higher probability of switching from expansions to contractions in the Markov-switching model. The robust results are no great surprise, as the two consumer confidence indices (UMCSI vs. CBCCI) are highly correlated (the correlation coefficient is 0.831484). However, it is worth noting that as discussed in Bram and Ludvigson (1998), the most important methodological difference between the two indexes is the sample size: 500 for the UMCSI and 3,500 for the CBCCI. Hence, because the UMCSI is based on a much smaller sample size than the CBCCI, it is more susceptible to measurement error. As a result, the CBCCI may provide more credible results in the empirical analysis.

5.2. Alternative Structural VAR Specifications

An alternative ordering in the VAR model. To check the robustness of the results, we first change the Wold ordering of the three-variable VAR model and set consumer confidence as the final variable in the ordering: $Y_t = [\pi_t \ \ x_t \ \ \mathrm{CCI}_t]'$. The empirical results are reported in columns (3) and (4) of Table 3 and column (2) of Table 4, and we denote them as VAR-last.

Barsky and Sims (2012)'s SVAR model. Furthermore, we follow Barsky and Sims (2012) in estimating a three-variable structural VAR model with Wold ordering: consumer confidence, consumption, and output.[5] A five-variable structural VAR proposed by Barsky and Sims (2012) with consumer confidence, consumption, output, inflation, and real interest rate (approximated by the federal funds rate minus the inflation rate) is also used. We report the results in columns (5)–(8) of Table 3 and columns (3)–(4) of Table 4, and denote them as BS-VAR3 (three-variable VAR) and BS-VAR5 (five-variable VAR), respectively.

Factor-augmented VAR model. Finally, we consider a factor-augmented VAR (FAVAR) model as an alternative approach to checking robustness. Using a factor model on a large panel of macroeconomic time series variables, we then augment the VAR model with the set of factors capturing the comovement of macroeconomic variables, so that the large panel of macroeconomic series may provide additional information and help isolate the confidence shocks. See Bernanke et al. (2005) for additional details.

Let X_t denote the informational macroeconomic variables, consisting of a panel of N stationary time series. We assume that

$$X_t = \Lambda F_t + \xi_t, \tag{10}$$

TABLE 3. Robustness checks: Probit models

	UMCSI		VAR-Last		BS-VAR3		BS-VAR5		FAVAR	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
f_t	**0.17**	0.12	**0.18**	**0.14**	**0.25**	**0.20**	**0.21**	**0.21**	**0.26**	**0.20**
	(0.09)	(0.09)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
f_{t-1}	**0.27**	**0.19**	**0.22**	**0.17**	**0.29**	**0.21**	**0.21**	**0.16**	**0.30**	**0.21**
	(0.09)	(0.09)	(0.07)	(0.08)	(0.08)	(0.09)	(0.07)	(0.09)	(0.08)	(0.10)
f_{t-2}	**0.35**	**0.35**	**0.27**	**0.35**	**0.34**	**0.37**	**0.22**	**0.29**	**0.34**	**0.38**
	(0.09)	(0.09)	(0.08)	(0.09)	(0.09)	(0.09)	(0.09)	(0.10)	(0.08)	(0.09)
f_{t-3}	**0.37**	**0.39**	**0.29**	**0.37**	**0.38**	**0.44**	**0.25**	**0.34**	**0.38**	**0.44**
	(0.09)	(0.09)	(0.08)	(0.09)	(0.09)	(0.10)	(0.09)	(0.11)	(0.09)	(0.09)
f_{t-4}	**0.36**	**0.34**	**0.23**	**0.29**	**0.34**	**0.40**	**0.22**	**0.31**	**0.31**	**0.38**
	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.10)	(0.10)	(0.11)
f_{t-5}	**0.32**	**0.33**	**0.19**	**0.26**	**0.28**	**0.34**	**0.20**	**0.29**	**0.27**	**0.33**
	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.08)	(0.09)	(0.08)	(0.08)
spread_{t-1}		−0.04		**−0.20**		**−0.22**		**−0.25**		**−0.20**
		(0.08)		(0.07)		(0.07)		(0.07)		(0.11)
π_{t-1}		0.32		**0.67**		0.20		**0.45**		0.41
		(0.31)		(0.24)		(0.23)		(0.25)		(0.34)
return_{t-1}		**−0.05**		**−0.06**		**−0.06**		**−0.06**		**−0.06**
		(0.03)		(0.02)		(0.02)		(0.02)		(0.03)
Constant	**−1.21**	**−1.23**	**−1.06**	**−1.07**	**−1.15**	**−0.94**	**−1.04**	**−0.87**	**−1.15**	**−1.04**
	(0.10)	(0.20)	(0.08)	(0.16)	(0.08)	(0.16)	(0.07)	(0.17)	(0.15)	(0.25)
Pseudo-R^2	0.20	0.22	0.15	0.24	0.24	0.30	0.12	0.22	0.24	0.31

