Firm Size and Cyclical Variations in Stock Returns

Gabriel Perez-Quiros Allan Timmermann*

July 15, 1999

ABSTRACT

Recent imperfect capital market theories predict the presence of asymmetries in the variation of small and large firms' risk over the economic cycle. Small firms with little collateral should be more strongly affected by tighter credit market conditions in a recession state than large, better collateralized ones. This paper adopts a flexible econometric model to analyse these implications empirically. Consistent with theory, small firms display the highest degree of asymmetry in their risk across recession and expansion states and this translates into a higher sensitivity of these firms' expected stock returns with respect to variables that measure credit market conditions.

Recent imperfect capital market theories (e.g., Bernanke and Gertler (1989), Gertler and Gilchrist (1994), Kiyotaki and Moore (1997)) predict that changing credit market conditions can have very different effects on small and large firms' risk. Agency costs induced by asymmetry in the information held by firms and their creditors make it necessary for firms to use collateral when borrowing in the credit markets. Small firms, it is argued, typically do not have nearly as much collateral as large firms and will not have the same ability to raise external funds. Therefore, small firms will be more adversely affected by lower liquidity and higher short-term interest rates.

Such theories do not simply have the cross-sectional implication that small firms' risk will be more strongly affected by tighter credit markets in all economic states. Based on the idea that a decline in a borrower's net worth raises the agency cost on external finance, the theories identify asymmetries in the effect of tighter credit market conditions on risk during recessions and expansions. In a recession, small firms' net worth, and hence their collateral, will be lower than usual and tighter credit markets will be associated with stronger adverse effects than during an expansion when these firms' collateral is higher. Large firms are less likely to experience similarly strong asymmetries over time since they have uniformly higher collateral across economic states. Therefore, a recession may result in a 'flight to quality', causing investors to stay away from the high-risk small firms and switch towards better collateralized, and hence safer, large firms, c.f. Bernanke and Gertler (1989).

Surprisingly little is known about how small firms' risk and expected returns vary over the economic cycle and whether they display the predicted asymmetries. Predictability of the mean and volatility of time-series of returns on common stock market indexes has been widely reported.[1]Similarly, cross-sectional studies have shown that small firms tend to pay higher and more volatile stock returns than large firms, both on a risk-adjusted and unadjusted basis.[2] However, far less work has been done on combining the time-series and cross-sectional evidence to model differences in the cyclical variations in small and large firms' stock returns. Some results indicate that firm size and cyclical variations in expected returns are closely linked, however. For example, Fama and French (1988) find that returns on an equal-weighted portfolio are more sensitive to variations in dividend yields, term- and default premia compared with returns on a value-weighted portfolio that puts more weight on large firms.

In this paper we document systematic differences in variations over the economic cycle in small and large firms' stock returns. In an attempt to capture the asymmetries predicted by theory, we adopt a flexible econometric framework which allows the conditional distribution of stock returns to vary with the state of the economy. We analyze how the sensitivity of risk and expected returns with respect to variables measuring credit market conditions depends on firm size.

Important insights can be gained from inspecting stock return data when testing for asymmetries in small and large firms' cost of external capital. Stock prices reflect investors' anticipation of the future state of the economy and should adjust quickly (in principle instantaneously) to the arrival of new information. In contrast, the dynamics of the adjustment observed in flow of funds data following monetary contractions is complicated by frictions in firms' access to bond markets, c.f. Christiano, Eichenbaum, and Evans (1996). Furthermore, the analysis can teach us something about the sources of variations in stock returns. Small firms' high mean returns have puzzled financial economists for a long time and Fama and French (1995) hypothesize that firm size matters in determining stock returns because it acts as a proxy for some unobserved, omitted risk factor. By studying the time-series of small and large firms' risk and risk premia in the context of a model that accounts for cyclical asymmetries, we are able to shed new light on the mechanism creating variations in expected stock returns.

Consistent with theory we find that small firms display the highest degree of asymmetry in their conditional return distribution across recession and expansion states. In a recession, small firms' risk is most strongly affected by worsening credit market conditions (as measured by higher interest rates, lower money supply growth, and higher default premia). These asymmetries produce sizeable variations in small firms' expected returns which increase rapidly during recessions. We present evidence that this reflects the comparatively higher risk of small firms. As recessions deepen, these firms rapidly lose collateral and their assets become more risky, causing investors to require a higher premium for holding their shares.

The plan of the paper is as follows. Section I discusses the theoretical motivation for size-related asymmetries in stock returns and Section II presents the econometric framework for incorporating asymmetries in the conditional distribution of stock returns. Section III reports empirical results for the model fitted to size-sorted portfolio returns, while Section IV provides a multivariate framework for analysis of the small firm risk premium. Section

V evaluates the asset allocation implications of the asymmetries in a simple out-of-sample forecasting experiment and also explores implications for the cyclical variation in the tradeoff between risk and returns. Section VI concludes.

I. Sources of Cyclical Asymmetries in Small and Large Firms' Risk and Expected Returns

A variety of sources can generate asymmetries in small and large firms' risk across different stages of the economic cycle. Size is widely considered a proxy for capital market access, albeit an imperfect one, and some theories predict asymmetries as an implication of capital market imperfections. Gertler and Gilchrist (1994), for example, argue that the informational asymmetries that increase firms' cost of external capital are most important to young firms, firms exposed to large idiosyncratic risks, and firms that are poorly collateralized, all of which tend to be smaller firms. Since small and large firms use very different sources of financing and have very different degrees of access to credit markets, they ought to be differently affected by credit constraints. Combining this with the finding that credit constraints are time-varying and bind most during recessions leads to the conclusion that small firms should be more adversely affected by worsening credit market conditions during a recession state.

Capital market imperfection theories focus on a balance sheet and a credit effect. We briefly describe these two effects and explain how they lead to size-related asymmetries. The premise of the balance sheet effect advanced by, e.g., Bernanke and Gertler (1989) and Kiyotaki and Moore (1997), is that borrowers' collateralizable assets determine their terms of credit. Worsening credit market conditions, as reflected by increasing interest rates, will weaken firms' balance sheets by lowering the present value of their collateral and by raising the interest costs deducted from their cash flows. Further pressure on firms' net cash flows is generated indirectly through the decline in sales which follows from tighter credit conditions.

If worsening credit market conditions work through firms' balance sheets, then their effect is likely to be strongest for small firms in a recession state where these firms' collateral has already been eroded and where credit constraints affect a wider proportion of small firms.

The credit channel effect works through tighter credit market conditions which initially decrease the pool of funds that banks can lend out, c.f. Bernanke and Blinder (1992) and Kashyap, Stein, and Wilcox (1993). The presence of reserve requirements means that this tighter liquidity prevents banks from lending as much money to firms as they could do under normal circumstances. Thus the most bank-dependent borrowers should be most strongly affected by tighter credit.

Partly because of the availability of less public information about small firms, these firms typically have to rely more on information-intensive sources of credit such as bank loans. Evidence in, e.g., Gertler and Hubbard (1988) and Gertler and Gilchrist (1994) suggests that small firms are by far the most dependent on bank loans and other intermediary sources of credit, while conversely large firms have better access to direct sources of credit such as commercial paper.[3] Again this leads to the conclusion that small firms' risk should be disproportionately affected by tighter credit market conditions particularly in a recession when these firms' need for credit is strongest.

The clearest direct link between firm size and asymmetries in the effect of monetary and real shocks on firm profitability has perhaps been provided by Cooley and Quadrini (1997). These authors present a general equilibrium model in which firm size is the key source of heterogeneity and matters because of decreasing returns to scale and because of the presence of a fixed and linear operating cost that is related to firm size. Firms borrow from financial intermediaries to establish working capital, using cumulated equity as collateral. Since the probability of firm failure is the main source of risk, both the amount of capital a firm can borrow and its borrowing rate are determined by the firm's collateral. Small firms' marginal profits are most sensitive to shocks as a result of their operating on a smaller scale. Since collateral is universally lower in a recession state, again this model implies that small firms' risk and their expected profit per unit of borrowed funds should be relatively higher in -- and more sensitive to -- this economic state.

Size-related cyclical asymmetries in risk and expected stock returns have not yet been analyzed empirically but it is clear that they are a logical consequence of the asymmetries in the volatility of corporate profits implied by these imperfect capital market theories.[4] The higher sensitivity of small firms' profits and asset values with respect to credit market shocks and their higher probability of becoming credit constrained or of defaulting means that small firms' relative risk should increase around recessions. Provided that this volatility cannot be diversified away, it should also translate into a disproportionately higher risk premium on small firms around recessions. Using a similar argument, Fama and French (1995) trace the cross-sectional firm size component in expected stock returns back to a common risk component in firms' profitability.

Cyclical asymmetries in small and large firms' risk are likely to lead to similar effects in expected returns and can be further confounded through the credit constraints operating on investors. Cooley and Quadrini (1997)'s model implies that small firms' default risk is particularly high in a recession state where overall collateral is low. This is also the time when consumers are more likely to be credit-constrained. It seems plausible that, in a general equilibrium, investors will be less willing to carry risk and that the small firm risk premium will go up in recessions. Combining the cyclical variation in volatility and small firms' higher sensitivity to the state of the economy, it follows that these firms' expected returns should display particularly strong cyclical asymmetries, something we test for in Section IV.

II. An Econometric Model of Asymmetries in Risk and Expected Stock Returns

Motivated by the discussion of asymmetries in the effect of changing economic conditions on firms' cost of external capital, our empirical analysis explicitly accounts for state dependence in risk and expected returns. To ensure that our empirical results are easy to interpret in the context of the literature we simply allow for two possible states and let the identity of these states be determined by the data. This latent state approach has several advantages relative to the alternative method of conditioning on some pre-defined state indicator. Inferred state probabilities provide important information about the directions in which variations in the conditional distribution of stock returns occur. Furthermore, it is not clear that variables such as industrial production or the NBER recession indicator would form a natural basis for defining separate states of nature. Each of these series has its own measurement problems and, in contrast with the forward-looking stock returns data, these data only become available 'after the fact'. Finally, our model is readily applicable to produce forecasts of stock returns while this is not the case for a model based on a pre-defined state.

More specifically, we use the Markov switching model introduced by Hamilton (1989) as a springboard for the analysis and we draw on Gray (1996)'s extension to Markov chains with time-varying transition probabilities. Let ρ_t be a portfolio's excess return in period t, while $\mathbf{X}_{t-1}$ is a vector of conditioning information (excluding a constant) used to predict ρ_t. Our Markov switching specification is quite general and lets the intercept term, regression coefficients and volatility of excess returns be a function of a single, latent state variable (S_t):

$$\rho_t = \beta_{0,s_t} + \boldsymbol{\beta}'_{s_t}\mathbf{X}_{t-1} + \epsilon_t, \epsilon_t \sim (0, h_{s_t}). \tag{1}$$

Suppose there are two states, denoted 1 and 2, so that $S_t = 1$, or $S_t = 2$. Then the coefficients and variance are either $(\beta_{0,1,}\boldsymbol{\beta}'_1, h_1)$ or $(\beta_{0,2,}\boldsymbol{\beta}'_2, h_2)$. Notice that both the risk and the expected return are allowed to vary across states.

To complete the description of the data generating process, it is necessary to specify how the underlying state evolves through time. We make the common assumption that the state transition probabilities follow a first-order Markov chain:

$$p_t \quad = \quad P(S_t = 1 | S_{t-1} = 1, \mathbf{y}_{t-1}) = p(\mathbf{y}_{t-1}) \tag{2}$$

$$
\begin{aligned}
1-p_t &= P(S_t=2|S_{t-1}=1,\mathbf{y}_{t-1}) = 1-p(\mathbf{y}_{t-1}) \\
q_t &= P(S_t=2|S_{t-1}=2,\mathbf{y}_{t-1}) = q(\mathbf{y}_{t-1}) \\
1-q_t &= P(S_t=1|S_{t-1}=2,\mathbf{y}_{t-1}) = 1-q(\mathbf{y}_{t-1}),
\end{aligned}
$$

where $\mathbf{y}_{t-1}$is a vector of variables that are publicly known at time $t-1$ and affect the state transition probabilities between periods $t-1$ and t. The standard formulation of the Markov switching model assumes that these transition probabilities are constant. However, recent empirical studies using this class of models suggest that this may be an oversimplification and let the probability of staying in a state depend on the duration of the state or on some other conditioning information.[5] This is particularly relevant to a model of stock returns since it is plausible that investors' information about the state transition probabilities is superior to that implied by the model with constant transition probabilities.

Provided that assumptions are made on the conditional density of the innovations, ϵ_t, the parameters of the model can be obtained by maximum likelihood estimation. Let $\boldsymbol{\theta}$ denote the vector of parameters entering the likelihood function for the data and suppose that the density conditional on being in state j, $\eta(\rho_t|S_t=j,\mathbf{X}_{t-1};\boldsymbol{\theta})$, is Gaussian:[6]

$$
\eta(\rho_t|\Omega_{t-1},S_t=j;\boldsymbol{\theta}) = \frac{1}{\sqrt{2\pi h_j}}\exp(\frac{-(\rho_t-\beta_{0,j}-\boldsymbol{\beta}_j'\mathbf{X}_{t-1})^2}{2h_j}), \tag{3}
$$

for j = 1,2. Here the information set Ω_{t-1} contains $\mathbf{X}_{t-1}$, ρ_{t-1}, $\mathbf{y}_{t-1}$, and lagged values of these variables: $\Omega_{t-1}=\{\mathbf{X}_{t-1},\ \rho_{t-1},\ \mathbf{y}_{t-1},\ \Omega_{t-2}\}$. Notice that we assume a constant relationship between the conditioning factors, $\mathbf{X}_{t-1}$, and excess returns *within* each state, but allow these coefficients to vary *between* states. The log-likelihood function takes the form

$$\ell(\rho_t|\Omega_{t-1};\boldsymbol{\theta}) = \sum_{t=1}^{T} \ln(\phi(\rho_t|\Omega_{t-1};\boldsymbol{\theta})), \quad (4)$$

where the density $\phi(\rho_t|\Omega_{t-1};\boldsymbol{\theta})$ is simply obtained by summing the probability-weighted state densities, $\eta(.)$, across the two possible states:

$$\phi(\rho_t|\Omega_{t-1};\boldsymbol{\theta}) = \sum_{j=1}^{2} \eta(\rho_t|\Omega_{t-1}, S_t = j;\boldsymbol{\theta})P(S_t = j|\Omega_{t-1};\boldsymbol{\theta}), \quad (5)$$

and $P(S_t = j|\Omega_{t-1};\boldsymbol{\theta})$ is the conditional probability of being in state j at time t given information at time $t-1$.

