Risk and Return: Some New Evidence

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Abstract

We develop a structural asset pricing model to investigate the relationship between stock market risk and return. The structural model is estimated using the conditional market variance implied by S&P 100 index option prices. Relative risk aversion is precisely identified and is found to be positive, with point estimates ranging from 3.06 to 4.01. However, the implied volatility data only spans the period November 1983 to May 1995. As a robustness check, the structural model is also examined with postwar monthly data, in which the conditional market variance is estimated. We again find a positive and significant risk-return relation and get similar point estimates for relative risk aversion. Additionally, we document some facts about stock market return. First, stock price movements are primarily driven by changes in investment opportunities, not by changes in market volatility. Second, there is some evidence of a leverage effect. Third, relative risk aversion is quite stable over time.

1 Introduction

The return on the market portfolio plays a central role in the capital asset pricing model (CAPM), the financial theory widely used by both academics and practitioners. However, the inter-temporal properties of the stock market return are not yet fully understood.[1] For example, there is an ongoing debate in the literature about the relationship between stock market risk and return and the extent to which stock market volatility moves stock prices. This paper provides new evidence on the risk-return relation by estimating a variant of Merton's (1973) inter-temporal capital asset pricing model (ICAPM)

In his seminal paper, Merton (1973) shows that the conditional excess market return $E_{t-1}e_{M,t}$ is a linear function of its conditional variance $E_{t-1}\sigma^2_{M,t}$ (the risk component) and its covariance with investment opportunities $E_{t-1}\sigma_{MF,t}$ (the hedging component),

$$E_{t-1}e_{M,t} = [\frac{-J_{WW}W}{J_W}]E_{t-1}\sigma^2_{M,t} + [\frac{-J_{WF}}{J_W}]E_{t-1}\sigma_{MF,t} \quad (1)$$

where $J(W(t), F(t), t)$ is the indirect utility function with subscripts denoting partial derivatives, $W(t)$ is wealth and $F(t)$ is a vector of state variables that describe investment opportunities. $\frac{-J_{WW}W}{J_W}$ is a measure of relative risk aversion, which is usually assumed to be constant, i.e., $\frac{-J_{WW}W}{J_W} = \gamma$. If people are risk averse, then γ should be positive.

Under certain conditions, Merton (1980) argues that the hedging component is negligible and the conditional excess market return is proportional to its conditional variance. Since Merton (1980), this specification has been subject to dozens of empirical investigations; however, these papers have drawn conflicting conclusions on the sign of γ. It is significantly positive in French, Schwert and Stambaugh (1987), significantly negative in Campbell (1987) and time-varying in Whitelaw (1994).

The failure to reach an agreement on the risk-return relation can be attributed to two factors. First, neither the conditional return nor the conditional variance are directly observable; certain restrictions must be imposed to identify these two variables. Instrumental variable (IV) models

[1] The expected stock market return was long considered to be constant until relatively recent work documenting the predictability of market returns (e.g., Fama and French (1989)). It is now well understood that time-varying expected returns are consistent with rational expectations. See Campbell and Cochrane (1999) and Guo (1999a) for recent examples of this literature.

and the autoregressive conditional heteroskedasticity (ARCH) model are the two most commonly used identification methods. In general, empirical results are sensitive to these restrictions. For example, Campbell (1987) finds that the results depend on the choice of instrumental variables. In particular, the nominal risk-free rate is negatively related to the return and positively related to the variance, and "these two results together give a perverse negative relationship between the conditional mean and variance for common stock" (Campbell (1987, p.391)). As for the ARCH model, if the conditional distribution of the return shock is changed from normal to student-t, the significant positive relation found by French, Schwert and Stambaugh (1987) disappears (see Baillie and DeGennaro (1990)). Second, there are no theoretical restrictions on the sign of correlation between risk and return. Backus and Gregory (1993) show that in a Lucas (1978) exchange economy, the correlation can be positive or negative depending on the time series properties of the pricing kernel.

This latter result suggests that the hedging component can be a significant pricing factor that has an important effect on the risk-return relation. If the hedging component is negatively correlated with and much more volatile than the conditional variance, then the correlation between stock market volatility and expected returns will be negative. In general, the risk-return relation can be time-varying as observed by Whitelaw (1994). However, the theory still requires a positive *partial* relationship between the stock market risk and return, i.e., that γ is positive. The more relevant empirical issue is to disentangle the risk component from the hedging component.

Scruggs (1998) obtains some promising results on the decomposition of the expected excess market return into risk and hedging components. Assuming that the long-term government bond return represents investment opportunities, he estimates equation (1) using a bivariate exponential GARCH model and finds that γ is positive and statistically significant. However, his approach has a couple of weaknesses. In order to identify equation (1), he assumes that the conditional correlation coefficient between stock returns and bond returns is constant, but Ibbotson Associates (1997) provide evidence that it actually changes sign over time in historical data. Moreover, his point estimate of γ is approximately 10, which is somewhat larger than many economists consider reasonable.

In contrast, this paper develops a structural asset pricing model based on Merton's (1973) ICAPM and implements estimation with instrumental variables.[2] In our structural model, the persistence of the conditional market variance and the volatility feedback effect are explicitly considered. Specifically, by modeling the market variance as an autoregressive process, we can capture the effect of innovations in variance on realized returns. This allows us to explain part of the unexpected return on a contemporaneous basis and hence improve the efficiency of the estimation and the identification of the features of interest.

French, Schwert and Stambaugh (1987), Pindyck (1988) and Campbell and Hentschel (1992) have all emphasized the volatility feedback effect.[3] French, Schwert and Stambaugh (1987) find a negative and statistically significant relationship between the shock to volatility and the ex post stock market return. However, the evidence for the relationship between ex ante risk and return is inconclusive in their OLS regression. Campbell and Hentschel (1992) consider the volatility feedback effect in a structural GARCH model and find a positive and statistically significant risk-return relation; though their point estimate of γ is very small. Pindyck (1988) uses a model similar to ours and his point estimate of γ is 3.35 with a standard error 0.744 in monthly data. However, the model restrictions are rejected by the data and his results are difficult to interpret.

The structural model also allows us to explicitly consider the possibility of an additional contemporaneous negative correlation between the stock price and its variance, i.e., the leverage effect documented by Black (1976) and Christie (1982). The contemporaneous variance of the stock market return is added to the estimation as a regressor to control for this effect, thereby avoiding a potential bias in the point estimate of γ. We also attempt to control for the fact that the error in the structural model may not be orthogonal to the contemporaneous regressors. To reduce the potential bias, we use Campbell's (1991) method to directly control for the revised expectation of the hedging component, the most important component of the error.

[2] French, Schwert and Stambaugh (1987) argue that full information maximum likelihood (FIML) estimators such as GARCH are generally more sensitive to model misspecification than instrumental variable estimators.

[3] The volatility feedback effect is first formalized in Poterba and Summers (1986) to question Pindyck's (1984) finding that changes in stock market volatility explain a large fraction of stock price movements. Poterba and Summers (1986) derive a structural model similar to ours and argue that the volatility effect is exaggerated in Pindyck (1984).

Another improvement over previous work is that we use non-overlapping monthly volatility implied by S&P 100 index option prices as the instrumental variable for the conditional variance $E_{t-1}\sigma^2_{M,t}$.[4] This implied volatility data has been found by Christensen and Prabhala (1998) to outperform past volatility in forecasting the future volatility of the S&P 100 index, and it subsumes the information content of past volatility in some specifications. Fleming (1998) documents a similar phenomenon. Interestingly, in our dataset, implied volatility performs even better. It not only subsumes the information content of past volatility in all specifications, but also subsumes the information content of financial variables that forecast stock market volatility. The implied volatility is therefore an efficient instrumental variable and improves the precision of our estimation.

We get several interesting results from the estimation of the structural model with implied volatility data. First, the restrictions imposed by the structural model are not rejected by the data. Second, the coefficient of relative risk aversion, γ, is positive and precisely estimated. For example, if the conditional variance follows an AR(1) process, the point estimate of γ is 4.01 with a standard error of 0.51. It varies slightly between 3.06 to 4.01 for different conditional variance processes. We get similar point estimates in subsamples both prior and subsequent to the 1987 stock market crash. Third, we find that stock price movements are driven mostly by changes in investment opportunities,[5] not by changes in stock market volatility. The two together explain 63% of the total variation in stock market returns, the latter explains only 14% of the variation.

One concern is that the implied volatility data only span the period from November 1983 to May 1995 (139 observations), which includes only one recession and a potential outlier, the 1987 stock market crash. In order to check the robustness of our results and to understand the business cycle patterns of stock market returns, we also estimate the structural model with postwar monthly data, in which the conditional market variance is estimated with instrumental variables.