Note: The entries in parentheses are the standard errors. Bold entries indicate significance at the 10% level or less. The Probit model is $P(d_t = 1) = \Phi(\alpha + \beta'\mathbf{f}_t + \delta'\mathbf{z}_{t-1})$, where $\Phi(\cdot)$ represents the cumulative standard normal distribution function, d_t denotes the recession indicator identified by the NBER, and $\mathbf{f}_t = [f_t, f_{t-1}, \ldots, f_{t-k}]$ is the measure of recession fears. The vector $\mathbf{z}_{t-1} = [\text{spread}_{t-1}\ \ \pi_{t-1}\ \ \text{return}_{t-1}]$, where spread_t is the yield curve spread spread, π_t is the rate of consumer prices inflation, and return_t is the stock return. UMCSI indicates that the University of Michigan Consumer Sentiment Index is used. VARLast indicates that the consumer confidence is ordered last in the structural VAR model. BS-VAR3 and BS-VAR5 represent the three-variable and five-variable structural VAR models proposed by Barsky and Sims (2012). FAVAR indicates the factor-augmented VAR model.

where F_t represents K unobserved common factors, Λ is an $N \times K$ matrix of factor loadings, and ξ_t denotes idiosyncratic components of X_t uncorrelated with F_t. That is, F_t is the force that governs the common dynamics of X_t. Then the FAVAR model we consider is

$$\begin{bmatrix} \text{CCI}_t \\ F_t \end{bmatrix} = \Phi(L) \begin{bmatrix} \text{CCI}_{t-1} \\ F_{t-1} \end{bmatrix} + u_t, \tag{11}$$

where $\Phi(L)$ is a lag polynomial. The error term u_t has mean zero with covariance matrix Σ_u. We use a two-step approach to estimate the FAVAR model. In the first step, we obtain $\hat{F}_t$ by the method of principal components. In the second step, we estimate the FAVAR model by replacing the unobservable factors F_t with $\hat{F}_t$. A recursive structure is assumed for the identification of the structural shocks in equation (11). The recursive ordering imposes the identifying assumption that the consumer confidence index does not respond to innovations from unobserved factors within a month as argued in Section 2.1. We follow Bernanke et al. (2005)

TABLE 4. Robustness checks: Markov-switching models

	UMCSI	VAR-Last	BS-VAR3	BS-VAR5	FAVAR	TVTP MS-AR(4)	TVTP MSI-AR(1)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
μ_0	**−0.89**	−0.23	**−0.66**	**−0.67**	**−0.65**	0.14	**−0.60**
	(0.08)	(0.19)	(0.19)	(0.19)	(0.19)	(0.20)	(0.17)
μ_1	**0.33**	**0.28**	**0.32**	**0.32**	**0.32**	**0.21**	**0.27**
	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.06)	(0.03)
σ	**0.57**						
	(0.02)						
σ_1		**1.24**	**1.12**	**1.11**	**1.11**	**1.27**	**1.10**
		(0.12)	(0.08)	(0.08)	(0.08)	(0.13)	(0.08)
σ_2		**0.51**	**0.56**	**0.56**	**0.55**	**0.46**	**0.56**
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
φ_1	**0.08**	**0.26**	**0.18**	**0.18**	**0.17**	**0.16**	**0.19**
	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
φ_2						**0.19**	
						(0.04)	
φ_3						**0.14**	
						(0.04)	
φ_4						**0.08**	
						(0.04)	
γ_0	**1.64**	**1.30**	**2.42**	**2.54**	**2.27**	**0.96**	**2.55**
	(0.55)	(0.54)	(1.22)	(1.25)	(1.01)	(0.45)	(1.30)
γ_1	**5.93**	**3.30**	**5.28**	**5.35**	**5.50**	**3.00**	**5.44**
	(2.09)	(0.50)	(0.96)	(1.01)	(1.00)	(0.43)	(1.05)
θ_0	−0.76	0.08	1.10	1.26	0.87	−0.20	**1.32**
	(0.58)	(0.47)	(0.70)	(0.89)	(0.54)	(0.31)	(0.76)
θ_1	**−2.18**	**−0.79**	**−1.76**	**−1.90**	**−2.01**	**−0.89**	**−1.89**
	(0.79)	(0.36)	(0.53)	(0.58)	(0.59)	(0.36)	(0.56)
LogLik	−361.86	−509.23	−503.28	−504.12	−502.66	−482.95	−503.17