From the total probability theorem it follows that the conditional state probabilities can be obtained recursively:

$$P(S_t = i|\Omega_{t-1};\boldsymbol{\theta}) = \sum_{j=1}^{2} P(S_t = i|S_{t-1} = j, \Omega_{t-1};\boldsymbol{\theta})P(S_{t-1} = j|\Omega_{t-1};\boldsymbol{\theta}). \quad (6)$$

Finally, by Bayes' rule the conditional state probabilities can be written as

$$P(S_{t-1} = j|\Omega_{t-1};\boldsymbol{\theta}) = P(S_{t-1} = j|\rho_{t-1}, \mathbf{X}_{t-1}, \mathbf{y}_{t-1}, \Omega_{t-2};\boldsymbol{\theta}) = \quad (7)$$
$$\frac{\eta(\rho_{t-1}|S_{t-1} = j, \mathbf{X}_{t-1}, \mathbf{y}_{t-1}, \Omega_{t-2};\boldsymbol{\theta})P(S_{t-1} = j|\mathbf{X}_{t-1}, \mathbf{y}_{t-1}, \Omega_{t-2};\boldsymbol{\theta})}{\sum_{j=1}^{2} \eta(\rho_{t-1}|S_{t-1} = j, \mathbf{X}_{t-1}, \mathbf{y}_{t-1}, \Omega_{t-2};\boldsymbol{\theta})P(S_{t-1} = j|\mathbf{X}_{t-1}, \mathbf{y}_{t-1}, \Omega_{t-2};\boldsymbol{\theta})}.$$

As shown by Gray (1996), equations (6) and (7) can be iterated on recursively to derive the state probabilities $P(S_t = i|\Omega_{t-1};\boldsymbol{\theta})$ and obtain the parameters of the likelihood function. The inferred state probabilities are driven by variations in the distribution of excess returns conditional on the included regressors. Systematic variations in these probabilities will be evidence supporting the presence of asymmetries in the conditional expectation and volatility of stock returns.

III. Empirical Results

A. Data and Model Specification

Our analysis uses excess returns on the size-sorted decile portfolios provided by the Center for Research in Security Prices.[7] The sample period begins in January 1954 and ends in December 1997, giving a total of 528 monthly observations. This sample was selected to conform with the period after the Accord which allowed T-bill rates to vary freely. Summary statistics for the excess return data are presented in Table I. Unsurprisingly, the mean and volatility of returns decline almost uniformly as one moves from portfolios comprising the smallest firms to portfolios consisting of larger firms.

To show the importance of business cycle asymmetries in the distribution of stock returns conditional on the prevailing credit market conditions, we model excess returns on each of the size-sorted decile portfolios as a function of an intercept term and lagged values of the one-month T-bill rate, a default premium, changes in the money stock, and the dividend yield. All are commonly-used regressors from the literature on predictability of stock returns and we briefly explain the main reason for their inclusion.

Based on the quantity theory of money, Fama (1981) argues persuasively that an unobserved negative shock to the growth in real economic activity induces a higher nominal T-bill rate through an increase in the current and expected future inflation rate. Expected real economic growth rates and stock prices should be positively correlated so this story predicts a negative correlation between interest rates and stock returns. We follow standard practice and include the one-month T-bill rate ($I1$) as a state variable proxying for investors' (unobserved) expectations of future economic activity. Since this short T-bill rate is also an indicator of the market-wide interest rate, it serves as a proxy for firms' interest costs, an important transmitter of tighter credit market conditions according to the imperfect capital market theories. Fama and Schwert (1977), Campbell (1987), Glosten et al. (1993), and Whitelaw (1994) use this regressor in stock return equations and find that it is negatively correlated with future returns.

The default premium (Def), sometimes called the 'quality spread', is defined as the difference between yields on Baa and Aaa rated corporate bond portfolios, both obtained from the DRI Basic Economics database. Small firms with little collateral are likely to be more exposed to bankruptcy risks during recessions so we would expect asymmetries to show up in the coefficients of this variable. Keim and Stambaugh (1986), Fama and French (1988), Fama and French (1989), and Kandel and Stambaugh (1990) were among the first to include this regressor in stock return regressions. They find that the default premium is positively correlated with future stock returns.

As our measure of changes in the economy's liquidity we use the growth in the money stock (ΔM), defined as the twelve-month log-difference in the monetary base reported by the St. Louis Federal Reserve. A further reason for including this regressor is that Fama (1981) finds that it is important to control for money supply when establishing the inflation-future real economic activity proxy story.

Finally, the dividend yield ($Yield$) is defined as dividends on the value-weighted CRSP portfolio over the previous twelve months divided by the stock price at the end of the month. Although it is not directly related to credit market conditions, this regressor (or yield proxies such as the inverse of the price level relative to its historical average) is widely used to model expected returns, c.f. Keim and Stambaugh (1986), Fama and French (1988), and Kandel and Stambaugh (1990) and it has been associated with slow mean reversion in stock returns across several economic cycles.[8] The common explanation for inclusion of this regressor is that it proxies for time variation in the unobservable risk premium since a high dividend yield indicates that dividends are being discounted at a higher rate.

Let ρ_t^i be the excess return on the i'th size-sorted decile portfolio in month t. We adopted the following conditional mean specification:

$$\rho_t^i = \beta_{0,s_t}^i + \beta_{1,s_t}^i I1_{t-1} + \beta_{2,s_t}^i Def_{t-1} + \beta_{3,s_t}^i \Delta M_{t-2} + \beta_4^i Yield_{t-1} + \epsilon_t^i, \quad (8)$$

where $\epsilon_t^i \sim N(0, h_{s_t}^i)$. Information on the rate of return variables is continuously available so only a single lag is used for these regressors while the money stock enters with a lag of two months, reflecting the publication delay for this variable. The conditional variance of excess returns, $h_{s_t}^i$, is allowed to depend on the state of the economy as well as on the level of the T-bill rate:

$$\ln(h_{s_t}^i) = \lambda_{0,s_t}^i + \lambda_{1,s_t}^i I1_{t-1}. \quad (9)$$

Our choice of conditional variance equation is based on the study of Glosten et al. (1993) who find that lagged interest rates are important in modeling the conditional volatility of monthly stock returns. ARCH effects were found to be relatively less important. In an attempt to keep an already complicated nonlinear specification as simple as possible, we do not include ARCH effects but later investigate such effects. For similar reasons we restrict the conditional volatility to include a constant and a single time-varying regressor.

Notice that we model state switching directly in the coefficients of the regressors in the conditional stock return equation whereas Whitelaw (1997b) assumes that the fundamental process (consumption growth in a Lucas (1978) model) follows a two-state process. The advantage of Whitelaw's approach is that the regression results can be interpreted in the context of an equilibrium asset pricing model, although they may critically depend on whether aggregate consumption growth is a reasonable proxy for investors' marginal rates of substitution. Our approach has the advantage that it builds closely on the models of risk and expected returns used in many empirical studies in finance and hence allows us to directly compare our results to that literature.

State transition probabilities are specified as follows:

$$\begin{aligned} p_t^i &= prob(s_t^i = 1 | s_{t-1}^i = 1, \mathbf{y}_{t-1}) = \Phi(\pi_0^i + \pi_1^i \Delta CLI_{t-2}) \\ q_t^i &= prob(s_t^i = 2 | s_{t-1}^i = 2, \mathbf{y}_{t-1}) = \Phi(\pi_0^i + \pi_2^i \Delta CLI_{t-2}), \end{aligned} \tag{10}$$

where ΔCLI_{t-2} is the two-month lagged value of the year-on-year log-difference in the Composite Leading Indicator, s_t^i is the state variable for the i'th portfolio and Φ is the cumulative density function of a standard normal variable. This specification is an attempt to capture parsimoniously investors' information on state transition probabilities through use of a simple summary statistic.[9]

B. Results

Along with all the other parameters obtained from estimating the Markov switching model to excess returns on each of the 10 size-sorted portfolios, estimates of the state transition probabilities are reported in Table II. Nine of 10 estimates of the coefficient on the change in the composite leading indicator are negative in state 1 while eight of 10 estimates are positive in state 2 and the remaining ones are small. The time variation in the transition probabilities hence ensures that the effect of an increase in the leading indicator is to decrease the probability of staying in state 1 and to increase the probability of staying in state 2. This suggests that state 1 and 2 are recession and expansion states, respectively, and subsequently we present further evidence that confirms this.

Variation over time and across states in the risk of stock returns is determined both by these transition probabilities and by the parameters of the conditional volatility equation. All sets of volatility parameters are estimated quite precisely, as revealed by their small standard errors. The estimated intercept term in the recession state generally implies a level of conditional variance between three and seven times larger than in the expansion state, depending on firm size. The biggest difference between the estimated intercept terms in the two states emerges for the portfolio comprising the smallest firms. In the recession state the estimated intercept term tends to decrease as one moves from the smallest to the largest firms. Likewise, the two portfolios comprising the largest firms have the smallest intercept term in the expansion state. For nine of 10 portfolios, the sensitivity of the conditional variance with respect to the lagged interest rate is highest in the recession state. There is no systematic relationship between firm size and the coefficient on the lagged interest rate in the volatility equation, however.

These volatility estimates confirm the finding in Schwert (1990) and Hamilton and Lin (1996) that stock return volatility is highest during economic recessions and extend this earlier finding in two directions. First, we find that there is a close relationship between firm size and return volatility and that the volatility of small firms is most strongly affected by a recession state. Second, the sensitivity of the conditional volatility of excess returns with respect to lagged interest rates tends to be higher during recessions than during expansions.[10]

Turning next to the mean equation, all 10 size-sorted portfolios generate negative and significant coefficients on the one-month lag of the T-bill rate in the recession state. Furthermore, there is a systematic relationship between firm size and these estimates. Moving from the smallest to the largest companies, these estimates increase almost uniformly from -18 to -7, so small firms' excess returns are most strongly negatively correlated with the short interest rate in the recession state. While seven of 10 of the estimated coefficients on the T-bill rate are still negative in the expansion state, they are much smaller in absolute value and only two coefficients are significant at conventional levels.

A similar relation between firm size and the coefficient estimates of the excess return equation emerges for the default premium in the recession state. In this state all portfolios generate coefficients of the default premium that are positive and eight of 10 are significant at conventional levels. Furthermore, the estimated coefficients tend to decrease as a function of firm size with the smallest firms generating estimates more than twice as large as those of the largest firms. Only two of the estimated coefficients on the default premium remain statistically significant and positive in the expansion state while three coefficients are negative and significant in this state. Hence the default premium is mainly important in the excess return equation during economic recessions and particularly so for small firms.[11] Small firms' collateral is likely to be very low during recessions, so the results match well with imperfect capital market theories that relate the cost of external capital to firm size and the economic state.

In the recession state, the change in the aggregate money supply generates positive coefficients for all 10 size-sorted portfolios with coefficient estimates that are largest for the smallest firms. Only the portfolio comprising the smallest firms produces a statistically significant coefficient on the monetary growth factor. In the expansion state the estimated coefficients on the monetary factor are positive for eight out of 10 portfolios, but none of these is significant and most coefficients are small compared to their values in the recession state. Thus higher monetary growth is associated with higher expected excess returns only for the smallest firms in the recession state. A possible non-causal explanation is that the Federal Reserve expands the monetary base mainly when the economy is in a deep recession and that small firms' risk and risk premium are highest in this state.

These results show that there is strong economic evidence of asymmetries in stock returns. However, they do not prove that asymmetries are statistically significant. In Table III we report a set of likelihood ratio tests for the existence of two states in the conditional mean and variance. As pointed out by Hansen (1992), the standard likelihood ratio test for multiple states is not appropriate in this context since the transition probability parameters are not identified under the null of a single state. Thus in the test for asymmetries in the conditional mean we condition on the existence of two states in the conditional volatility and vice versa. The resulting likelihood ratio test follows a standard chi-squared distribution.

The null of symmetry in the volatility equation is very strongly rejected for all 10 portfolios while four of 10 portfolios lead to a strong rejection of symmetry in the conditional mean. The portfolios for which symmetry in the mean equation cannot be rejected have very different coefficients in the two states, so we attribute the failure to reject the null for some of the portfolios to the fact that mean returns are very noisy. When we tested for symmetry in the individual regression coefficients, seven of 10 portfolios led to a rejection of the null at the five percent critical level while nine of 10 portfolios rejected the null at the 10 percent level. These results show that asymmetries are not only economically, but also statistically important for the volatility of every single portfolio and for the conditional mean of most portfolios.