[4] The implied volatility data is constructed by Christensen and Prabhala (1998) and is kindly provided to us by N. Prabhala.

[5] We use the risk-free rate and the dividend yield as instrumental variables for investment opportunities, as suggested by Guo (1999a). The yield spread between 6-month commercial paper and 3-month Treasury bills is also found to be a significant predictor, although it is not significant in the full postwar monthly sample that is discussed below.

Similar results are found in this longer dataset. γ is positive and statistically significant. The point estimate is comparable to that from the implied volatility data, although with a somewhat larger standard error due to the loss of efficiency associated with the use of instrumental variables for the conditional market variance. We again find that stock price movements are driven mostly by changes in investment opportunities. With the longer time series, we also find some additional interesting results. First, we detect a significant leverage effect. Second, γ is stable over time, although it is somewhat smaller during recessions. Smaller risk aversion during recessions is consistent with recent evidence of mean reversion in stock market returns. Third, the hedging component of expected returns is strongly counter-cyclical.

The remainder of the paper is organized as follows. Section 2 presents a log-linear structural model of stock returns. The data are discussed in Section 3, and the empirical investigation is conducted in Section 4. Section 5 concludes the paper.

2 A Log-Linear Asset Pricing Model

In this section, we derive a structural asset pricing model based on Merton's ICAPM and Campbell and Shiller's (1988) log-linearization method. The log-linear approximation provides both tractability and accuracy.

Following Campbell and Shiller (1988), the continuously compounded market return $r_{M,t+1}$ is defined as

$$r_{M,t+1} = \log(P_{M,t+1} + D_{M,t+1}) - \log(P_{M,t}) \tag{2}$$

where $P_{M,t+1}$ is the stock price at the end of period t+1 and $D_{M,t+1}$ is the dividend paid out during period t+1. Throughout this paper, we use upper case to denote the level and lower case to denote the log.

Using a first order Taylor expansion around the steady state of the log dividend price ratio $\overline{d-p}$, equation (2) can be rewritten as a first order difference equation for the stock price

$$r_{M,t+1} \approx k + \rho p_{M,t+1} - p_{M,t} + (1-\rho) d_{M,t+1} \tag{3}$$

where

$$\rho = \frac{1}{1+\exp(\overline{d-p})}$$
$$k = -\log(\rho) - (1-\rho)\log(\frac{1}{\rho}-1)$$

ρ is set to be 0.997 as in Chapter 7 of Campbell, Lo and MacKinlay (1997).

Solving equation (3) forward and imposing the transversality condition $\lim_{j\to\infty}\rho^j p_{M,t+j} = 0$, we get the stock price as a function of future dividend flows and discount rates

$$p_{M,t} = \frac{k}{1-\rho} + \sum_{j=0}^{\infty}\rho^j[(1-\rho)d_{M,t+1+j} - r_{M,t+1+j}] \tag{4}$$

Equation (4) is simply an accounting identity, which should also hold ex ante

$$p_{M,t} = \frac{k}{1-\rho} + E_t\sum_{j=0}^{\infty}\rho^j[(1-\rho)d_{M,t+1+j} - r_{M,t+1+j}] \tag{5}$$

Substituting equation (5) into equation (3), we can decompose the ex post stock return into two parts – the expected return and the shocks to this return:

$$\begin{aligned} r_{M,t+1} - E_t r_{M,t+1} &= E_{t+1}\sum_{j=0}^{\infty}\rho^j\Delta d_{M,t+1+j} - E_t\sum_{j=0}^{\infty}\rho^j\Delta d_{M,t+1+j} \\ &\quad -[E_{t+1}\sum_{j=1}^{\infty}\rho^j r_{M,t+1+j} - E_t\sum_{j=1}^{\infty}\rho^j r_{M,t+1+j}] \end{aligned} \tag{6}$$

where $\Delta d_{M,t+1+j}$ is dividend growth.

For the excess market return $e_{M,t+1} \equiv r_{M,t+1} - r_{f,t+1}$, where $r_{f,t+1}$ is the nominal risk-free rate, equation (6) can be rewritten as

$$\begin{aligned} e_{M,t+1} - E_t e_{M,t+1} &= E_{t+1}\sum_{j=0}^{\infty}\rho^j\Delta d_{M,t+1+j} - E_t\sum_{j=0}^{\infty}\rho^j\Delta d_{M,t+1+j} \\ &\quad -[E_{t+1}\sum_{j=1}^{\infty}\rho^j e_{M,t+1+j} - E_t\sum_{j=1}^{\infty}\rho^j e_{M,t+1+j}] \\ &\quad -[E_{t+1}\sum_{j=1}^{\infty}\rho^j r_{f,t+1+j} - E_t\sum_{j=1}^{\infty}\rho^j r_{f,t+1+j}] \end{aligned} \tag{7}$$

Combining equation (7) and a variant of Merton's ICAPM,[6]

$$E_t e_{M,t+1} = \omega + \gamma E_t \sigma^2_{M,t+1} + \lambda E_t \sigma_{MF,t+1} \tag{8}$$

we get

$$\begin{aligned} e_{M,t+1} &= \omega + \gamma E_t \sigma^2_{M,t+1} + \lambda E_t \sigma_{MF,t+1} \\ &\quad -[E_{t+1} \sum_{j=1}^{\infty} \gamma \rho^j \sigma^2_{M,t+1+j} - E_t \sum_{j=1}^{\infty} \gamma \rho^j \sigma^2_{M,t+1+j}] \\ &\quad + \eta_{d,t+1} + \eta_{f,t+1} + \eta_{F,t+1} \end{aligned} \tag{9}$$

where

$$\begin{aligned} \eta_{d,t+1} &= E_{t+1} \sum_{j=0}^{\infty} \rho^j \Delta d_{M,t+1+j} - E_t \sum_{j=0}^{\infty} \rho^j \Delta d_{M,t+1+j} \\ \eta_{f,t+1} &= -[E_{t+1} \sum_{j=1}^{\infty} \rho^j r_{f,t+1+j} - E_t \sum_{j=1}^{\infty} \rho^j r_{f,t+1+j}] \\ \eta_{F,t+1} &= -[E_{t+1} \sum_{j=1}^{\infty} \lambda \rho^j \sigma_{MF,t+1+j} - E_t \sum_{j=1}^{\infty} \lambda \rho^j \sigma_{MF,t+1+j}] \end{aligned}$$

Poterba and Summers (1986) argue that conditional market volatility follows an AR(1) process. However, in our dataset it is better described by an AR(2) process for samples that include the 1987 stock market crash. Consequently, we consider the AR(2) process

$$\sigma^2_{M,t+1} = \alpha + \beta_1 \sigma^2_{M,t} + \beta_2 \sigma^2_{M,t-1} + \varepsilon_{M,t+1} \tag{10}$$

with the AR(1) process as a special case when $\beta_2 = 0$.

Equation (9) and equation (10) imply

$$\begin{aligned} e_{M,t+1} &= \omega + \frac{\gamma \rho \alpha}{1 - \rho \beta_1 - \rho^2 \beta_2} + \frac{\gamma}{1 - \rho \beta_1 - \rho^2 \beta_2} [E_t \sigma^2_{M,t+1} - \rho E_{t+1} \sigma^2_{M,t+2}] \\ &\quad + \frac{\gamma \rho \beta_2}{1 - \rho \beta_1 - \rho^2 \beta_2} [\sigma^2_{M,t} - \rho \sigma^2_{M,t+1}] \\ &\quad + \lambda E_t \sigma_{MF,t+1} + \eta_{d,t+1} + \eta_{f,t+1} + \eta_{F,t+1} \end{aligned} \tag{11}$$

[6] Note that a constant term ω is added in equation (8). We also use the notation $\frac{-J_{WW}W}{J_W} = \gamma$ and $\frac{-J_{WF}}{J_W} = \lambda$. γ is the constant relative risk aversion coefficient. λ is a function of the state variables and is not necessarily constant.

or

$$
\begin{aligned}
e_{M,t+1} &= \omega + \frac{\gamma\alpha}{1-\rho\beta_1-\rho^2\beta_2} \\
&+ \frac{\gamma[\beta_1\sigma^2_{M,t} + \beta_2\sigma^2_{M,t-1} - (\rho\beta_1+\rho^2\beta_2)\sigma^2_{M,t+1}]}{1-\rho\beta_1-\rho^2\beta_2} \\
&+ \lambda E_t\sigma_{MF,t+1} + \eta_{d,t+1} + \eta_{f,t+1} + \eta_{F,t+1}
\end{aligned} \tag{12}
$$

We focus on equation (11) since it allows us to fully exploit the information content in the implied volatility data.