Note: The entries in parentheses are the standard errors. Bold entries indicate significance at the 10% level or less. The Markov-switching autoregressive model is $\varphi(L)(x_t - \mu_{S_t}) = \epsilon_t$, $\epsilon_t \sim$ i.i.d.$\mathcal{N}(0, \sigma^2_{S_t})$, $S_t = \{0, 1\}$. The transition probabilities for TVTP are specified as $p_t^{00}(f_t) = \frac{\exp\{\gamma_0+\theta_0 f_t+\eta_0 z_{t-1}\}}{1+\exp\{\gamma_0+\theta_0 f_t+\eta_0 z_{t-1}\}}$ and $p_t^{11}(f_t) = \frac{\exp\{\gamma_1+\theta_1 f_t+\eta_1 z_{t-1}\}}{1+\exp\{\gamma_1+\theta_1 f_t+\eta_1 z_{t-1}\}}$. UMCSI indicates that the University of Michigan Consumer Sentiment Index is used. VARLast indicates that the consumer confidence is ordered last in the structural VAR model. BS-VAR3 and BS-VAR5 represent the three-variable and five-variable structural VAR models proposed by Barsky and Sims (2012). FAVAR indicates the factor-augmented VAR model. TVTP-MSI-AR(1) indicates the TVTP Matkov-switching model with regime shifting in the intercept. LogLik represents the value of log-likelihood function.

in including three factors in the VAR; however, the results are not sensitive to alternative numbers of factors. The informational macroeconomic variables consists of a balanced panel of 90 macroeconomic time series, which are initially transformed to induce stationarity, as in Bernanke et al. (2005). The description of the series in X_t and their transformation are described in an Appendix, which

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is available upon request. Empirical results are reported in column (9) of Table 3 and column (5) of Table 4 and denoted as FAVAR.

Clearly, the main conclusion is unchanged when we adopt alternative specifications of the VAR models to identify the structural shocks to consumer confidence.

5.3. Alternative Markov-Switching Models

Finally, we consider alternative specifications of the Markov-switching model. In column (6) of Table 4, we estimate a TVTP-MS-AR(4) model. The results are similar quantitatively and qualitatively to the results from the TVTP-MS-AR(1) model, except that the estimate of θ_0 is negative but statistically insignificant. There still exists strong evidence that recession fears lead to a higher probability of switching to a recession state from an expansion state. We also consider a TVTP Markov-switching autoregressive model that is characterized by switching in the intercept, rather than the mean,

$$\varphi(L)x_t = \mu_{S_t} + \epsilon_t, \quad \epsilon_t \sim \mathcal{N}\left(0, \sigma^2_{S_t}\right), \tag{12}$$

and denote it as TVTP-MSI-AR(q). As shown in Clements and Krolzig (2003), in contrast to the MS-AR model considered so far, the MSI-AR model implies a smooth transition, rather than a once-and-for-all jump, in the level of the process after a shift in regime. The estimation results reported in column (7) of Table 4 suggest that our main findings remain unchanged.

6. CONCLUDING REMARKS

This paper has examined whether increased fear of recession leads to economic downturns. In particular, we ask two questions. First, does greater market pessimism increase the probability of recessions? Furthermore, if it does, how does recession fear affect the probability? Does pessimism cause a higher probability of switching from a expansion state to a recession state and/or a higher probability of trapping the economy in a depressed state?

We first used structural VAR models to identify negative structural shocks to consumer confidence as a measure of recession fear. We then used probit models to examine whether the probability of a U.S. recession increases as a result of recession fear. Finally, time-varying-transition-probability Markov-switching models were applied to investigate how the fear of recession affects the probability of switching between recessions and expansions.

The empirical results suggested that recession fear does lead to a higher probability of economic downturns. Furthermore, strong evidence exists that an increase in market pessimism may push the economy from an expansion state to a recession state. We also found some weaker evidence suggesting that a lack of consumer confidence may trap the economy in a depressed regime longer. We concluded that a greater lack of confidence indeed pushes the economy into a downturn. We showed that the empirical results are robust to different measures of consumer confidence and different structural VAR models for identifying structural shocks, as well as different specifications of Markov-switching models.

NOTES

1. Results for unit root tests are available upon request.
2. The results for variance decompositions are available upon request.
3. The plot of the smoothed probabilities from the FTP model is available upon request.
4. As the sample span is shorter when UMCSI is used, it is found that a TVTP-MS-AR(1) model with constant variance fits the data better.
5. Monthly personal consumption expenditures, available from FRED, are used as the measure of consumption.

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