To further interpret the two latent states identified by the data on the portfolios comprising the smallest and largest firms, Figure 1 plots the estimated probability of being in state 1 at time t conditional on period $t-1$ information ($\Pr(s_t = 1|\Omega_{t-1}; \widehat{\theta})$). As they depend only on ex ante information, in principle these probabilities could reflect investors' view of the likelihood that state 1 occurs next period.[12] NBER recession periods are also shown in Figure 1 in the form of shaded areas. The state probabilities are quite noisy, particularly for the small firms. State 1 is effectively a mixture of a high volatility state and a recession state, as evidenced by the tendency of state 1 to pick up outlier observations such as October 1987. This may be the inevitable result of return volatility coupled with the model's success at identifying a high volatility state. Still, there is clearly a business cycle component in the state probabilities: the correlation between p_{1t} and the NBER indicator is 0.30 for the smallest firms and 0.31 for the largest firms. Furthermore, the probability of being in state 1 tends to increase prior to and during recessions and rapidly decreases after recession periods.

Figure 2 presents time series of the estimated transition probabilities p_t and q_t for the smallest and largest firms. For the smallest firms, these probabilities vary substantially over the economic cycle, confirming our earlier conjecture that a constant transition probability is too simple an assumption when modeling stock returns.[13] For both small and large firms, the probability of staying in the low-variance, high-mean (expansion) state increases after recessions and decreases rapidly prior to and during most recessions. Furthermore, for the smallest firms the probability of staying in the high volatility state rapidly declines after recessions and increases towards the end of expansions. While this last finding does not apply to the largest firms, notice that the coefficients on the leading indicator are smaller and not statistically significant for these firms.[14]

So far our empirical analysis has followed common practice in financial studies in its measurement of credit market conditions by means of a 1-month T-bill rate and the growth in the monetary base. However, some recent studies consider the Federal Funds Rate as the basic instrument of monetary policy (e.g., Taylor (1993), Clarida, Gali, and Gertler (1997)). These studies propose different policy rules that relate the Fed Funds Rate to the gaps between expected inflation and output and these variables' target levels.[15]

Strongin (1995) argues that the "mix of nonborrowed to total reserves," defined as nonborrowed reserves divided by the lagged value of total reserves, can be used to separately identify the supply shocks in monetary policy from the demand shocks due to the Fed policy of accommodating short run reserve demand disturbances.[16]

We investigate the significance of changes in the credit market measures by estimating the mixture model to the smallest and largest firms' excess returns using the Federal Funds Rate and the nonborrowed to total reserves ratio in place of $I1$ and ΔM. Table IV shows that while the scale of some of the regressors changes, the qualitative results are very robust. In fact, the findings based on these alternative credit market measures are even more in line with the theoretical predictions discussed in Section I. The lagged value of the short interest rate remains most strongly negatively correlated with the smallest firms' excess returns in the recession state. Furthermore, the coefficient of the monetary policy variable is positive, statistically significant, and much larger in the excess return equation during the recession state.[17] The higher level of volatility during recessions also remains consistent with theory.

IV. A Joint Model of Small and Large Firms' Risk and Expected Returns

So far the excess return models have been estimated separately for each portfolio and hence do not impose the condition that the recession state occurs simultaneously for all portfolios. While the plots in Figure 1 are quite noisy, particularly for the smallest firms, more precise estimates of the underlying state may be obtained from a bivariate model imposing a common state process driving all excess return series. Also, the jointly estimated model provides a natural framework for extracting the variation in the risk premium on small over large firm portfolios. Finally, a jointly estimated model allows us to formally test the hypothesis that small firms display a higher degree of asymmetry than larger firms, a key prediction of the underlying theory. For these reasons we generalize the previous framework by estimating a bivariate Markov switching model to excess returns on the portfolios comprising the smallest and largest firms. Two rather than 10 portfolios are considered in order to keep the estimations feasible. Let $\boldsymbol{\rho}_t = (\rho_t^s, \rho_t^l)'$ be the (2 x 1) vector consisting of excess returns on the smallest and largest firms. The estimated model is

$$\boldsymbol{\rho}_t = \boldsymbol{\beta}_{0,s_t} + \boldsymbol{\beta}_{1,s_t} I1_{t-1} + \boldsymbol{\beta}_{2,s_t} Def_{t-1} + \boldsymbol{\beta}_{3,s_t} \Delta M_{t-2} + \boldsymbol{\beta}_4 Yield_{t-1} + \epsilon_t \quad (11)$$

where $\boldsymbol{\beta}_{k,s_t}$ is a (2 x 1) vector with elements

$$\boldsymbol{\beta}_{k,s_t} = \begin{pmatrix} \beta_{k,s_t}^s \\ \beta_{k,s_t}^l \end{pmatrix},$$

and $\boldsymbol{\epsilon}_t \sim N(0, \Omega_{s_t})$ is a vector of residuals. Ω_{s_t} is a positive semi-definite (2 x 2) matrix containing the variances and covariances of the residuals of the smallest and largest firms' excess returns in state s_t. The diagonal elements of this variance-covariance matrix (Ω_{ii,s_t}) take the same form as in the univariate specification, while the off-diagonal terms (Ω_{ij,s_t}) assume a state-dependent correlation between the residuals (ξ_{s_t}):

$$\ln(\Omega_{ii,s_t}) = \lambda_{0,i,s_t} + \lambda_{1,i,s_t} I1_{t-1}, \quad (12)$$

$$\Omega_{ij,s_t} = \xi_{s_t} (\Omega_{ii,s_t})^{1/2} (\Omega_{jj,s_t})^{1/2}, i \neq j.$$

We maintain the transition probabilities from the univariate model:

$$p_t = prob(s_t = 1|s_{t-1} = 1) = \Phi(\pi_0 + \pi_1 \Delta CLI_{t-2}) \quad (13)$$

$$q_t = prob(s_t = 2|s_{t-1} = 2) = \Phi(\pi_0 + \pi_2 \Delta CLI_{t-2}), \quad (14)$$

but now impose the restriction that the same latent state variable drives excess returns on both portfolios ($s_t \equiv s_t^1 = s_t^{10}$). Results from this estimation are presented in Table V. Compared with the parameter estimates in Table II, little is changed by imposing a common state process. Most importantly, the asymmetries in the coefficients of the interest rate and default premium in the conditional mean equation are very similar to the evidence found for the univariate specifications. This is important to the economic interpretation of our results since it indicates that the latent process represents a pervasive, economy-wide state variable.

Table V also presents results from testing the proposition that the asymmetry across recession and expansion states in small firms' parameter estimates exceeds the asymmetry observed for large firms. Recall that state 1 and 2 broadly correspond to recession and expansion states, respectively. For each set of coefficients we test the null that

$$\left|\beta^s_{j,1} - \beta^s_{j,2}\right| = \left|\beta^l_{j,1} - \beta^l_{j,2}\right| \tag{15}$$

against the alternative hypothesis that the coefficient differential is largest for the small firms. The null of identical asymmetries for small and large firms is strongly rejected at standard critical levels for the interest rate coefficient and the default premium in the conditional mean. Symmetry is also rejected for the intercept coefficient in the volatility equation. Hence these results formalize the notion that cyclical asymmetries in the risk and expected returns are largest for small firms.

Figure 3 provides plots of the expected excess returns using the parameter estimates from Tables II and V. The series based on the univariate and bivariate models are extremely similar. Predicted excess returns of both small and large firms tend to decline systematically during expansions and increase rapidly during -- and in some cases prior to -- recessions. In addition, the scale of variation in the smallest firms' expected excess returns is roughly twice as large as that of the largest firms, again indicating the greater sensitivity of small firms' stock returns with respect to the state of the economy.[18]

The bottom window in Figure 3 sheds light on the variation in the difference between the small and large firms' expected return by plotting $\widehat{\rho}^s_{t+1}$ - $\widehat{\rho}^l_{t+1}$, the expected return differential from the bivariate model. This differential is positive almost 60 percent of the time, namely in 306 out of 528 months, and has a positive overall mean of 0.52 percent per month.

Movements in the expected small firm premium are closely related to the state of the economy: it tends to be small and even negative prior to and during the early recession phase only to increase sharply during later stages of most recessions. Consistent with the theories described in Section I, a possible economic interpretation of this finding is that, as recessions grow deeper, small firms rapidly lose collateral and their assets become more risky, causing investors to require a higher premium for holding their shares.

V. Economic Significance of Asymmetries

This section explores the economic significance of the empirical findings reported so far in two further ways. First, we study the asset allocation implications of the asymmetries in returns by estimating the two-state model recursively, forecasting stock returns one step ahead and implementing the forecast in a simple investment rule. This exercise establishes a conservative estimate of the asset allocation implications of our findings. Second, we consider the cyclical variation in small and large firms' risk premia implied by the variation in risk and expected returns. This analysis sheds light on the sources of time-varying risk and the extent to which they are related to firm size.

A. Asset Allocation Implications of Out-of-Sample Predictions

There is always the risk that a flexible, nonlinear model as complex as ours overfits the data. To avoid potential problems from overfitting requires studying out-of-sample forecasts. Once implemented in a simple asset allocation rule, these forecasts can be used to assess the portfolio implications of the asymmetries in stock returns.

To avoid conditioning on information which was not known historically, we re-estimate the parameters of the model recursively each month. Diebold and Rudebusch (1991) observe that the composite leading indicator has been revised numerous times, so it is important to avoid using the information implicit in later revisions. Let ΔCLI_t^{τ} denote the value of ΔCLI applying to month t based on the CLI series released at time $\tau \geq t$. In each period we then use the most recent series of ΔCLI at that point in time to forecast excess returns. i.e. we use ΔCLI_{t-2}^{t-2} to forecast ρ_t.

To account for difficulties in precisely estimating our nonlinear model, we use an expanding window of the data starting with observations from 1954:1. We begin the sample in 1976:3 to avoid the disruptive effects of a set of major revisions of the CLI in 1975.[19]

Recursive out-of-sample predictions of excess returns on the smallest and largest firms are plotted in Figure 4 along with plus-minus two standard error bands. Reassuringly, the predictions are very similar to the in-sample forecasts. The correlation between the out-of-sample and in-sample predictions are 0.86 and 0.81 for the smallest and the largest firms, respectively. This suggests that we have not over-fitted the model.

Our measure of the economic value of the predictions is based on the performance of a simple stylized trading rule which, if excess returns are predicted to be positive, goes long in the equity portfolio under consideration, otherwise holds T-bills. Return and risk characteristics for such switching portfolios are presented in Table VI. In the full sample both switching portfolios generate Sharpe ratios that are higher than those of the respective buy-and-hold portfolios. This improved risk-return tradeoff reflects a slightly lower mean but a significantly lower standard deviation of returns. Again the full sample results conceal interesting variation across recession and expansion periods. In recessions the mean returns on the switching portfolios are more than twice as high as those of the respective benchmark portfolios while the standard deviation is about one third lower than that of the buy-and-hold portfolio. Consequently, the switching portfolios have far higher Sharpe ratios than the buy-and-hold portfolios in recessions. During expansions, however, the Sharpe ratios on the switching portfolios are actually lower than or equal to those generated by the buy-and-hold strategy.

These results indicate that the information in the forecasts is not only statistically but also economically significant. They are consistent with our earlier finding that the premium per unit of risk varies considerably over the economic cycle. Compared to the buy-and-hold portfolios, the switching portfolios generate particularly high Sharpe ratios during recession months. Thus a successful equilibrium model attempting to explain the time-variation in expected returns must be able to display very considerable variation in risk premia across recession and expansion states.

B. Cyclical Variation in Risk and Conditional Sharpe Ratios

The discussion in Section I suggests that asymmetries in expected returns result from asymmetries in the conditional volatility (risk). Certainly this explanation is consistent with the test results in Tables III and V which show that symmetry can be rejected both for the conditional mean and volatility equations and that small firms' returns display the largest asymmetries. Time-varying expected returns can be driven either by variations in the level of risk or by changes in the premium per unit of risk, and both components need to be investigated. To analyze the first component, we plot in the upper window of Figure 5 the conditional volatility of the smallest and largest firms' excess returns. Notice that this measure of risk reflects the switching probabilities and not simply the standard deviation of returns in a given state. The top window shows that, prior to and during economic recessions, the conditional volatility tends to increase for both small and large firms. It also shows that small firms' conditional volatility almost always exceeds that of the large firms.[20]

If the increasing expected return on small firms during recessions reflects their higher risk, then small firms' volatility relative to that of large firms ought to increase in recession states and decline early in expansion states. To see if this implication is borne out by the data, we plot in the lower window of Figure 5 the ratio of the conditional volatility of small firms relative to that of the large firms. As predicted by theory, this ratio tends to increase prior to and during recessions and declines early in the expansions, although the series is very noisy.

The extent to which higher conditional risk shows up as a higher expected returns depends of course on the price of risk. If this declines in states where small firms are more risky, then it will be difficult to explain small firms' higher expected returns during recessions as being driven by risk. Time-variations in the price of risk can be very sizeable as evidenced by Kandel and Stambaugh (1990) and Whitelaw (1997a)'s finding of a strong cyclical component in the conditional Sharpe ratio of U.S. stocks. Whitelaw finds that the conditional Sharpe ratio is low around peaks of the economy but very high around troughs, indicating that investors require a higher compensation per unit of non-diversifiable risk in recession states.

Figure 6 plots estimates of the conditional Sharpe ratios for small and large firms. Interestingly, the conditional Sharpe ratios are very similar for the two portfolios and they display very strong cyclical patterns. In line with Whitelaw's findings, the ratios tend to increase during recessions only to drop rapidly in the ensuing expansion states.[21] Hence the rapid increase during recessions in small and large firms' expected returns appears to be the result of a rise in their level of risk confounded by an increase in the expected premium per unit of risk.