The are several ways to estimate the hedging component $\lambda E_t\sigma_{MF,t+1}$. Scruggs (1998) assumes that λ is constant and estimates $E_t\sigma_{MF,t+1}$ with a bivariate exponential GARCH model. Campbell (1996) uses the product of the conditional forecasting errors of market returns and the state variables to approximate it. In this paper, we assume that the hedging component $\lambda E_t\sigma_{MF,t+1}$ is a linear function of the state variables $\mathrm{X}_{k,t}$, $k = 1, ...K$,[7] or

$$
\lambda E_t\sigma_{MF,t+1} = \sum_{k=1}^{K} \lambda_k X_{k,t} \tag{13}
$$

Equation (13) is an unconstrained version of Campbell's (1996) method. As we mentioned earlier, the IV model is not as sensitive to misspecification as the GARCH model.

Another advantage of equation (13) is that it allows us to calculate the revision term $\eta_{F,t+1}$ directly as in Campbell and Shiller (1988), Campbell (1991) and Campbell and Ammer (1993). Since $\eta_{d,t+1}+\eta_{f,t+1}+\eta_{F,t+1}$ might be correlated with the contemporaneous regressors, least squares estimators of equation (11) could be biased if we treat the sum $\eta_{d,t+1}+\eta_{f,t+1}+\eta_{F,t+1}$ as the regression error. Further identification of $\eta_{F,t+1}$ will greatly reduce this potential bias since $\eta_{F,t+1}$ is the most important component of the sum $\eta_{d,t+1} + \eta_{f,t+1} + \eta_{F,t+1}$.[8]

[7] Here, we assume that the state variables do not contain the same information as the conditional market variance in forecasting future market returns. As we will see later, the instrumental variables we choose satisfy this assumption.

[8] Shiller (1981) challenges the traditional view that stock return innovations come mostly from dividend shocks by showing that stock prices move too much to be justified by subsequent changes in dividends. His paper initiated a debate on why stock market volatility is so high. Recent research suggests that "excess" stock market volatility is due to the high persistence of expected stock market returns. For example, Campbell and Ammer (1993) find that the revision of expected returns accounts for more than 86% of the innovations in stock market returns in postwar monthly data. We find similar results in this paper.

Following Campbell and Shiller (1988), among others, we assume that the excess market return $e_{M,t+1}$ and state variables $X_{k,t+1}$, $k = 1, ...K$ follow a first-order VAR process:

$$\begin{bmatrix} e_{M,t+1} \\ X_{t+1} \end{bmatrix} = A \begin{bmatrix} e_{M,t} \\ X_t \end{bmatrix} + \nu_{t+1} \tag{14}$$

where X_{t+1} is a K-by-1 vector of the state variables and A is the companion matrix of the VAR. It is straightforward to show that

$$\begin{aligned} \eta_{F,t+1} &= -[E_{t+1}\sum_{j=1}^{\infty}(\rho\lambda)^j \sigma_{MF,t+1+j} - E_t \sum_{j=1}^{\infty}(\rho\lambda)^j \sigma_{MF,t+1+j}] \\ &= e1'\rho A(I - \rho A)^{-1}\nu_{t+1} \end{aligned} \tag{15}$$

where $e1 = [1, 0...0]$ and I is an identity matrix.

Black (1976) and Christie (1982) argue for a leverage effect, i.e., a negative contemporaneous correlation between volatility and stock price that is independent of the volatility feedback effect. Nelson (1991) and Glosten, Jagannathan and Runkle (1993) emphasize the importance of the leverage effect in the investigation of the risk-return relation and they all find a significant leverage effect in ARCH models as well. Since the contemporaneous market variance $\sigma^2_{M,t+1}$ enters equation (12) with a negative coefficient,[9] volatility feedback has the same effect on stock price as leverage. Therefore, the estimation of equation (11) is biased if we ignore the leverage effect. The structural model allows us to test and control for the leverage effect in a straightforward way. Since the leverage effect implies only a contemporaneous relation between stock price and volatility, we add an additional contemporaneous market variance term as a regressor in equation (11), without any constraint on its coefficient. The coefficient should be negative if there is a leverage effect.[10]

After substituting equations (13) and (15) into equation (11) and taking the leverage effect into

[9]In our data, β_1 is positive and larger than the absolute value of β_2. Given that ρ is positive and slightly less than one, $\frac{-(\rho\beta_1+\rho^2\beta_2)}{1-\rho\beta_1-\rho^2\beta_2}$ in equation (12) should be negative.

[10]Another way to test the volatility feedback effect is via the regression $\log(\frac{\sigma_{M,t}}{\sigma_{M,t-1}}) = \alpha_0 + \alpha_1 r_{M,t} + \varepsilon_t$. If there is no volatility feedback effect, α_1 should be greater than minus one. French, Schwert and Stambaugh (1987) find that α_1 is statistically significantly less than minus one and argue that the feedback effect is important. We find similar results.

account, we obtain the equation that is estimated in this paper:

$$
\begin{aligned}
e_{M,t+1} &= \omega + \frac{\gamma\rho\alpha}{1-\rho\beta_1-\rho^2\beta_2} + \frac{\gamma}{1-\rho\beta_1-\rho^2\beta_2}[E_t\sigma^2_{M,t+1} - \rho E_{t+1}\sigma^2_{M,t+2}] \\
&+\frac{\gamma\rho\beta_2}{1-\rho\beta_1-\rho^2\beta_2}[\sigma^2_{M,t} - \rho\sigma^2_{M,t+1}] \\
&+\sum_{k=1}^{K}\lambda_k X_{k,t} + \theta e1'\rho A(I-\rho A)^{-1}\nu_{t+1} + \delta\overline{\sigma^2_{M,t+1}} \\
&+\eta_{d,t+1} + \eta_{f,t+1}
\end{aligned} \tag{16}
$$

Note, we use the de-meaned market variance $\overline{\sigma^2_{M,t+1}}$ instead of $\sigma^2_{M,t+1}$ itself so that the fitted values $\widehat{\gamma}E_t\sigma^2_{M,t+1}$ and $\sum_{k=1}^{K}\widehat{\lambda_k}X_{k,t}$ can be interpreted as the risk component and the hedging component, respectively. In other words, the mean of the conditional expected market return $\widehat{\omega} + \widehat{\gamma}E_t\sigma^2_{M,t+1} + \sum_{k=1}^{K}\widehat{\lambda_k}X_{k,t}$ is set to the unconditional mean of the market return.

3 Data Description

The structural model is estimated with two sets of data. The first dataset utilizes the volatility implied by S&P 100 index (OEX) option prices as an instrumental variable for expected market variance. The second dataset adopts the commonly used financial variables to estimate the expected market volatility.

3.1 Implied Volatility Data

3.1.1 Data Construction

The implied volatility data $IVOL_t$ used in this paper is constructed by Christensen and Prabhala (1998). It is non-overlapping monthly data spanning the period from November 1983 to May 1995, with a total of 139 observations.

The monthly excess market return and variance are constructed from daily excess market returns. The daily market return data are daily value-weighted market returns (VWRET) from CRSP. The daily risk-free rate data is not easily available. Following Nelson (1991) among others, we assume that the risk-free rate is constant within each month and calculate the daily risk-free rate by dividing the monthly risk-free rate by the number of trading days in the month. The daily excess market return is then calculated by subtracting the daily risk-free rate from the daily market return. The monthly risk-free rate data are the short-term government bill rates taken from Ibbotson Associates (1997).

As in Christensen and Prabhala (1998), the monthly market variance is defined as

$$\sigma^2_{M,t} = \sum_{k=1}^{\tau t} (e_{t,k} - \overline{e_t})^2 \tag{17}$$

where τt is the number of days to expiration of the OEX option at month t, $e_{t,k}$ is the daily excess market return and $\overline{e_t} = \frac{1}{\tau t} \sum_{k=1}^{\tau t} e_{t,k}$. The monthly excess market return is the sum of the daily excess market returns,

$$e_t = \sum_{k=1}^{\tau t} e_{t,k} \tag{18}$$

Both realized and implied variances of S&P 100 index returns are larger than the realized market variance $\sigma^2_{M,t}$.[11] This is not surprising since the S&P 100 is not a well-diversified portfolio. We scale $IVOL_t$ by regressing $\sigma^2_{M,t}$ on a constant and $IVOL_t$ and use the fitted value $IVOL_{M,t}$ as the expected market variance. The point estimate of slope is 0.46 with a standard error of 0.05. Figure 1 shows a scatter plot of market variance $\sigma^2_{M,t}$ against implied variance $IVOL_t$, and the straight line is the fitted value from the regression. The stock market crash for October 1987 is an outlier. To see if this unusual event has any significant effect, we exclude the observation of October 1987 from the regression. The point estimate of the slope is 0.62 with a standard error 0.09. The corresponding scatter plot is shown in Figure 2. There is no significant difference between the implications of the two regressions.

The hedging component is estimated using three instrumental variables – the dividend yield (FSDXP), the stochastically detrended risk-free rate (RREL) and the spread between yields on 6-month commercial paper and 3-month Treasury bills (CP). RREL is defined as follows

$$RREL_t = rf_t - \frac{1}{12} \sum_{k=1}^{12} rf_{t-k} \tag{19}$$

[11] In our sample, the means of monthly realized and implied variance of the S&P 100 index return are 22 and 20 basis points, respectively. The realized market variance has a mean of 13 basis points.

FSDXP and RREL are the variables most often used to forecast stock market return in literatures, e.g., Campbell, Lo and MacKinlay (1997).[12] We also find that CP has some predictive power in our sample. The risk-free rate is taken from Ibbotson Associates (1997). The dividend yield, 6-month commercial paper yield and 3-month Treasury bill yield are all taken from the Basic Economics database.

3.1.2 The Efficiency of Implied Volatility

Christensen and Prabhala (1998) find that implied volatility $IVOL_t$ outperforms past volatility in forecasting the future volatility of the S&P 100 index return. We find that it performs even better as a forecast for the volatility of the value-weighted index.

It is well known that we can predict stock market volatility with financial variables, such as the nominal risk-free rate in Campbell (1987) and the yield spread between 6-month commercial paper and 3-month Treasury bills (CP) in Whitelaw (1994). Here we only consider the following variables used by Whitelaw (1994), which are all taken from the Basic Economics database.

1. DEF – the yield spread between Baa-rated and Aaa-rated bonds
2. CP – the yield spread between six-month commercial paper and three-month Treasury bills
3. FYGT1 – the one-year Treasury bill yield
4. FSDXP – the dividend yield

We assume that market variance $\sigma^2_{M,t}$ is a linear function of its own lags, the instrumental variables X_k listed above and the scaled implied volatility $IVOL_{M,t}$

$$\sigma^2_{M,t} = c + \sum_{k=1}^{4} a_k X_{k,t-1} + b * \sigma^2_{M,t-1} + d * IVOL_{M,t} + \zeta_t \tag{20}$$

If the implied volatility is efficient, all other variables should enter equation (20) insignificantly. Assuming that ζ_t is independently distributed, we estimate equation (20) with OLS and White's

[12] In a general equilibrium asset pricing model, Guo (1999a) shows that the dividend yield and risk-free rate predict stock market returns.

(1980) heteroskedasticity consistent standard errors are calculated. The estimation results are reported in Table 1.

In model 1, we include only the four instrumental variables as regressors. DEF and FSDXP are statistically significant, while FYGT1 and CP are not. The adjusted R^2 is 18%, indicating that the instrumental variables have significant predictive power for stock market variance. The addition of lagged stock market variance does not qualitatively change these results. While the past variance enters equation (20) significantly in model 2, DEF and FSDXP remain significant.

In model 3, we add the scaled implied volatility $IVOL_{M,t}$ to the forecasting equation and find that it is highly significant. However, now neither past variance nor the instrumental variables are significant. To check the robustness of these results, we include only past variance and implied volatility in model 4 and the past variance is again insignificant. This is slightly surprising since implied volatility does not always subsume the information content of past volatility in Christensen and Prabhala (1998). For example, they find that past volatility has significant predictive power in the following specification:

$$\log(\sigma_t) = c + a * \log(\sigma_{t-1}) + b * \log(IVOL_t) + \xi_t \tag{21}$$

We estimate this alternative specification (model 5) and the past variance still remains insignificant at the 5% level. Therefore, neither past volatility nor the instrumental variables provide additional information over the implied volatility in forecasting the stock market variance. The implied volatility $IVOL_{M,t}$ used in this paper is an efficient instrumental variable for future stock market variance and hence it should improve the estimation efficiency of the structural model.

3.2 Monthly Data

The structural model is also estimated with postwar monthly data, spanning the period from May 1953 to December 1998. The monthly stock market variance $\sigma^2_{M,t}$ is again constructed from daily return data

$$\sigma^2_{M,t} = \sum_{k=1}^{\tau t} (r_{t,k} - \overline{r_t})^2 \tag{22}$$

where $r_{t,k}$ is the market return on the kth day of month t, τt is the number of trading days in month t and $\overline{r_t} = \frac{1}{\tau t}\sum_{k=1}^{\tau t} r_{t,k}$. We use daily market return data constructed by Schwert (1990) before July 2, 1962 and the daily value-weighted market return (VWRET) from CRSP thereafter.

We assume that the conditional market variance is a linear function of the state variables $X_{k,t-1}$ and its own lags

$$\sigma^2_{M,t} = c + \sum_{k=1}^{4} a_k X_{k,t-1} + \sum_{i=1}^{I} b_i \sigma^2_{M,t-i} + \zeta_t \quad (23)$$

Using DEF, CP, FSDXP and RREL as instrumental variables for $X_{k,t-1}$ and including only statistically significant lags, we estimate equation (23) with OLS and use the fitted value $\widehat{\sigma^2_{M,t}}$ as the expected market variance.

The estimation results over three subsamples – prior to the 1987 crash, subsequent to the 1987 crash, and the full sample – are reported in Table 2. The stock market crash of October 1987 has a confounding effect on stock market variance. While only one-period lagged market variance is statistically significant in both the pre- and post-1987 stock market crash subsamples, two-period lagged market variance is also statistically significant in the full sample. Moreover, the instrumental variables also have significant predictive power.

The monthly value-weighted market return (VWRET) and the risk-free rate from CRSP are used to construct the monthly excess market return. We also use RREL and FSDXP as instrumental variables for the hedging component, while CP is dropped since it does not predict stock market returns.

4 Empirical Results

In this section, we estimate the structural model with both implied volatility data and postwar monthly data. A positive and significant risk-return relation is detected in both datasets.

4.1 Econometric Strategy

Equation (16) is the structural model we estimate in this paper; however, γ and β_1 cannot be separately identified by equation (16) alone. As an alternative, we estimate the parameters α, β_1

and β_2 separately using the variance equation and substitute their point estimates $\widehat{\alpha}$, $\widehat{\beta_1}$ and $\widehat{\beta_2}$ into equation (16) as constants.[13] After substitutions, the structural model becomes a linear function of the underlying parameters to be estimated:

$$\begin{aligned} e_{M,t+1} &= \omega + \frac{\gamma\rho\widehat{\alpha}}{1-\rho\widehat{\beta_1}-\rho^2\widehat{\beta_2}} + \frac{\gamma}{1-\rho\widehat{\beta_1}-\rho^2\widehat{\beta_2}}[E_t\sigma^2_{M,t+1} - \rho E_{t+1}\sigma^2_{M,t+2}] \\ & +\frac{\gamma\rho\widehat{\beta_2}}{1-\rho\widehat{\beta_1}-\rho^2\widehat{\beta_2}}[\sigma^2_{M,t} - \rho\sigma^2_{M,t+1}] \\ & +\sum_{k=1}^{K}\lambda_k X_{k,t} + \theta e1'\rho A(I-\rho A)^{-1}\nu_{t+1} + \delta\overline{\sigma^2_{M,t+1}} \\ & +\eta_{d,t+1} + \eta_{f,t+1} \end{aligned} \tag{24}$$

Assuming that $\eta_{d,t+1} + \eta_{f,t+1}$ is orthogonal to the other right hand side variables[14] and is independently distributed, equation (24) can be estimated with OLS. Given the strong ARCH pattern in the monthly market return data, the conventional OLS standard errors are inappropriate. Consequently, we calculate White's (1980) heteroskedasticity consistent standard errors instead.

The variance equation (10) implies that the expected variance follows an ARMA(2,1) process

$$E_t\sigma^2_{M,t+1} = \alpha + \beta_1 E_{t-1}\sigma^2_{M,t} + \beta_2 E_{t-2}\sigma^2_{M,t-1} + \beta_1\varepsilon_{M,t} + \beta_2\varepsilon_{M,t-1} \tag{25}$$

Given that implied volatility is an efficient predictor of future market variance as shown in Section 3, we use equation (25) instead of equation (10) to estimate the conditional variance process.

If β_2 is zero, equation (25) can be estimated with OLS. Otherwise we first estimate equation (10) and then substitute the fitted value of the lagged error $\varepsilon_{\widehat{M,t-1}}$ back into equation (25) and

[13] Note that since $\sigma^2_{M,t+1}$ enters the right hand side of equation (16), the error term $\eta_{d,t+1} + \eta_{f,t+1}$ should be orthogonal to the error term $\varepsilon_{M,t+1}$ in the variance equation (10). Thus there is no efficiency gain in estimating the two equations together. In fact, we get almost identical results from the joint estimation.