VI. Conclusion

This study presents evidence of two important asymmetries in the risk and return on stocks. First, the conditional distribution of stock returns is very different in recession and expansion states. The volatility of returns is more sensitive to interest rate changes in recession periods. Likewise, firms' expected returns are more sensitive to changes in interest rates, default premia and monetary growth during recessions. Second, small firms' risk and expected returns are most strongly affected by a recession state as noticed by the higher sensitivity of their regression coefficients with respect to changes in the underlying economic state. Large firms' expected returns also display important state dependencies, but these are weaker when compared to those observed in the smallest firms' return equation.

These findings have implications for return modeling, for our understanding of the economic sources underlying time variation in conditional stock returns, and for the economic value of predictability of returns. On the first point, the empirical evidence suggests that cyclical asymmetries in risk and expected returns are sufficiently significant to be explicitly modeled and could be important to studies of the significance of macroeconomic and 'style' factors in the cross-section of stock returns. Empirical models of risk factors traditionally assume a constant-coefficient setup and, using the methodology introduced by Fama and MacBeth (1973), the conventional approach is to construct a time-series of risk premia based on monthly cross-sectional regressions. Then a full-sample test for the significance of the risk premia is conducted. Of course, this procedure should be strictly regarded as a test of a non-zero average risk premium, computed across different states of nature. It is quite possible that some factors earn a significant risk premium in some states of the world, even though they have a zero risk-premium on average.

Combining the cross-sectional evidence on firm size with the time-series evidence on the evolution in conditional returns, our findings also have implications for understanding the sources of predictable components in stock returns. Small firms' risk and expected returns are most strongly affected by variations in the underlying state and the rapid increase in the premium on small over large firms' stock returns as recession periods progress is consistent with a risk premium interpretation. Fama and French (1995) note that the 1981-82 recession turned into a prolonged earnings depression for small firms, so these appear to be exposed to cyclical risk factors in a fundamentally different way from large firms. Because of their lack of access to credit markets, small firms may have a higher probability than larger firms of not recovering from a recession period.

Finally, the large cyclical variation in small and large firms' conditional returns has significant asset allocation implications. Recent studies on optimal portfolio and consumption decisions show that time-varying investment opportunities can have important effects on investors' portfolio choice. Using a Bayesian approach to analyze timing decisions, Kandel and Stambaugh (1996) find that the optimal portfolio is quite sensitive to predicted asset returns, even after accounting for estimation uncertainty. Brandt (1998) and Viceira (1998) extend these findings to a multi-period setting and show that investors' intertemporal hedging incentives can add further to the expected welfare gains from market timing. This literature has so far concentrated on the case with a single risky and a single risk-free asset. Our results suggest that the timing over the economic cycle of investment weights on 'style' factors such as firm size also significantly affects the time-series of portfolio risk and return. Hence portfolios that replicate returns on these factors should be added to the set of risky assets considered in future work on optimal investment strategies. Our findings also suggest the presence of a switching factor in conditional returns which may not evolve as smoothly as the time-varying risk considered in the above studies and thus is more difficult to hedge intertemporally. Accounting for this source of risk in an optimal timing strategy is likely to be important to portfolio performance.

Notes

* Federal Reserve Bank of New York, and University of California, San Diego, respectively. We thank Justin McCrary and Shawn Cole for excellent research assistance. An anonymous referee and the editor, René Stulz, provided numerous suggestions that greatly improved the paper. We are grateful to Wouter den Haan, David Marshall, and seminar participants at University of Aarhus, University of California, Santa Barbara, and Washington State University for discussion and comments. The views expressed are those of the authors and do not necessarily reflect those of the Federal Reserve Bank of New York or the Federal Reserve System.

[1]A subset of these studies includes Breen, Glosten, and Jagannathan (1989), Campell (1987), Campbell, and Lettau (1999), Fama and French (1988), Fama and French (1989), Fama and Schwert (1977), Ferson (1989), Ferson and Harvey (1991), Glosten, Jagannathan, and Runkle (1993), Hamilton and Lin (1996), Kandel and Stambaugh (1990), Pesaran and Timmerman (1995), Whitelaw (1994).

[2]Studies finding that firm size accounts for a significant part of the cross-sectional variation in stock returns include Banz (1981), Reinganum (1981), and Fama and Rench (1992).

[3]Gertler and Gilchrist (1994) find differences in small and large firms' sources of credit even after controlling for cyclicality of the industries in which the firms are operating.

[4]Imperfect capital market theories have predominantly been concerned with changes in small and large firms' sales and inventories resulting from a shift in the underlying economic state and there is strong empirical support of cyclical asymmetries in these variables. Gertler and Gilchrist (1994) re-

port that small firms' sales decline sharply relative to those of larger firms following periods of tight money and during recessions. Interestingly, Gertler and Gilchrist conduct a test of asymmetric effects across high and low growth samples resulting from shifts in the Federal funds rate. While there is no evidence of asymmetries for large firms, the evidence is much stronger and highly significant for small firms. Kashyap, Lamont, and Stein (1994) find that small firms' inventory investments were significantly liquidity constrained during the 1974-75 and 1981-82 recessions.

[5]Filardo (1994) analyzes monthly output data and models time-varying transition probabilities as a function of the leading indicator. Gray (1996), in his analysis of weekly interest rates, lets the transition probabilities depend on past interest rates, and Durland and McCurdy (1994) let the transitions depend on the duration of the time spent by the process in a given state.

[6]This is not a particularly strong assumption since mixtures of normals are capable of accomodating a wide range of densities with non-zero skewness and fat tails.

[7]Excess returns were computed by subtracting the return on a one-month T-bill rate, obtained from the Fama-Bliss risk-free rates files on the CRSP tapes, from the return on the stock portfolios. These and all other returns were measured as continuously compounded monthly rates of return.

[8]For this reason we assume that the coefficient on the dividend yield in the return equation is not state-dependent. Our empirical results are robust to relaxing this assumption, however.

[9]For nine out of 10 portfolios a likelihood ratio test of the restriction that the intercept terms in the transition probability are identical in the two

states could not be rejected. Thus we chose this simpler specification with a single common intercept which also was found to have better convergence properties in the estimations.

[10]In an attempt to keep the Markov switching specification as simple as possible, the results in Table II do not incorporate ARCH effects. To investigate the importance of this, we estimated an exponential ARCH specification with leverage effects similar to those modeled by Glosten et al. (1993):

$$\ln(h^i_{s_t}) = \lambda^i_{0,s_t} + \lambda^i_{1,s_t} I_{t-1} + \lambda^i_{2,s_t} \epsilon^i_{t-1}/\sqrt{h^i_{t-1}} + \lambda^i_{3,s_t}(|\epsilon^i_{t-1}|/\sqrt{h^i_{t-1}} - \sqrt{2/\pi}).$$

The term multiplying $\epsilon^i_{t-1}/\sqrt{h^i_{t-1}}$ represents the leverage effect. We found that ARCH effects are only statistically significant in the recession state while leverage effects are only significant in the expansion state. Most importantly, the coefficients and standard errors of the variables in the conditional mean equation change very little as a result of the inclusion of ARCH effects. In fact, the correlation between the in-sample predictions of excess returns implied by the Markov switching models with and without ARCH effects is 0.966 for the smallest firms and 0.934 for the largest firms.

[11]The negative sign on the default premium in the expansion state is difficult to explain. However, in a model that included a term premium as an additional regressor, the coefficient on the default premium in the expansion state ceased to be statistically significant for most of the portfolios. Thus it seems likely that the default premium is correlated with some variable that is omitted from our model.

[12]These probabilities are computed as $(p_t \Pr(s_{t-1} = 1|\Omega_{t-1}; \widehat{\theta}) + (1 -$

$q_t)\,\Pr(s_{t-1} = 2|\Omega_{t-1}; \widehat{\theta}))$ and are thus smoothed by the state transition probabilities.

[13]Ang and Bekaert (1998) model the dynamics of interest rates by means of a regime switching model and find that the regimes in the U.S. interest rate process correspond to the U.S. business cycle.

[14]The relatively small variation over time in the transition probabilities for the largest firms still has important economic implications since the transition probabilities are so close to one. For example, an increase in the probability of staying in a given state from 0.90 to 0.95 will, if it remains constant, double the expected time spent in the state from 10 to 20 periods.

[15]Bernanke and Mihov (1995) and Goodfriend (1991) argue that the Fed's implicit target was the Fed Funds Rate even during the period of official reserves targeting.

[16]In order to compare our model with the specification suggested by Strongin (1995), we need the ratio of nonborrowed to total reserves for the period 1954.01 to 1995.12. The data used by Strongin is not available prior to 1959.01, but the Federal Board publication Banking and Monetary Statistics 1941-1970, pages 596-600, gives total and borrowed reserves from which we may infer nonborrowed reserves. These series are neither adjusted for reserve requirements nor seasonally adjusted. Comparing the adjusted reserve data for the period 1959 to 1995 to unadjusted reserve data for the same period, we noted that the first-differenced logarithm of the series are virtually indistinguishable. Hence we use the growth rate of the Federal Board data from 1954.01 to 1958.12 to backward-index the series and adopt the x11 procedure to seasonally adjust the data.

[17]Thorbecke (1997) uses a single-state model to investigate the effect of monetary policy on small and large firms' stock returns. Consistent with our findings, he finds some evidence that monetary shocks have a larger loading on small firms' returns.

[18]Interestingly, the correlation between returns on the portfolios comprising small and large firms is lower in the recession state than in the expansion state. This is consistent with a story according to which small firms are disproportionately strongly affected by bad news in the recession state.

[19]The real-time CLI series used by Diebold and Rudebusch (1991) stops in 1988:12, so we updated their series for the period 1989 to 1997. Breaks in the definition of CLI will not pose a problem to our forecast at a given point in time since this relies only on a single series of the leading indicator. However, if there are dramatic shifts across series in the definition of the leading indicator, then this can give rise to fluctuations in the parameter estimates and conditional forecasts.

[20]Comparing Figures 3 and 5 it can be seen that our volatility estimates lead expected returns by several months. This is in line with Whitelaw (1994)'s finding that conditional volatility leads expected returns by a few months and generates a positive relation between expected returns and lagged conditional volatility.

[21]In the context of a two-state equilibrium model with time-varying transition probabilities Whitelaw (1997b) shows that we should expect to observe such a cyclical component in the conditional Sharpe ratio. Stock prices depend on asset payoffs in all future periods while investors' marginal rate of substitution only depends on consumption in the current and following pe-

riod. It follows that the correlation between stock returns and the marginal rate of substitution varies through time in the two-state model with cyclical transition probabilities. High transition probabilities can raise volatility without raising risk premia and thus generate substantial variation in the conditional Sharpe ratio. Equilibrium models with constant transition probabilities do not generate the same variations over time in the conditional Sharpe ratio.

References

Ang, Andrew, and Geert Bekaert, 1998, Regime switches in interest rates, NBER Working Paper 6508, Stanford University.

Banz, Rolf, 1981, The relationship between return and market value of common stocks, *Journal of Financial Economics* 9, 3-18.

Bernanke, Ben, and Alan S. Blinder, 1992, The federal funds rate and the transmission of monetary policy, *American Economic Review* 82, 901-922.

Bernake, Ben, and Ilian Mihov, 1995, Measuring monetary policy, NBER Working paper 5145.

Bernanke, Ben, and Mark Gertler, 1989, Agency costs, net worth, and business fluctuations, *American Economic Review* 79, 14-31.

Brandt, Michael W., 1998, Estimating portfolio and consumption choice: A conditional Euler equations approach, *Journal of Finance*, forthcoming.

Breen, William, Lawrence Glosten, and Ravi Jagannathan, 1989, The economic significance of predictable variations in stock index returns, *Journal of Finance* 44, 1177-1189.

Campbell, John Y., 1987, Stock returns and the term structure, *Journal of Financial Economics* 18, 373-399.

Campbell, John Y., and Martin Lettau, 1999, Dispersion and volatility in stock returns: An empirical investigation, NBER Working Paper 7144.

Campbell, John Y., and Luis M. Viceira 1998, Consumption and portfolio decision when expected returns are time varying, Mimeo, Harvard Business School.

Christiano, Lawrence, Martin Eichenbaum, and Charles Evans, 1996, The effects of monetary policy shocks: Evidence from the flow of funds, *Review of Economics and Statistics* 78, 16-34.

Clarida, Richard, Jordi Gali, and Mark Gertler, 1997, Monetary policy rules and macroeconomic stability: Evidence and some theory, Mimeo, Columbia University.

Cooley, Thomas and Vincenzo Quadrini, 1997, Monetary policy and the financial decisions of firms, Mimeo, University of Rochester.

Diebold, Francis X., and Glenn D. Rudebusch, 1991, Forecasting output with the composite leading index: An ex ante analysis, *Journal of the American Statistical Association* 86, 603-610.

Durland, J. Michael, and Thomas H. McCurdy, 1994, Duration dependent transitions in a market model of US GNP growth, *Journal of Business and Economic Statistics* 12, 279-288.

Fama, Eugene F., 1981, Stock returns, real activity, inflation, and money, *American Economic Review* 71, 545-565.

Fama, Eugene F., and Kenneth R. French, 1988, Dividend yields and expected stock returns, *Journal of Financial Economics* 22, 3-25.

Fama, Eugene F., and Kenneth R. French, 1989, Business conditions and expected returns on stocks and bonds, *Journal of Financial Economics* 25, 23-49.

Fama, Eugene F., and Kenneth R. French, 1992, The cross-section of expected stock returns, *Journal of Finance* 47, 427-465.