[14] By definition, revisions to the dividend and the real interest rate $\eta_{d,t+1}+\eta_{f,t+1}$ are orthogonal to the instrumental variables $X_{k,t}, k = 1, ...K$, $\sigma_{M,t}$ and $E_t\sigma_{M,t+1}$. They may be correlated with $\sigma_{M,t+1}$ and $E_{t+1}\sigma_{M,t+2}$; however, these correlations are likely to be small since most market return innovations are due to revisions in expected returns, which are controlled for in equation (24). The revision to the hedging component $e1'\rho A(I-\rho A)^{-1}\nu_{t+1}$ is not highly correlated with $\eta_{d,t+1} + \eta_{f,t+1}$ either. Therefore, the bias in the estimation of equation (24), if there is any, should be small.

estimate either an unconstrained version

$$E_t\sigma^2_{M,t+1} = \alpha + \beta_1 E_{t-1}\sigma^2_{M,t} + \beta_2 E_{t-2}\sigma^2_{M,t-1} + \beta_3 \overset{\wedge}{\varepsilon_{M,t-1}} + \varepsilon'_{M,t} \tag{26}$$

or a constrained version

$$E_t\sigma^2_{M,t+1} = \alpha + \beta_1 E_{t-1}\sigma^2_{M,t} + \beta_2 (E_{t-2}\sigma^2_{M,t-1} + \overset{\wedge}{\varepsilon_{M,t-1}}) + \varepsilon''_{M,t} \tag{27}$$

For the specification test, we also estimate an unrestricted version of the structural model

$$\begin{aligned} e_{M,t+1} &= a_0 + a_1 E_t\sigma^2_{M,t+1} + a_2 E_{t+1}\sigma^2_{M,t+2} + a_3\sigma^2_{M,t} + a_4\sigma^2_{M,t+1} \\ &\quad + \sum_{k=1}^{K} \lambda_k X_{k,t} + \theta e1'\rho A(I-\rho A)^{-1}\nu_{t+1} \\ &\quad + \eta_{d,t+1} + \eta_{f,t+1} \end{aligned} \tag{28}$$

We again assume that $\eta_{d,t+1} + \eta_{f,t+1}$ is orthogonal to the other right hand side variables and is independently distributed. Equation (28) is then estimated with OLS.

The structural model imposes the following restrictions:

$$\begin{aligned} a_1 &= \frac{\gamma}{1-\rho\widehat{\beta_1}-\rho^2\widehat{\beta_2}} \\ a_2 &= -\frac{\gamma\rho}{1-\rho\widehat{\beta_1}-\rho^2\widehat{\beta_2}} \\ a3 &= \frac{\gamma\rho\widehat{\beta_2}}{1-\rho\widehat{\beta_1}-\rho^2\widehat{\beta_2}} \\ a4 &= -\frac{\gamma\rho^2\widehat{\beta_2}}{1-\rho\widehat{\beta_1}-\rho^2\widehat{\beta_2}} \end{aligned}$$

If the structural model is correctly specified, then $a1$ should be positive and $a2$ should be negative.[15] Moreover, the two coefficients should have almost identical absolute values. Similarly, $a3$ and $a4$ should have opposite signs and almost the same absolute values. We use the F-statistic $F(K,N) = \frac{(R^2_U - R^2_R)/K}{R^2_U/N}$ to test the joint significance of the restrictions imposed by the structural model, where R^2_U and R^2_R are the R^2s of equations (28) and (24), respectively, K is number of restrictions imposed by the structural model, and N is the degrees of freedom of equation (28).

[15]Since ρ is about 0.997 in the monthly data, $a1$ ($a2$) is positive (negative) as long as the conditional market variance is stationary, which cannot be rejected with either the implied volatility data or the postwar monthly data.

4.2 Implied Volatility Data

The scaled implied volatility $IVOL_{M,t}$ is used as an instrumental variable for the expected market variance $E_t\sigma^2_{M,t+1}$ in the estimation of equations (24), (26) or (27) and (28). To summarize the results, the restrictions imposed by the structural model are not rejected by the data and the volatility feedback effect greatly increases the power to detect a positive risk-return relation. The relative risk aversion coefficient is precisely estimated because of the efficiency of implied volatility. The negative risk-return relation found in the early literature is therefore attributed to the inefficient models and instrumental variables that they use.

4.2.1 Unrestricted model

To illustrate how well the restrictions imposed by the structural model square with data, we first present the empirical results for the unrestricted model, which are reported in Table 3.

In case 1, we adopt the conventional specification used in the risk-return literature by regressing the stock market return on the expected market variance. The point estimate of the slope a_1 is 4.03 with a standard error of 1.81. If the hedging component is not correlated with the risk component and there is no leverage effect, a_1 is an unbiased estimator of relative risk aversion, γ.[16] The conventional specification thus provides evidence that risk is positively priced. Our results are in sharp contrast to previous instrumental variable estimations, e.g., Campbell (1987) and Whitelaw (1994), which uniformly find a negative risk-return relation. The difference may be due to the fact that implied volatility $IVOL_{M,t}$ is a much more efficient instrumental variable or to the difference in the sample periods.

We focus only on stock market variance in cases 2 and 3. If the conditional market variance follows an AR(1) process, only current and one-period ahead expected market variances enter the structural model. This is case 2 of Table 3. The slope parameters a_1 and a_2 are both statistically significant and have the expected signs. The R^2 is 10%. In case 3, we include both expected and realized market variances as required under the assumption of an AR(2) process for conditional market variance. All the slope parameters have the expected signs and all are statistically significant

[16] This is the exact regression that Merton (1980) proposes.

except $a3$. The R^2 is about 14%. Volatility changes explain only a small fraction of stock price movements. In a similar study, Pindyck (1984) regresses the excess market return on the change in the market variance and gets an R^2 of 48.8%. However, Poterba and Summers (1986) argue that the volatility effect is overstated in Pindyck (1984) because of the method that he uses to construct the conditional market variance. Our results support the conclusions of Poterba and Summers (1986).

Case 4 is the standard stock market return predictability regression. We use three forecasting variables, namely CP, RREL and FSDXP. RREL is statistically significant and has the same sign found in previous studies. However, FSDXP is not statistically significant, possibly because it captures only the long-horizon variations in expected market returns,[17] and our data is monthly, spanning less than 12 years. CP is positive and statistically significant. The predictive power of CP might be attributed to our particular sample.[18] The R^2 is about 6%, indicating moderate predictability of stock market returns. Note that the R^2 in case 4 is six times as large as that in case 1. Therefore, the hedging component explains much more of the variation in expected market returns than the risk component.

In equation (16) or (24), the decomposition of expected market returns into risk and hedging components is biased if the instrumental variables for the hedging component contain the same information as the conditional market variance. To explore this issue, we regress stock market returns on both the expected market variance and the instrumental variables for the hedging component in case 5. All point estimates are close to their counterparts in case 2 and case 4, in which the two components are estimated separately. Moreover, the R^2 in case 5 is about 17%, which is slightly larger that the sum of the R^2s of case 2 and case 4. We also get similar results if we add the realized market variances, as in case 6. Therefore, the instrumental variables for the hedging component do not contain the same information as the conditional market variance and

[17] For example, Campbell, Lo and MacKinlay (1997) find that the dividend yield has more predictive power over longer horizons, while the risk-free rate only forecasts short-run stock market returns. See Guo (1999a) for a theoretical explanation of this result.

[18] CP has not been found to forecast stock market return in earlier studies, a result we duplicate in the postwar monthly data.

our decomposition is not biased.

The structural model requires that the absolute values of a_1 and a_2 be approximately equal to each other. However, the two are somewhat different in cases 2, 3, 5 and 6. One possible reason is that the error term $\eta_{d,t+1} + \eta_{f,t+1} + \eta_{F,t+1}$ is not orthogonal to the right hand side variables. As a remedy, we control for $\eta_{F,t+1}$ by adding $e1'\rho A(I - \rho A)^{-1}\nu_{t+1}$ as a regressor in case 7. The absolute values of a_1 and a_2 are now 6.65 and 6.93 respectively. CP and RREL also remain statistically significant. The R^2 of case 7 is about 64%, which is about five times as large as that of case 3. Therefore, the hedging component explains a much larger fraction of stock price movements than does the risk component. This should not be a surprise since expected returns are driven mostly by the hedging component, as mentioned earlier. The coefficients on both one-period lagged and contemporaneous market variance, namely $a3$ and $a4$, are small and statistically insignificant. This suggests that β_2 is close to zero, or that conditional market variance follows an AR(1) process.[19]

4.2.2 Structural Model

The estimation results for the unrestricted model suggest an AR(1) process for the conditional market variance. For the sake of robustness, we consider both AR(1) and AR(2) processes in the estimation of the structural model.