Fama, Eugene F., and Kenneth R. French, 1995, Size and book-to-market factors in earnings and returns, *Journal of Finance* 50, 131-155.

Fama, Eugene F., and James D. MacBeth, 1973, Risk, return, and equilibrium: Empirical tests, *Journal of Political Economy* 81, 607-636.

Fama, Eugene F., and G. William Schwert, 1977, Asset returns and inflation, *Journal of Financial Economics* 5, 115-146.

Ferson, Wayne E., 1989, Changes in expected security returns, risk, and the level of interest rates, *Journal of Finance* 44, 1191-1217.

Ferson, Wayne E., and Campbell R. Harvey, 1991, The variation of economic risk premiums, *Journal of Political Economy* 99, 385-415.

Filardo, Andrew J., 1994, Business cycle phases and their transitional dynamics, *Journal of Business and Economic Statistics* 12, 299-308.

Gertler, Mark, and R.Glenn Hubbard, 1988, Financial factors in business fluctuations, in *Financial Market Volatility* (Federal Reserve Bank of Kansas City, Kansas City, Mo.).

Gertler, Mark, and Simon Gilchrist, 1994, Monetary policy, business cycles, and the behavior of small manufacturing firms, *Quarterly Journal of Economics* 109, 309-340.

Glosten, Lawrence R., Ravi Jagannathan, and David Runkle, 1993, On the relation between the expected value and the volatility of the nominal excess return on stocks, *Journal of Finance* 48, 1779-1801.

Goodfriend, Marvin, 1991, Interest rates and the conduct of monetary policy, *Carnegie-Rochester Series on Public Policy* 34, 7-30.

Gray, Stephen F., 1996, Modeling the conditional distribution of interest rates as a regime switching process, *Journal of Financial Economics* 42, 27-62.

Hamilton, James D., 1989, A new approach to the economic analysis of non-stationary time series and the business cycle, *Econometrica* 57, 357-384.

Hamilton, James D., and Gang Lin, 1996, Stock market volatility and the business cycle, *Journal of Applied Econometrics* 11, 573-593.

Hansen, Bruce E., 1992, The likelihood ratio test under nonstandard conditions: testing the Markov switching model of GNP, *Journal of Applied Econometrics* 7, S61-S82.

Kandel, Shmuel, and Robert F. Stambaugh, 1990, Expectations and volatility of consumption and asset returns, *Review of Financial Studies* 3, 207-232.

Kandel, Shmuel, and Robert F. Stambaugh, 1996, On the predictability of stock returns: An asset-allocation perspective, *Journal of Finance* 51, 385-424.

Kashyap, Anil K., and David Wilcox, 1993, The monetary transmission mechanism: Evidence from the composition of external finance, *American Economic Review* 83, 78-98.

Kashyap, Anil K., Owen A. Lamont, and Jeremy C. Stein, 1994, Credit conditions and the cyclical behavior of inventories, *Quarterly Journal of Economics* 109, 565-592.

Keim, Donald B., and Robert F. Stambaugh, 1986, Predicting returns in the stock and bond markets, *Journal of Financial Economics* 17, 357-390.

Kiyotaki, Nobuhiro and John Moore 1997, Credit cycles, *Journal of Political Economy* 105, 211-248.

Lucas, Robert E., 1978, Asset prices in an exchange economy, *Econometrica* 46, 1429-1446.

Pesaran, M. Hashem, and Allan Timmermann, 1995, Predictability of stock returns: Robustness and economic significance, *Journal of Finance* 50, 1201-1228.

Reinganum, Marc R., 1981, Misspecification of capital asset pricing: Empirical anomalies based on earnings yields and market values, *Journal of Financial Economics* 9, 19-46.

Schwert, G. William, 1990, Stock returns and real activity: A century of evidence, *Journal of Finance* 45, 1237-1257.

Strongin, Steve, 1995, The identification of monetary policy disturbances. Explaining the liquidity puzzle, *Journal of Monetary Economics* 35, 463-497.

Taylor, John B., 1993, Discretion versus policy rules in practice, *Carnegie-Rochester Series on Public Policy* 39, 195-214.

Thorbecke, Willem, 1997, On stock market returns and monetary policy, *Journal of Finance* 52, 635-654.

Whitelaw, Robert F., 1994, Time variations and covariations in the expectation and volatility of stock market returns, *Journal of Finance* 49, 515-541.

Whitelaw, Robert F., 1997a, Time-varying Sharpe ratios and market timing, Working paper, New York University.

Whitelaw, Robert F., 1997b, Stock market risk and return: An equilibrium analysis, Working paper, New York University.

Table I

Moments of Monthly Excess Returns: Size-sorted CRSP Portfolios, 1954-1997

This table reports the mean, standard deviation, coefficient of skewness, and coefficient of kurtosis of the continuously compounded excess returns on the size-sorted CRSP decile portfolios. Excess returns are calculated as the difference between monthly stock returns and the one-month T-bill rate.

Decile	Mean	Standard Deviation	Coefficient of Skewness	Coefficient of Kurtosis
1(smallest)	0.920	7.309	0.367	8.511
2	0.760	6.429	-0.238	9.038
3	0.715	5.966	-0.530	8.802
4	0.699	5.690	-0.626	8.825
5	0.620	5.576	-0.738	8.684
6	0.698	5.340	-0.804	8.339
7	0.697	5.067	-0.910	7.925
8	0.620	4.766	-0.801	7.713
9	0.638	4.564	-0.701	6.954
10 (largest)	0.506	4.042	-0.530	5.405

Table II

Markov Switching Models for Excess Returns

On the Size-sorted Decile Portfolios

The following Markov switching model was estimated separately for excess returns on each of the size-sorted portfolios:

$\rho^i_t = \beta^i_{0,St} + \beta^i_{1,St} I1_{t-1} + \beta^i_{2,St} Def_{t-1} + \beta^i_{3,St} \Delta M_{t-2} + \beta^i_4 Yield_{t-1} + \varepsilon^i_t$

$\varepsilon^i_t \sim N(0,h^i_{St,t})$, $\ln(h^i_{St,t}) = \lambda^i_{0,St} + \lambda^i_{1,St} I1_{t-1}$

$p^i_t = Prob(s^i_{t=1}|s^i_{t-1=1}) = \Phi(\pi^i_0 + \pi^i_1 \Delta CLI_{t-2})$, $q^i_t = Prob(s^i_{t=2}|s^i_{t-1=2}) = \Phi(\pi^i_0 + \pi^i_2 \Delta CLI_{t-2})$

$i = \{1,\ldots,10\}$

where ρ^i_t is the monthly excess returns on the i^{th} size-sorted decile portfolio, $I1$ is the one-month T- bill rate, Def is the default premium, ΔM is the annual rate of growth of the monetary base, Yield is the dividend yield, and DCLI is the annual rate of growth of the Composite Index of Leading Indicators. The sample period is 1954-1997. Standard errors appear in parentheses to the right of the parameter estimates. All parameters are estimated by maximum likelihood.

Panel A: Deciles One to Five

Mean Parameters	First Decile (Smallest Firms)		Second Decile		Third Decile		Fourth Decile		Fifth Decile	
Constant, State 1	-0.016	(0.020)	-0.035	(0.018)	-0.037	(0.016)	-0.007	(0.016)	-0.008	(0.017)
Constant, State 2	0.002	(0.012)	-0.001	(0.011)	-0.007	(0.010)	-0.011	(0.009)	-0.015	(0.010)
Interest Rate (*I1*), State 1	-18.462	(4.835)	-16.156	(4.523)	-14.416	(3.891)	-14.662	(5.497)	-13.905	(4.659)
Interest Rate (*I1*), State 2	2.199	(1.859)	1.040	(2.249)	0.587	(1.518)	-5.043	(1.546)	-4.146	(1.599)
Default Premium (*Def*), State 1	64.690	(19.962)	74.875	(20.161)	73.164	(17.349)	32.221	(18.747)	28.582	(17.766)
Default Premium (*Def*), State 2	-47.192	(14.562)	-47.398	(15.217)	-38.756	(11.930)	25.089	(8.675)	18.093	(10.184)
Money Growth (ΔM), State 1	0.700	(0.336)	0.350	(0.299)	0.180	(0.243)	0.355	(0.267)	0.306	(0.269)
Money Growth (ΔM), State 2	0.030	(0.089)	0.116	(0.095)	0.150	(0.092)	0.030	(0.072)	0.050	(0.073)
Dividend Yield (*Yield*)	0.616	(0.399)	0.884	(0.335)	0.918	(0.291)	0.646	(0.276)	0.728	(0.319)
Variance Parameters										
Constant, State 1	-5.562	(0.299)	-6.087	(0.356)	-6.306	(0.290)	-6.791	(0.331)	-6.991	(0.270)
Constant, State 2	-7.409	(0.242)	-7.313	(0.231)	-7.580	(0.239)	-7.746	(0.252)	-7.826	(0.201)
Interest Rate(*I1*), State 1	176.026	(66.984)	235.903	(76.388)	242.404	(63.925)	358.556	(68.680)	401.407	(68.740)
Interest Rate(*I1*), State 2	146.856	(43.847)	127.540	(40.399)	153.746	(42.268)	207.148	(46.140)	238.350	(35.983)
Transition Probability Parameters										
Constant	1.253	(0.152)	1.336	(0.176)	1.487	(0.176)	1.863	(0.190)	1.980	(0.199)
Leading Indicator (ΔCLI), State 1	-0.153	(0.067)	-0.190	(0.075)	-0.168	(0.071)	-0.016	(0.101)	-0.170	(0.109)
Leading Indicator (ΔCLI), State 2	0.024	(0.056)	0.013	(0.056)	0.051	(0.072)	0.046	(0.129)	0.051	(0.101)
Log Likelihood Value	726.20		791.75		834.59		857.09		864.86	

Table II (continued)

Markov Switching Models for Excess Returns On the Size-sorted Decile Portfolios

Panel B: Deciles Six to Ten										
Mean Parameters	Sixth Decile		Seventh Decile		Eighth Decile		Ninth Decile		Tenth Decile (Largest Firms)	
Constant, State 1	-0.023	(0.020)	-0.027	(0.019)	-0.031	(0.017)	-0.038	(0.016)	-0.017	(0.013)
Constant, State 2	-0.004	(0.010)	-0.001	(0.010)	0.005	(0.011)	0.003	(0.011)	-0.001	(0.009)
Interest Rate (*I1*), State 1	-13.144	(3.808)	-13.264	(3.298)	-13.445	(3.124)	-12.149	(2.782)	-7.627	(2.848)
Interest Rate (*I1*), State 2	-5.822	(2.171)	-5.097	(1.722)	-7.706	(2.078)	-7.006	(1.828)	-2.691	(1.526)
Default Premium (*Def*), State 1	28.430	(17.132)	30.674	(17.084)	31.305	(14.362)	31.602	(13.321)	19.179	(13.374)
Default Premium (*Def*), State 2	17.658	(10.154)	13.702	(10.833)	21.631	(9.571)	15.625	(10.641)	15.017	(9.529)
Money Growth (ΔM), State 1	0.328	(0.208)	0.353	(0.180)	0.326	(0.170)	0.270	(0.147)	0.171	(0.186)
Money Growth (ΔM), State 2	-0.092	(0.130)	-0.153	(0.096)	-0.221	(0.129)	-0.234	(0.122)	-0.174	(0.077)
Dividend Yield (*Yield*)	1.027	(0.457)	1.093	(0.376)	1.209	(0.382)	1.329	(0.357)	0.686	(0.264)
Variance Parameters										
Constant, State 1	-7.376	(0.254)	-7.359	(0.227)	-7.551	(0.208)	-7.544	(0.208)	-6.524	(0.279)
Constant, State 2	-7.664	(0.287)	-7.873	(0.354)	-7.602	(0.323)	-7.475	(0.312)	-8.192	(0.299)
Interest Rate(*I1*), State 1	443.577	(67.156)	380.926	(58.188)	397.387	(54.855)	357.773	(54.799)	87.224	(54.577)
Interest Rate(*I1*), State 2	201.464	(44.502)	210.094	(50.134)	168.169	(46.074)	148.627	(42.997)	212.662	(55.652)
Transition Probability Parameters										
Constant	2.034	(0.208)	1.942	(0.218)	2.200	(0.244)	2.055	(0.240)	1.517	(0.225)
Leading Indicator (ΔCLI), State 1	-0.052	(0.104)	-0.002	(0.046)	-0.012	(0.049)	0.006	(0.075)	0.045	(0.085)
Leading Indicator (ΔCLI), State 2	-0.115	(0.094)	-0.100	(0.085)	-0.140	(0.119)	-0.059	(0.143)	0.032	(0.081)
Log Likelihood Value	878.03		900.37		929.48		941.96		990.67	

Table III

Tests for Identical Mean and Variance Across States in the Markov Switching Model

This table reports the outcome of the Likelihood ratio tests for equality of pairs of parameters across the two states in the Markov switching model described below. The test for identical mean parameters assumes that there are two states in the conditional variance equation, while the test for identical variance parameters assumes that there are two states in the conditional mean equation. The following Markov switching model was estimated separately for excess returns on each of the size-sorted portfolios.

$\rho^i_t = \beta^i_{0,St} + \beta^i_{1,St} I1_{t-1} + \beta^i_{2,St} Def_{t-1} + \beta^i_{3,St} \Delta M_{t-2} + \beta^i_4 Yield_{t-1} + \varepsilon^i_t$

$\varepsilon^i_t \sim N(0, h^i_{St,t})$, $\ln(h^i_{St,t}) = \lambda^i_{0,St} + \lambda^i_{1,St} I1_{t-1}$

$p^i_t = Prob(s^i_{t=1}|s^i_{t-1=1}) = \Phi(\pi^i_0 + \pi^i_1 \Delta CLI_{t-2})$, $q^i_t = Prob(s^i_{t=2}|s^i_{t-1=2}) = \Phi(\pi^i_0 + \pi^i_2 \Delta CLI_{t-2})$

$i = \{1, \ldots, 10\}$

where ρ^i_t is the monthly excess returns on the i'th size-sorted decile portfolio, *I1* is the one-month T- bill rate, *Def* is the default premium, ΔM is the annual rate of growth of the monetary base, *Yield* is the dividend yield, and ΔCLI is the annual rate of growth of the Composite Index of Leading Indicators. The sample period is 1954-1997. The p-value reports the probability that the null hypothesis of symmetry across states is valid.

Panel A: Test for Identical Mean Parameters

	First Decile (Smallest Firms)	Second Decile	Third Decile	Fourth Decile	Fifth Decile
Unrestricted Log Likelihood Value	726.20	791.75	834.59	857.09	864.86
Log Likelihood Value with ($\beta^i_{q,St=1}=\beta^i_{q,St=2}$, q={1,2,3,4})	717.60	788.14	831.67	854.72	862.43
p-value	0.00	0.12	0.21	0.31	0.30

	Sixth Decile	Seventh Decile	Eighth Decile	Ninth Decile	Tenth Decile (Largest Firms)
Unrestricted Log Likelihood Value	878.03	900.36	929.48	941.95	990.67
Log Likelihood Value with ($\beta^i_{q,St=1}=\beta^i_{q,St=2}$, q={1,2,3,4})	874.22	893.53	920.87	935.79	985.20
p-value	0.11	0.01	0.00	0.02	0.03

Panel B: Test for Identical Variance Parameters

	First Decile (Smallest Firms)	Second Decile	Third Decile	Fourth Decile	Fifth Decile
Unrestricted Log LikelihoodValue	726.20	791.75	834.59	857.09	864.86
Log Likelihood Value with ($\lambda^i_{q,St=1}=\lambda^i_{q,St=2}$, q={0,1})	671.54	739.59	790.75	814.92	828.55
p-value	0.00	0.00	0.00	0.00	0.00

	Sixth Decile	Seventh Decile	Eighth Decile	Ninth Decile	Tenth Decile (Largest Firms)
Unrestricted Log Likelihood Value	878.03	900.36	929.48	941.95	990.67
Log Likelihood Value with ($\lambda^i_{q,St=1}=\lambda^i_{q,St=2}$, q={0,1})	847.91	875.66	906.43	925.23	970.97
p-value	0.00	0.00	0.00	0.00	0.00

Table IV

Markov Switching Model Estimates for Size-Sorted Portfolios Using Alternative Measures of Monetary Policy

The following Markov switching model was estimated separately for excess returns on each of the smallest and largest firms:

$$\rho^i_t = \beta^i_{0,St} + \beta^i_{1,St} Fed_{t-1} + \beta^i_{2,St} Def_{t-1} + \beta^i_{3,St} Res_{t-2} + \beta^i_4 Yield_{t-1} + \varepsilon^i_t$$

$$\varepsilon^i_t \sim N(0,h^i_{St,t}),\ \ln(h^i_{St,t}) = \lambda^i_{0,St} + \lambda^i_{1,St} Fed_{t-1}$$

$$p^i_t = \text{Prob}(s^i_{t=1}|s^i_{t-1=1}) = \Phi(\pi^i_0 + \pi^i_1 \Delta CLI_{t-2}),\ q^i_t = \text{Prob}(s^i_{t=2}|s^i_{t-1=2}) = \Phi(\pi^i_0 + \pi^i_2 \Delta CLI_{t-2})$$

$$i = \{1,10\}$$

where ρ^i_t is the monthly excess returns on the i^{th} size-sorted decile portfolio, *Fed* is the federal funds rate, *Def* is the default premium, *Res* is the ratio of contemporaneous nonborrowed to once-lagged total reserves, *Yield* is the dividend yield, and ΔCLI is the annual rate of growth of the Composite Index of Leading Indicators. The sample period is 1954-1997. Standard errors appear in parentheses to the right of the parameter estimates.

Mean Parameters	Smallest Firms		Largest Firms	
Constant, State 1	-0.480	(0.243)	-0.315	(0.155)
Constant, State 2	-0.127	(0.109)	-0.017	(0.103)
Federal Funds Rate (*Fed*), State 1	-7.024	(3.263)	-2.325	(2.121)
Federal Funds Rate (*Fed*), State 2	2.588	(1.583)	-3.355	(1.500)
Default Premium (*Def*), State 1	59.109	(22.354)	23.943	(15.844)
Default Premium, (*Def*) State 2	-55.701	(14.447)	-5.712	(12.109)
Reserves Ratio (*Res*), State 1	0.475	(0.248)	0.284	(0.159)
Reserves Ratio (*Res*), State 2	0.129	(0.107)	0.018	(0.106)
Dividend Yield (*Yield*)	0.875	(0.455)	0.888	(0.254)
Variance Parameters				
Constant, State 1	-5.388	(0.284)	-6.826	(0.314)
Constant, State 2	-7.361	(0.236)	-7.600	(0.314)
Federal Funds Rate (*Fed*), State 1	114.971	(51.650)	126.739	(50.850)
Federal Funds Rate (*Fed*), State 2	121.580	(36.982)	59.311	(58.196)
Transition Probability Parameters				
Constant	1.240	(0.154)	-0.007	(0.370)
Leading Indicator (ΔCLI), State 1	-0.144	(0.070)	-0.116	(0.151)
Leading Indicator (ΔCLI), State 2	0.023	(0.066)	0.168	(0.149)
Log Likelihood Value		727.13		988.89

Table V

Bivariate Markov Switching Model for Excess Returns On The Portfolios Comprising the Smallest and Largest Firms

The following Markov switching model was estimated for excess returns on the smallest and largest firms:

$\boldsymbol{\rho}_t = \boldsymbol{\beta}_{0,St} + \boldsymbol{\beta}_{1,St} I1_{t-1} + \boldsymbol{\beta}_{2,St} Def_{t-1} + \boldsymbol{\beta}_{3,St} \Delta M_{t-2} + \boldsymbol{\beta}_4 Yield_{t-1} + \boldsymbol{\varepsilon}_t$

$\varepsilon_t \sim N(0, \boldsymbol{\Omega}_{St}),\ \boldsymbol{\Omega}_{St} \in \Re^{2x2}$

$\ln(\Omega_{ii,St}) = \lambda^i_{0,St} + \lambda^i_{1,St} I1_{t-1}$

$\Omega_{ij,St} = \xi_{St} (\Omega_{ii,St})^{1/2} (\Omega_{jj,St})^{1/2},\quad i \neq j$

$p^i_t = Prob(s^i_{t=1} | s^i_{t-1=1}) = \Phi(\pi^i_0 + \pi^i_1 \Delta CLI_{t-2}),\ q^i_t = Prob(s^i_{t=2} | s^i_{t-1=2}) = \Phi(\pi^i_0 + \pi^i_2 \Delta CLI_{t-2})$

where $\boldsymbol{\rho}_t$ is a (2x1) vector of excess returns on decile portfolios comprising the the smallest and largest firms.'$\beta_{k,St}$ is a (2x1) vector of coefficients for the k[th] parameter for the smallest and largest firms, respectively, *I1* is the one-moth T-bill rate, *Def* is the default premium, ΔM is the annual the monetary base, *Yield* is the dividend yield, and ΔCLI is the annual rate of growth of the Composite Index of Leading Indicators. The sample period is 1954-1997. $\beta_{k,St} = (\beta^s_{k,St}, \beta^l_{k,St})$ is the k[th] coefficient in State S_t for the smallest and largest firms, respectively. Standard errors appear in parentheses to the right of the parameter estimates. The correlation and transition probability parameters are common to both deciles. For each set of coefficients, the p-value reports the probability of the restriction that the smallest and largest firms' asymmetries are identical against the alternative that the asymmetries are largest for the smallest firms. The table shows evidence of asymmetry in the coefficients of the interest rate and default premium variables in the mean equation, and of the intercepts in the variance equation.

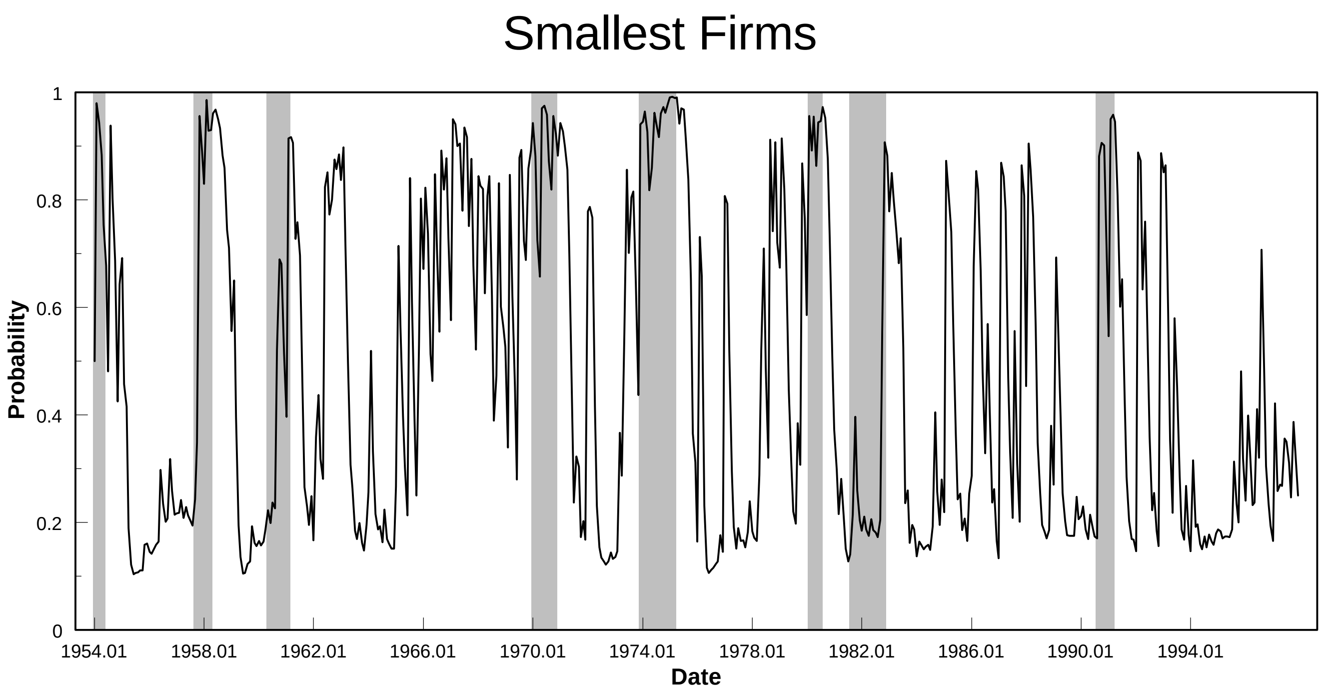
Mean Parameters	First Decile (Smallest Firms)		Tenth Decile (Largest Firms)		Tests for Identical Asymmetries	
					Constant: $(\beta^s_{0,1}-\beta^s_{0,2})=(\beta^l_{0,1}-\beta^l_{0,2})$	
Constant, State 1	-0.026	(0.031)	-0.035	(0.014)	Log Likelihood Value	1815.19
Constant, State 2	-0.005	(0.012)	0.007	(0.009)	p-value	(0.35)
					Interest Rate: $(\beta^s_{1,1}-\beta^s_{1,2})=(\beta^l_{1,1}-\beta^l_{1,2})$	
Interest Rate (*I1*), State 1	-19.044	(5.313)	-7.839	(2.614)	Log Likelihood Value	1812.57
Interest Rate (*I1*), State 2	-2.397	(1.794)	-1.737	(1.544)	p-value	(0.01)
					Default Premium: $(\beta^s_{2,1}-\beta^s_{2,2})=(\beta^l_{2,1}-\beta^l_{2,2})$	
Default Premium (*Def*), State 1	65.935	(23.732)	35.538	(13.207)	Log Likelihood Value	1813.79
Default Premium (*Def*), State 2	-24.266	(13.120)	-14.931	(11.622)	p-value	(0.05)
					Money Growth: $(\beta^s_{3,1}-\beta^s_{3,2})=(\beta^l_{3,1}-\beta^l_{3,2})$	
Money Growth (ΔM), State 1	0.656	(0.464)	0.321	(0.207)	Log Likelihood Value	1815.27
Money Growth (ΔM), State 2	-0.013	(0.101)	-0.028	(0.083)	p-value	(0.41)
Dividend Yield (*Yield*)	1.038	(0.377)	0.595	(0.267)		
Variance Parameters					Constant: $(\lambda^s_{0,1}-\lambda^s_{0,2})=(\lambda^l_{0,1}-\lambda^l_{0,2})$	
Constant, State 1	-4.622	(0.316)	-6.416	(0.319)	Log Likelihood Value	1811.66
Constant, State 2	-6.978	(0.234)	-7.238	(0.186)	p-value	(0.00)
					Interest Rate: $(\lambda^s_{1,1}-\lambda^s_{1,2})=(\lambda^l_{1,1}-\lambda^l_{1,2})$	
Interest Rate (*I1*), State 1	-2.282	(55.480)	64.116	(59.985)	Log Likelihood Value	1814.90
Interest Rate (*I1*), State 2	97.664	(48.763)	60.202	(40.579)	p-value	(0.23)
		Parameters Common To Both Deciles				
Correlation Parameters						
Correlation, State 1		0.535	(0.144)			
Correlation, State 2		0.609	(0.187)			
Transition Probability Parameters						
Constant		1.225	(0.138)			
					CLI Coefficient: $\pi_1=\pi_2$	
Leading Indicator (ΔCLI), State 1		-0.146	(0.082)		Log Likelihood Value	1813.42
Leading Indicator (ΔCLI), State 2		-0.001	(0.068)		p-value	(0.03)
Unconstrained Log Likelihood value		1815.61				

Table VI

Out-of-Sample Trading Results (1976:3 - 1997:12)

Trading results are based on positions in the size-sorted decile portfolios from the CRSP tapes and in one-month T-bills. The buy-and-hold strategy simply reinvests all funds in the relevant size-sorted equity portfolios, while the switching portfolios take a long position in the size-sorted portfolio if the recursively predicted excess return is positive, otherwise the position switches into one-month T-bills. Mean returns and standard deviations (S.D.) have been annualized.