Table 4a reports estimation results for the structural model without controlling for $\eta_{F,t+1}$, i.e., $e1'\rho A(I - \rho A)^{-1}\nu_{t+1}$ is excluded in equation (24). We consider four cases. Conditional market variance is assumed to follow an AR(1) process in case 1 and to follow an AR(2) process in the other three cases. In case 2, we ignore the moving average term $\varepsilon_{M,t-1}$ in equation (25). In case 3 and case 4, equations (26) and (27) are estimated, respectively. The variance process is reported in the upper panel of Table 4a. The conditional variance is not persistent in any of the cases, possibly because of the short-lived 1987 stock market crash. In cases 2, 3 and 4, three alternative identification schemes generate similar point estimates for the AR(2) process of the conditional

[19] Christensen and Prabhala (1998) find that implied volatility is best described by an ARMA(1,1) process according to the Box-Jenkins test, although an AR(1) also fits the data well. Given that the nonsynchronous sampling used by Christensen and Prabhala (1998) may induce an artificial moving average component in the implied volatility, it is possible that the conditional market variance indeed follows an AR(1) process.

market variance. Moreover, the restriction imposed by equation (25) is not rejected by the F-test.

The results for the structural model are reported in lower panel of Table 4a. Four specifications produce similar results: γ is precisely estimated with point estimates ranging from 4.8 to 6.3; CP and RREL are statistically significant; the leverage effect is negative and significant; and the F-test cannot reject the restrictions imposed by the structural model, indicating that our model is well specified. However, the AR(1) case fits the data best: the F-statistic is smaller and the R^2 is higher in the AR(1) case than in the AR(2) cases. This is consistent with earlier results from the unrestricted model.

The results for the structural model controlling for $\eta_{F,t+1}$ are reported in the lower panel of Table 4b.[20] Four specifications again produce similar results: γ is precisely estimated with point estimates ranging from 3.06 to 4.01; the revision of the hedging component $\eta_{F,t+1}$ is highly significant; and the F-test cannot reject the restriction imposed by the structural model. There are some differences between Table 4a and Table 4b. The leverage effect is now positive in all cases. It is also statistically significant except in the AR(1) case. The instrumental variables CP and RREL are only significant in the AR(1) case, although they are marginally significant in all other cases. Given that the AR(1) process fits the data best, the leverage effect should be interpreted as inconclusive.

Market variance jumps during the 1987 stock market crash and decreases to the pre-crash level very quickly. To check if this unusual event has any significant effect on our results, we estimate equation (24) with both pre-crash and post-crash subsamples, in which the months of crash are excluded. The results are reported in Table 4c. The upper panel reports results for the market variance process. For both subsamples, the market variance follows an AR(1) process and is more persistent in the post-crash sample than in the pre-crash sample. The lower panel reports the results for the structural model, which is estimated both with and without controlling for $\eta_{F,t+1}$. For the post-crash sample, the point estimates of γ are close to those reported in Tables 4a and 4b, although with much larger standard errors due to the small sample size. The F-test does not reject the restrictions imposed by the structural model in either specification. For the pre-crash sample, the point estimate of γ is -3.81 if we do not control for $\eta_{F,t+1}$, however, the F-test rejects

[20] The upper panel reports the same variance process as in Table 4a.

this specification strongly. It is 5.14 if we control for $\eta_{F,t+1}$ and the F-test does not reject the specification. Given that there is no significant difference between the subsamples and the full sample, we can conclude that the major results of Tables 4a and 4b are not caused by the 1987 stock market crash. Interestingly, the leverage effect is negative and large, although not statistically significant, in all cases in Table 4c. Therefore, the positive leverage effect found in Table 4b is likely caused by the 1987 stock market crash.

Using the point estimates of case 4 in Table 4b, we decompose the expected excess return $Ee_{M,t}$ into the risk component $\widehat{\gamma} E_t \sigma^2_{M,t}$ and the hedging component $\sum_{k=1}^{K} \widehat{\lambda_k} X_{k,t-1}$. The three series are plotted in Figures 3-5, respectively, with shaded areas indicating economic contractions. All three variables jump dramatically during the 1987 stock market crash and decrease to their pre-crash levels very quickly. They also rise during the period July 1990-March 1991, the only recession in our sample. It is clear that the hedging component is more volatile than the risk component.

Campbell and Cochrane (1999) argue that relative risk aversion is time-varying and is higher during business downturns. To investigate this, we add a recession dummy variable for γ – it takes the value 1 during the July 1990-March 1991 contraction and zero otherwise. The coefficient on the recession dummy is not statistically significant. This is not a surprise since there is only one recession in our sample. We will investigate this issue with a longer time series later in the paper.

In conclusion, we find a positive and significant risk-return relation. The relative risk aversion is precisely estimated and its point estimate falls in a reasonable range.[21] Due to the small sample and the possible influence of the 1987 stock market crash, evidence on the leverage effect is inconclusive. We cannot draw any conclusions about the time-varying nature of relative risk aversion either because there is only one recession in our sample. To address these problems, we also estimate the structural model with postwar monthly data. The gain is the increase in sample size; the potential loss is that we have to estimate the conditional market variance with instrumental variables, which are not as efficient as the implied volatility data.

[21] Mehra and Prescott (1985) argue that relative risk aversion should be less than 10. Many others believe that it is less than 5. See Kocherlakota (1996) for a discussion of reasonable ranges for the relative risk aversion coefficient.

4.3 Post-War Monthly Data

For the postwar monthly data, we regress the realized market variance on its own lags and instrumental variables and then use the fitted value as the expected market variance $E_t\sigma^2_{M,t+1}$. The results of the variance regression are reported in Table 2. Conditional market variance follows an AR(1) process in both the pre- and post-1987 stock market crash subsamples and follows an AR(2) process in the whole sample.

We only consider the AR(2) process in the estimation of the structural model if the whole sample is used. As before, we estimate the conditional market variance process (equation (25)) in three ways. In case 1, we assume away the moving average term $\beta_2\varepsilon_{M,t-1}$. Case 2 and case 3 correspond to equation (26) and equation (27), respectively. The estimation results are reported in the upper panels of Table 5a and Table 5b. The point estimates are similar in case 1 and case 3 and are quite different in case 2. The restriction that $\beta_2 = \beta_3$ that is imposed in case 2 is rejected by the F-test. The Durbin-Watson statistic is also small in case 2. Consequently, the conditional variance process may be better described by the point estimates of case 1 or case 3 than of case 2. Intuitively, since the point estimate of β_2 is small in cases 1 and 3, ignoring the moving average term $\beta_2\varepsilon_{M,t-1}$ should have little effect on the estimation results. In fact the Durbin-Watson statistic of case 1 is 1.96, indicating that there is no significant serial correlation in the error. On the other hand, $\varepsilon_{\widehat{M,t-1}}$ may be a bad instrumental variable since there might be potentially large measurement errors in the realized market variance. Inclusion of $\varepsilon_{\widehat{M,t-1}}$ in case 2 and case 3 actually introduces serial correlation in the error, since the Durbin-Watson statistic are smaller in both cases.

The lower panel of Table 5a reports the estimation results for the structural model with no control for $\eta_{F,t+1}$. The estimation is relatively sensitive to how we identify the market variance process, i.e., equation (25). γ is significantly positive in both case 1 and case 3, however it is insignificant in case 2. This is not a surprise since the market variance process is not properly estimated in case 2, as shown earlier. Therefore, we focus only on case 1 and case 3. The point estimates of γ are somewhat smaller than those in Table 4a. The leverage effect is negative and significant in both cases. The restrictions imposed by the structural model are not rejected by the F-test only in case 1.

The lower panel of Table 5b reports the estimation results for the structural model controlling for $\eta_{F,t+1}$. The relative risk aversion γ is again positive and significant in both cases 1 and 3. Its point estimates are somewhat smaller than those of Table 4b. The leverage effect is negative and significant too. The restrictions imposed by the structural model are not rejected by F-test in either case 1 or case 3.

We also estimate the structural model with a recession dummy for γ. The results are reported in Table 5c. We use the pre-1987 stock market crash sample as well as the whole postwar sample. The upper panel is the market variance process. An AR(1) process is estimated for the pre-1987 stock market crash sample. For the whole sample, we estimate an AR(2) process with equation (27). The structural model is reported in the lower panel. We consider two cases for each sample: with and without controlling for $\eta_{F,t+1}$. The relative risk aversion coefficient γ is positive and significant in all cases. Its point estimates are comparable to those we get with implied volatility data. Interestingly, the recession dummy for γ is negative in all cases in Table 5c, although it is significant only in the pre-1987 stock market crash sample when controlling for $\eta_{F,t+1}$. Given the small magnitude of the recession dummy, the relative risk aversion γ seems relatively stable over time. The negative recession dummy should not necessarily be interpreted as indicating that shareholders are less risk averse during recessions. Alternatively, the recession dummy may capture some hedging component that is not captured by the instrumental variables.[22] Intuitively, investors require lower returns if the capital loss during recessions is temporary than if it is permanent.

Using the point estimates of case 4 in Table 5c, we decompose the expected excess return $Ee_{M,t}$ into the risk component $\gamma E_t \sigma^2_{M,t}$ and the hedging component[23] $\sum_{k=1}^{K} \lambda_k X_{k,t-1}$. We plot these three series in Figures 6-8, respectively, with shaded areas indicating business contractions. All three variables, especially the expected excess return and the hedging component, are countercyclical. The hedging component is much more volatile than the risk component, and changes in expected excess returns are driven mostly by the hedging component.

[22] In the calibration of a dynamic asset pricing model, Guo (1999a) shows that although the price-dividend ratio and the term premium are correlated with expected stock returns, they are not as efficient as expected stock returns in predicting future stock returns.

[23] Note that we include the recession dummy for γ in the hedging component.

In conclusion, we also find a positive relation between risk and return in the postwar monthly data. The point estimate of relative risk aversion is close to that found using implied volatility data. Expected returns, conditional volatility and the hedging component are all counter-cyclical. The risk aversion coefficient is stable over time, although it is somewhat smaller during recessions.

5 Conclusion

This paper estimates a variant of Merton's (1973) intertemporal capital asset pricing model, and we find a positive relationship between stock market risk and return. Relative risk aversion is moderate and stable over time; therefore, the power utility function describes the data fairly well. The conflicting results found in previous studies are probably due to the fact that they do not distinguish the risk component from the hedging component. Such a decomposition also helps us to better understand stock market returns as well as their relationship to the macro economy.

Although stock market volatility is positively priced, it only explains a small fraction of stock price movements. Most stock price movements are driven by changes in investment opportunities. Surprisingly, the importance of investment opportunities has long been ignored in academic research and existing economic theories cannot explain why they move so dramatically and the macroeconomic forces behind them. Some recent research tries to fill this gap. For example, Campbell and Cochrane (1999) address changing investment opportunities in a habit formation model. In their model, when consumption approaches the habit level, the agent becomes extremely risk averse and demands a large expected return. Guo (1999a) uses an infinite horizon heterogeneous agent model in which only one type of agent holds stocks. If there are borrowing constraints and idiosyncratic labor income shocks, shareholders require a large equity premium when their borrowing constraints are close to binding. The investment opportunities are therefore determined by shareholders' liquidity conditions.[24] In contrast, Whitelaw (1999) generates large changes in investment opportunities by modeling the underlying economy as a two regime process. Because regimes are persistent, regime shifts represent large movements in investment opportunities with corresponding changes

[24] Aiyagari and Gertler (1998) and Allen and Gale (1994) emphasize the liquidity effect on stock market volatility.

in required returns.

In this paper, we also find that the hedging component is strongly counter-cyclical. Although it is well known that stock market returns forecasts future aggregate output, the connection between the two has not been much studied. Further research in this direction should help us better understand business cycles.

Finally, the focus of this paper is on understanding risk and expected returns at the market level in a time series context; however, a significant piece of the empirical asset pricing literature focuses on the cross-section of expected returns across individual securities or portfolios. Interestingly, the importance of hedging changes in the investment opportunity set at the aggregate level is also likely to have strong implications in the cross-section. In particular, if volatility is not the primary source of priced risk at the market level, then the dynamic CAPM will not hold, and market betas will not be the correct proxies for expected returns in the cross-section. Clearly, this issue warrants further investigation from both an empirical and theoretical standpoint.

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Table 1: The Efficiency of Implied Volatility

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
DEF	**.24E-02**	**.15E-02**	.73E-03		
	(.68E-03)	**(.68E-03)**	(.61E-03)		
CP	.12E-02	.10E-03	.12E-03		
	(.89E-03)	(.49E-03)	(.47E-03)		
FSDXP	**-.16E-02**	**-.13E-02**	-.65E-03		
	(.71E-03)	**(.65E-03)**	(.57E-03)		
FYGT1	.17E-03	.22E-03	.80E-04		
	(.15E-03)	(.13E-03)	(.12E-03)		
$\sigma^2_{M,t-1}$		**.50**	.33	.34	.16
		(.18)	(.21)	(.23)	(.91E-01)
$ivol_{M,t}$			**.62**	**.70**	**.84**
			(.13)	**(.13)**	**(.16)**
$\overline{R^2}$	.18	.37	.45	.45	.35
DW	1.15	2.17	2.38	2.40	2.15

In models 1-4, we estimate equation (20). In model 5, we estimate equation (21). The sample covers the period from November 1983 to May 1995 with a total of 139 observations. To save space, the intercept is not reported. Heteroskedasticity consistent standard errors (White (1980)) are reported in parentheses. Variables that are different from zero at the 5% significance level are in bold.

Table 2: Volatility Predictability Regressions

	Subperiod		
Variable	1953:5-1987:8	1988:6-1998:12	1953:6-1998:12
DEF	**.25E-03**	**.18E-02**	.71E-03
	(.10E-03)	**(.79E-03)**	(.39E-03)
CP	**.66E-03**	.21E-03	**.11E-02**
	(.16E-03)	(.69E-03)	**(.36E-03)**
FSDXP	-.42E-05	**-.80E-03**	-.31E-03
	(.50E-04)	**(.28E-03)**	(.20E-03)
RREL	.90E-01	-.44E-01	.20
	(.50E-01)	(.21)	(.16)
$\sigma^2_{M,t-1}$	**.38**	**.34**	**.12**
	(.67E-01)	**(.14)**	**(.57E-01)**
$\sigma^2_{M,t-2}$			**.07**
			(.26E-01)
$\overline{R^2}$	.32	.28	.09
DW	2.08	2.04	2.00

Equation (23) is estimated for various subsamples. To save space, the intercept term is not reported. Heteroskedasticity consistent standard errors (White (1980)) are reported in the parentheses. Variables that are different from zero at the 5% significance level are in bold.

Table 3: Unrestricted Model: The Implied Volatility Data

Parameter	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7
a_0	.25E-02	**.12E-01**	**.93E-02**	-.84E-02	-.11E-02	-.30E-02	.12E-01
	(.36E-02)	(.39E-02)	**(.42E-02)**	(.18E-01)	(.16E-01)	(.16E-01)	(.10E-01)
a_1	**4.03**	**8.88**	**11.08**		**6.53**	**12.60**	**6.65**
	(1.81)	**(1.84)**	**(2.67)**		**(1.64)**	**(2.60)**	**(1.98)**
a_2		**-12.02**	**-9.09**		**-13.41**	**-9.32**	**-6.93**
		(2.29)	**(2.72)**		**(1.71)**	**(2.42)**	**(1.59)**
a_3			3.39			-1.38	-.43
			(2.16)			(2.44)	(2.04)
a_4			**-6.38**			**-7.27**	2.64
			(-3.07)			**(2.94)**	(2.43)
CP				**.26E-01**	**.30E-01**	**.39E-01**	**.18E-01**
				(.93E-02)	**(.98E-02)**	**(.12E-01)**	**(.80E-02)**
RREL				**-7.53**	**-8.26**	**-11.74**	**-6.16**
				(3.76)	**(3.74)**	**(4.29)**	**(3.01)**
FSDXP				-.97E-04	-.25E-03	-.20E-01	-.51E-02
				(.93E-02)	(.45E-02)	(.47E-02)	(.32E-02)
θ							**-.53**
							(.50E-01)
R^2	.01	.10	.14	.06	.17	.22	.64
DW	2.04	2.10	2.16	2.15	2.20	2.24	1.74
log-likelihood	267.70	274.10	277.09	270.93	279.38	283.96	336.99

We estimate the unrestricted structural model in equation (28) with the implied volatility data. Heteroskedasticity consistent standard errors (White (1980)) are reported in the parentheses. Variables that are different from zero at the 5% significance level are in bold.