	T-Bills	Smallest Firms		Largest Firms	
		Buy-And-Hold	Switching Portfolio	Buy-And-Hold	Switching Portfolio
Full Sample					
Mean Return	6.73	15.89	14.82	13.52	12.12
S.D. of Return	0.80	23.32	15.94	14.09	9.72
Sharpe Measure	-------	0.39	0.51	0.48	0.55
Recessions					
Mean Return	9.76	11.78	26.62	10.10	28.34
S.D. of Return	0.91	30.16	20.58	18.62	10.96
Sharpe Measure	-------	0.07	0.82	0.02	1.70
Expansions					
Mean Return	6.34	16.43	13.29	13.97	10.01
S.D. of Return	0.77	22.33	15.29	13.43	9.40
Sharpe Measure	-------	0.45	0.45	0.57	0.39



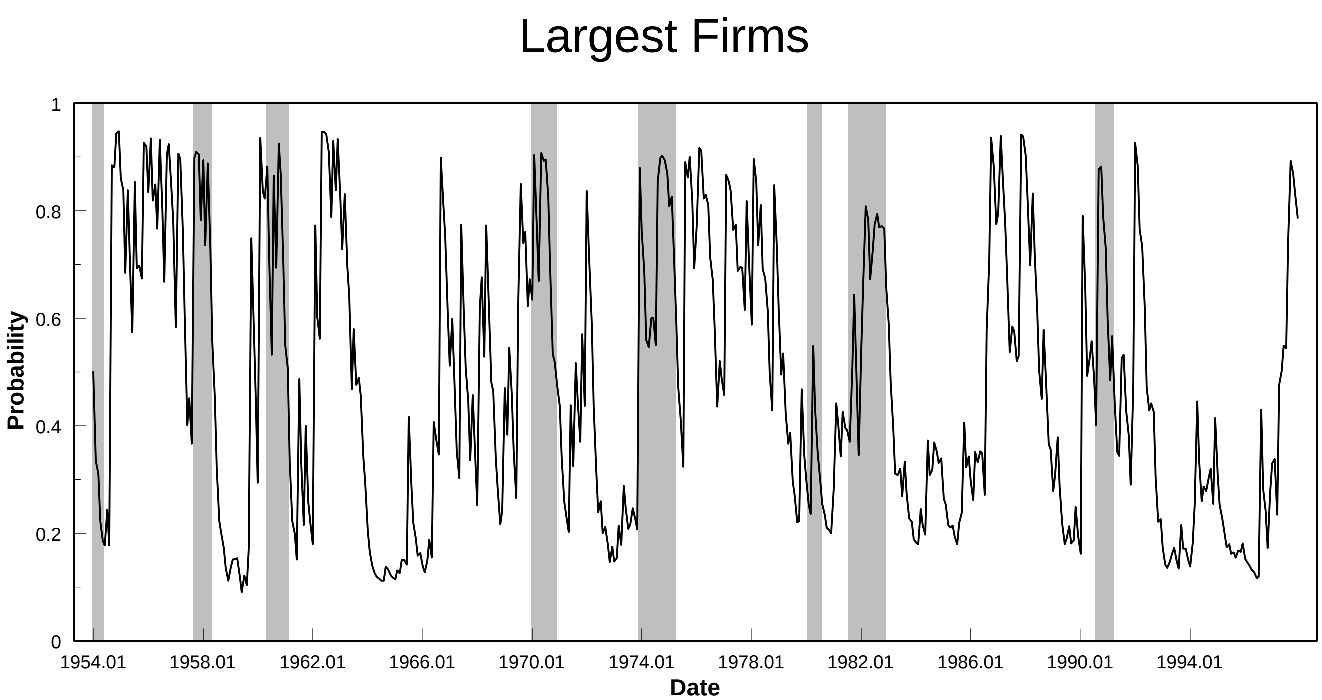


Figure 1. Markov switching model, probability of high variance and low mean state. These graphs present the time series of the probability of being in state 1 at time *t* conditional on information in period *t-1*. Shaded areas indicate NBER recession periods.

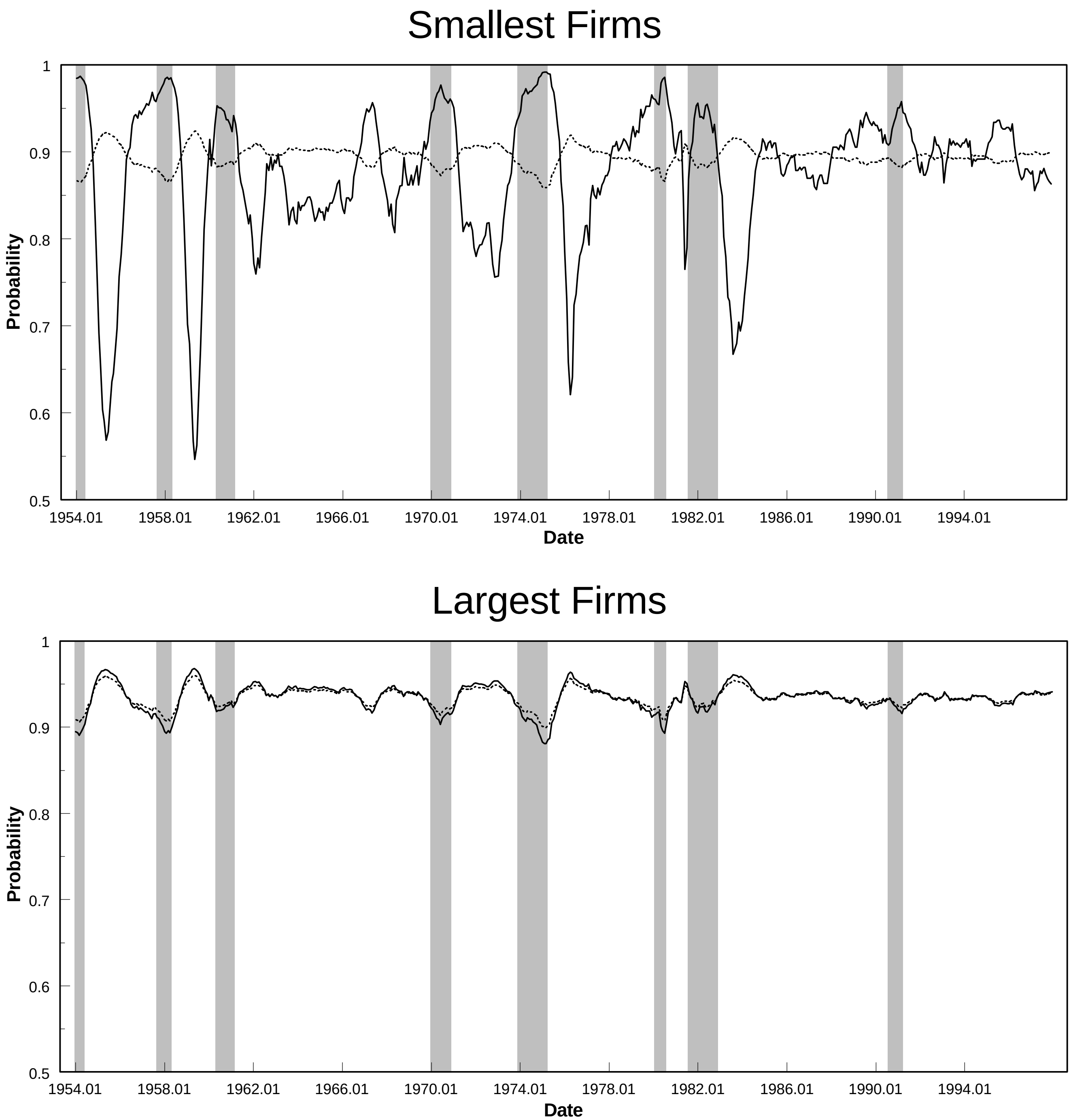


Figure 2. Markov switching model, transition probabilities. The solid lines give the probability of moving from a high variance and low mean state to another high variance and low mean state. The dotted lines are the probability of moving from a low variance and high mean state to another low variance and high mean state. Shaded areas indicate NBER recession periods.

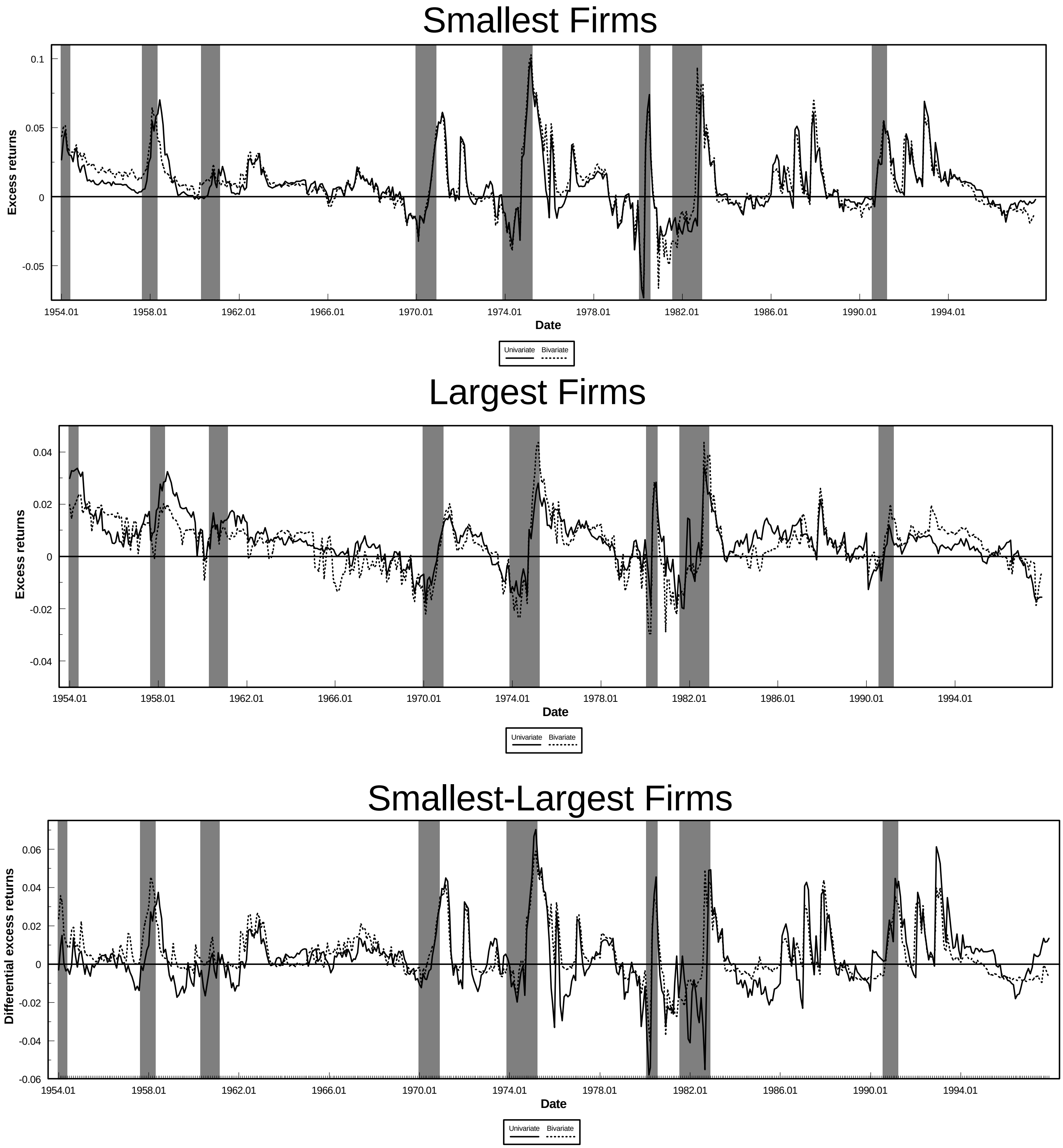


Figure 3. Predicted excess returns, univariate and bivariate Markov switching models. This figure plots the expected excess returns as well as their differential for deciles one and 10 based on the parameter estimates given in Tables II and V. Shaded areas indicate NBER recession periods.

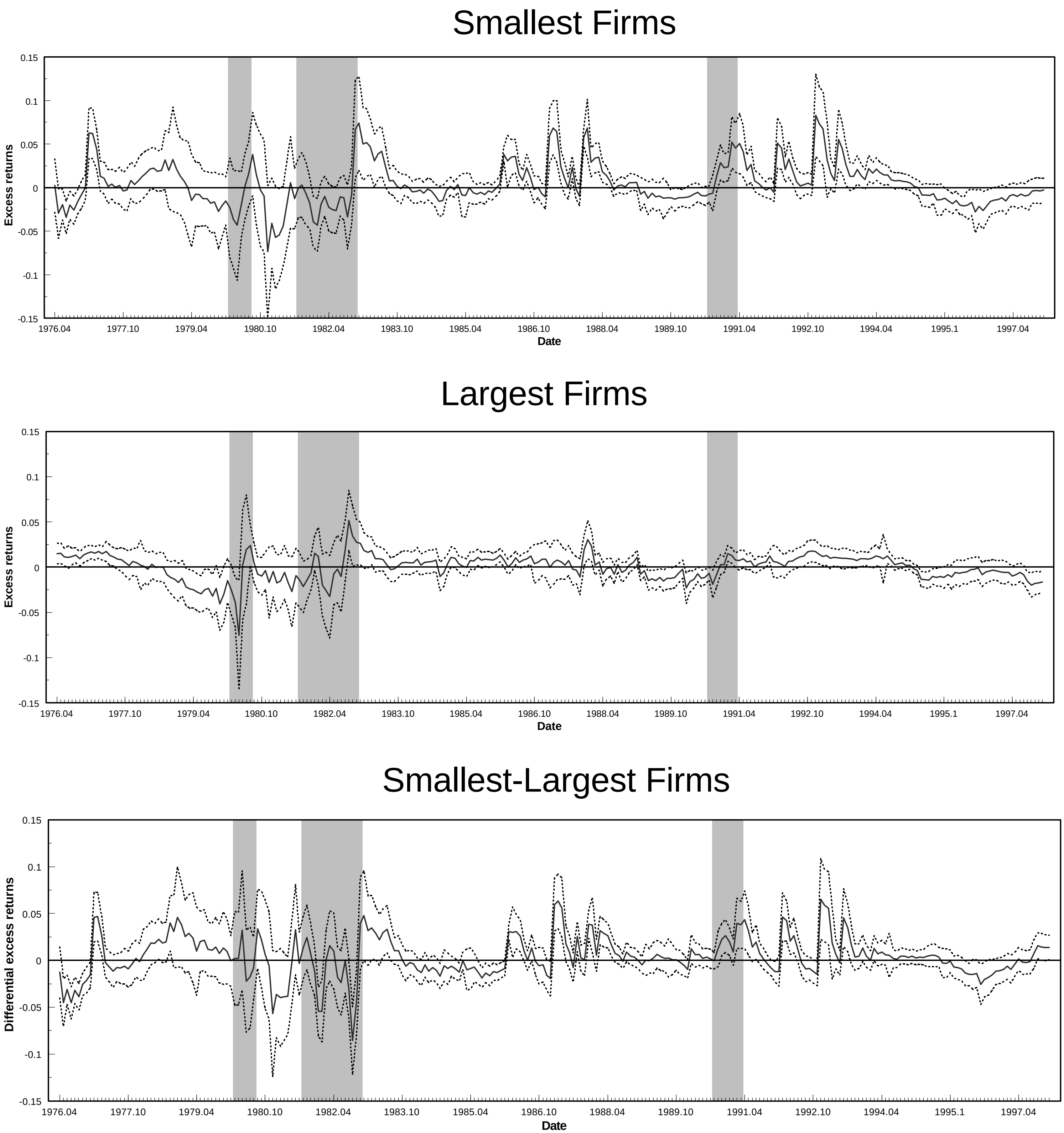
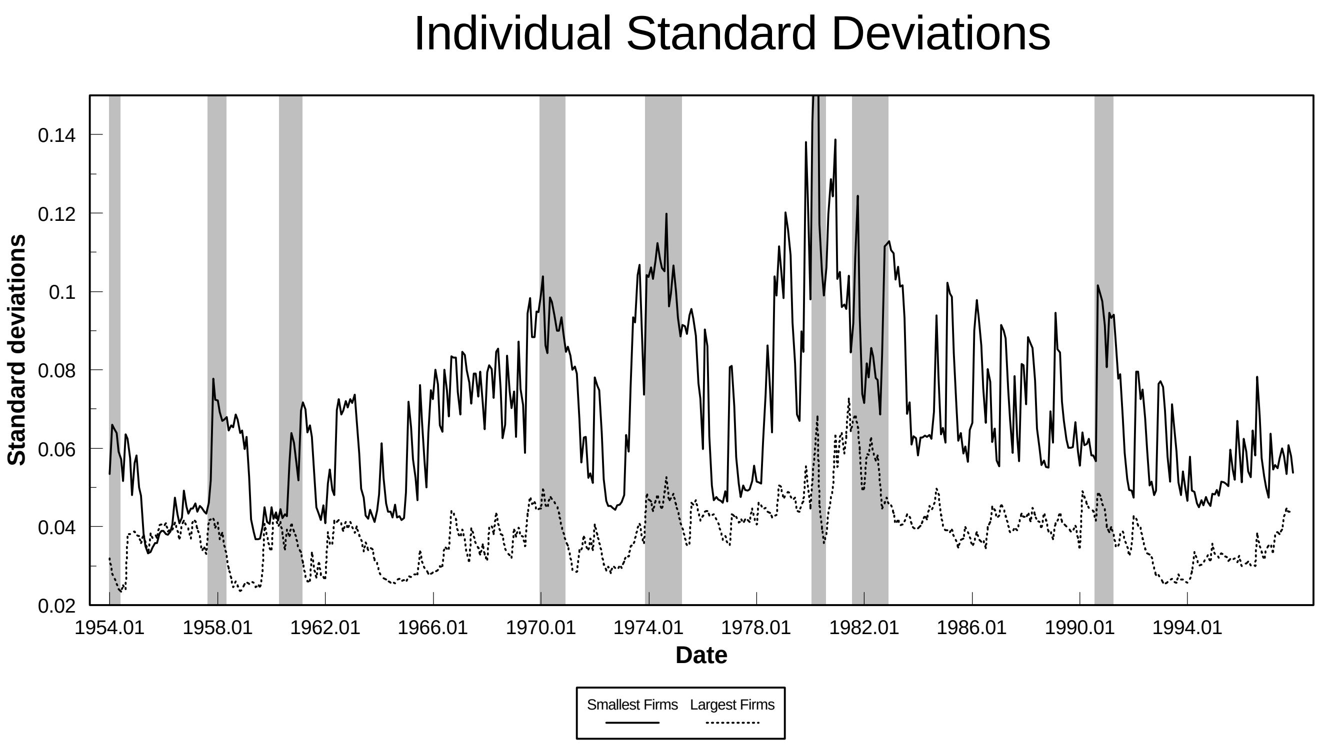


Figure 4. Out-of-sample forecasts of excess returns. In the first two panels, the solid lines indicate predicted excess returns. In the bottom panel, the solid line indicates predicted differential excess returns, defined as the difference between excess returns on the smallest firms and the largest firms. The dotted lines are plus-minus two standard error bands. The forecast of period *t* excess returns is based on parameters estimated using period *t-1* information only. Shaded areas indicate NBER recession periods.



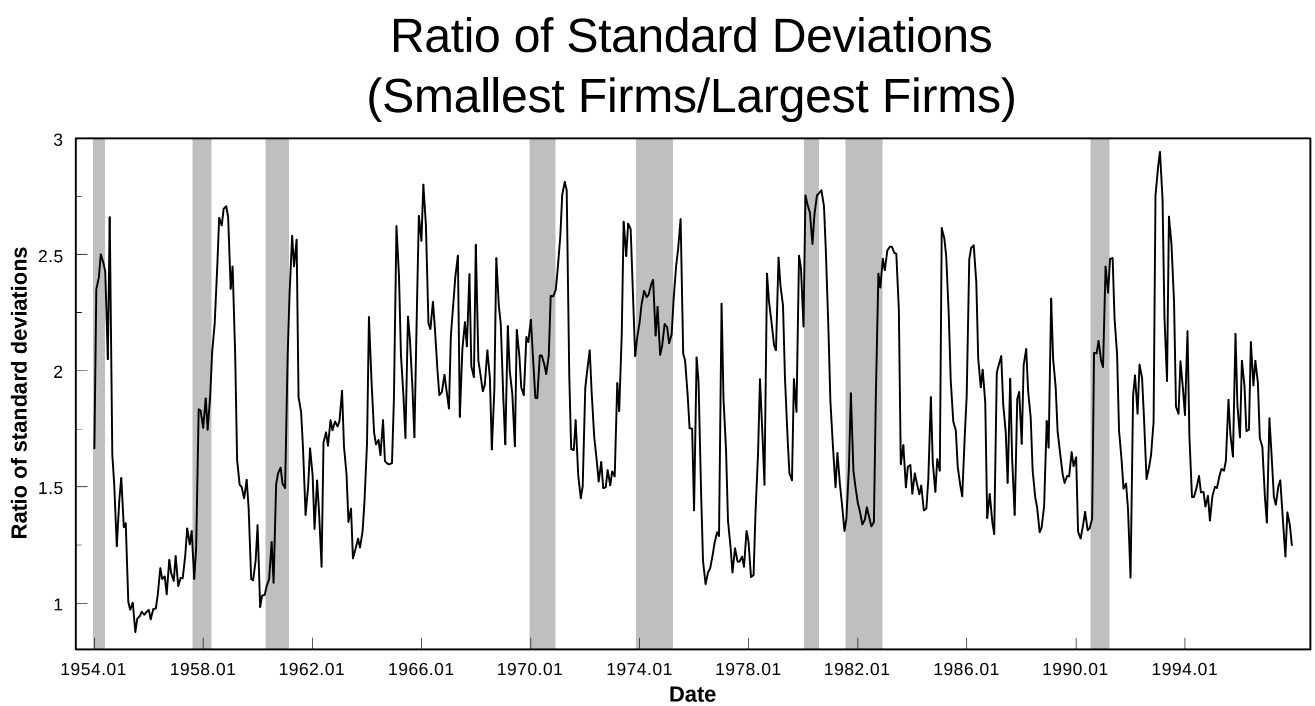


Figure 5. Conditional volatility of smallest and largest firms' excess returns. The upper graph plots standard deviation of the conditional returns for the smallest and largest firms. The lower graph plots the ratio of the standard deviation of the smallest firms over the standard deviations of the largest firms. Shaded areas indicate NBER recession periods.

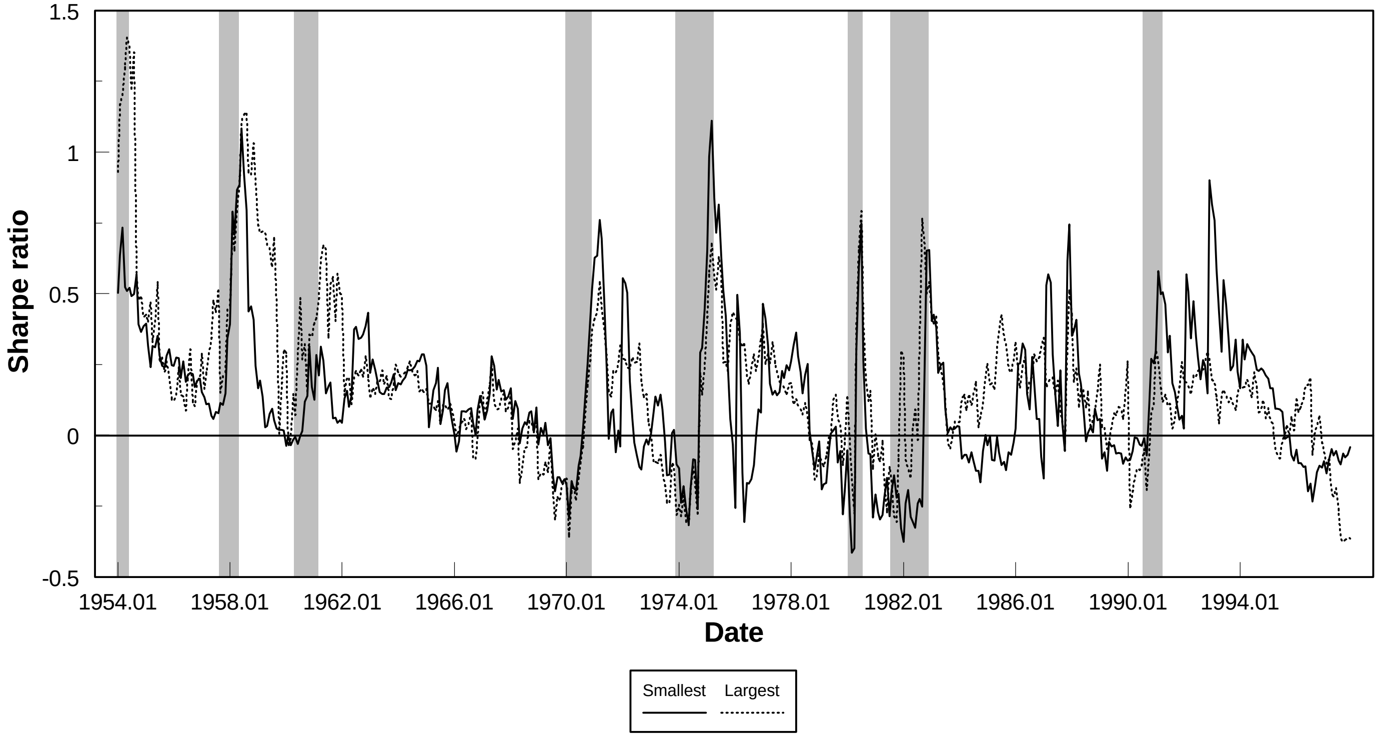


Figure 6. Sharpe ratio of smallest and largest firms. For the portfolios comprising the smallest and largest firms the graph plots the conditional Sharpe ratio derived as the predicted excess returns over the conditional volatility. Shaded areas indicate NBER recession periods.