Table 4: Structural Model: Implied Volatility Data

Panel A: No Control for $\eta_{F,t+1}$

Parameter	Case 1	Case 2	Case 3	Case 4
	Equation (25)			
α	**.80E-03**	**.67E-03**	**.77E-03**	**.84E-03**
	(.13E-03)	**(.14E-03)**	**(.12E-03)**	**(.15E-03)**
β_1	**.41**	**.33**	**.23**	**.24**
	(.78E-01)	**(.85E-01)**	**(.85E-01)**	**(.86E-01)**
β_2		**.18**	**.19**	.13
		(.85E-01)	**(.46E-01)**	(.82E-01)
β_3				**.23**
				(.62E-01)
R^2	.16	.19	.26	.27
DW	2.14	2.03	2.03	2.08
	Equation (24)			
ω	.18E-01	-.15E-01	-.16E-01	-.17E-01
	(.16E-01)	(-.16E-01)	(.16E-01)	(.16E-01)
γ	**6.29**	**4.79**	**5.52**	**6.25**
	(.80)	**(.79)**	**(.94)**	**(.95)**
CP	**.37E-01**	**.33E-01**	**.33E-01**	**.34E-01**
	(.99E-02)	**(.10E-01)**	**(.10E-01)**	**(.10E-01)**
RREL	**-10.66**	**-9.61**	**-9.52**	**-9.84**
	(3.67)	**(3.72)**	**(3.73)**	**(3.71)**
FSDXP	-.17E-02	-.15E-02	-.15E-02	-.16E-02
	(.45E-02)	(.46E-02)	(.46E-02)	(.46E-02)
δ	**-6.70**	**-5.67**	**-5.58**	**-5.90**
	(1.62)	**(1.62)**	**(1.62)**	**(1.61)**
R^2	.22	.21	.21	.21
DW	2.26	2.26	2.26	2.26
F-test	1.01	2.73	2.96	2.75
(Critical Value)	(3.84)	(3.00)	(3.00)	(3.00)

Panel B: Controlling for $\eta_{F,t+1}$

Parameter	Case 1	Case 2	Case 3	Case 4
		Equation (25)		
α	**.80E-03**	**.67E-03**	**.77E-03**	**.84E-03**
	(.13E-03)	**(.14E-03)**	**(.12E-03)**	**(.15E-03)**
β_1	**.41**	**.33**	**.23**	**.24**
	(.78E-01)	**(.85E-01)**	**(.85E-01)**	**(.86E-01)**
β_2		**.18**	**.19**	.13
		(.85E-01)	**(.46E-01)**	(.82E-01)
β_3				**.23**
				(.62E-01)
R^2	.16	.19	.26	.27
DW	2.14	2.03	2.03	2.08
		Equation (24)		
ω	.87E-02	.11E-01	.11E-01	.95E-02
	(.99E-02)	(-.10E-01)	(.10E-01)	(.10E-01)
γ	**4.01**	**3.06**	**3.53**	**3.99**
	(.51)	**(.47)**	**(.56)**	**(.58)**
CP	**.17E-01**	.15E-01	.15E-01	.16E-01
	(.81E-02)	(.83E-02)	(.83E-02)	(.83E-02)
RREL	**-5.92**	-5.23	-5.17	-5.38
	(2.81)	(2.87)	(2.87)	(2.85)
FSDXP	-.50E-02	-.50E-02	-.50E-02	-.50E-02
	(.31E-02)	(.31E-02)	(.31E-02)	(.31E-02)
δ	2.36	**3.04**	**3.10**	**2.89**
	(1.45)	**(1.41)**	**(1.41)**	**(1.42)**
θ	**-.53**	**-.54**	**-.54**	**-.54**
	(.49E-01)	**(.50E-01)**	**(.50E-01)**	**(.49E-01)**
R^2	.64	.64	.64	.64
DW	1.74	1.74	1.74	1.74
F-test	.01	.24	.27	.17
(Critical Value)	3.84	3.00	3.00	3.00

Panel C: Subsamples

Parameter	Post-Crash		Pre-Crash	
		Equation (25)		
α	**.32E-03**		**.69E-03**	
	(.94E-04)		**(.19E-03)**	
β_1	**.72**		**.50**	
	(.77E-01)		**(.13)**	
R^2	.52		.26	
D-W	2.16		1.93	
		Equation (24)		
	No $\eta_{F,t}$	With $\eta_{F,t}$	No $\eta_{F,t}$	With $\eta_{F,t}$
ω	-.35E-01	.42E-02	-.28E-02	.36E-02
	(.28E-01)	(.18E-01)	(.62E-01)	(.32E-01)
γ	4.97	3.20	-3.81	5.14
	(2.55)	(1.94)	(5.56)	(2.78)
CP	.40E-01	**.52E-01**	.29E-01	**.29E-01**
	(.23E-01)	**(.17E-01)**	(.29E-01)	**(.15E-01)**
RREL	-11.70	**-12.97**	-10.64	**-9.91**
	(7.73)	**(5.71)**	(8.04)	**(4.71)**
FSDXP	.51E-02	-.86E-02	-.21E-02	-.63E-02
	(.99E-02)	(.64E-02)	(.12E-01)	(.69E-02)
δ	-7.49	-1.96	-11.95	-4.64
	(4.38)	(2.52)	(11.23)	(4.57)
θ		**-.50**		**-1.19**
		(.61E-01)		**(.13)**
R^2	.20	.62	.14	.74
DW	2.32	2.42	2.09	1.51
F-test	.22	2.01	9.30	.05
(Critical Value)	3.96	3.96	3.96	3.96

The structural model of equation (24) is estimated with the implied volatility data. The upper panel is the conditional variance estimation in equation (25) and the lower panel is the structural model. Heteroskedasticity consistent standard errors (White (1980)) are reported in the parentheses. Variables that are different from zero at the 5% significance level are in bold.

Table 5: Structural Model: Postwar Monthly Data

Panel A: No Control for $\eta_{F,t+1}$

Variable	Case 1	Case 2	Case 3
	Equation (25)		
α	**.23E-03**	**.26E-03**	**.32E-03**
	(.35E-04)	**(.24E-04)**	**(.45E-04)**
β_1	**.93**	**.67**	**.88**
	(.43E-01)	**(.18E-01)**	**(.28E-01)**
β_2	**-.12**	**.12**	**-.14**
	(.43E-01)	**(.50E-02)**	**(.28E-01)**
β_3			**.13**
			(.47E-02)
R^2	.69	.85	.87
DW	1.96	1.42	1.72
	Equation (24)		
ω	-.49E-02	-.28E-02	-.56E-02
	(.74E-02)	(.71E-02)	(.75E-02)
γ	**2.87**	1.10	**3.35**
	(1.12)	(1.47)	**(1.31)**
RREL	**-8.69**	**-8.60**	**-8.78**
	(1.97)	**(2.01)**	**(1.99)**
FSDXP	.19E-02	.19E-02	.20E-02
	(.20E-02)	(.19E-02)	(.20E-02)
δ	**-6.06**	**-5.07**	**-6.30**
	(.91)	**(1.82)**	**(.88)**
R^2	.18	.17	.18
DW	2.06	2.07	2.05
F-test	3.00	15.73	8.67
(Critical Value)	3.00	3.00	3.00

Panel B: Controlling for $\eta_{F,t+1}$

Parameter	Case 1	Case 2	Case 3
		Equation (25)	
α	**.23E-03**	**.26E-03**	**.32E-03**
	(.35E-04)	**(.24E-04)**	**(.45E-04)**
β_1	**.93**	**.67**	**.88**
	(.43E-01)	**(.18E-01)**	**(.28E-01)**
β_2	**-.12**	**.12**	**-.14**
	(.43E-01)	**(.50E-02)**	**(.28E-01)**
β_3			**.13**
			(.47E-02)
R^2	.69	.85	.87
DW	1.96	1.42	1.72
		Equation (24)	
ω	-.42E-02	.64E-02	.35E-02
	(.44E-02)	(.43E-02)	(.44E-02)
γ	**1.87**	-.33	**2.46**
	(.93)	(.86)	**(1.12)**
RREL	**-3.48**	**-3.69**	**-3.51**
	(1.39)	**(1.50)**	**(1.38)**
FSDXP	.25E-03	-.13E-03	-.24E-03
	(.20E-02)	(.12E-02)	(.12E-02)
δ	**-2.08**	**-2.35**	**-2.25**
	(.33)	**(.91)**	**(.35)**
θ	**-.92**	**-.93**	**-.93**
	(.35E-01)	**(.36E-01)**	**(.35E-01)**
R^2	.74	.73	.74
DW	2.22	2.20	2.22
F-test	.87	2.7	1.54
(Critical Value)	3.00	3.00	3.00

Panel C: Time-Varying γ

Variable	1953-1987		1953-1998	
	Equation (25)			
α	**.24E-03**		**.32E-03**	
	(.50E-04)		**(.23E-04)**	
β_1	**.78**		**.88**	
	(.54E-01)		**(.28E-01)**	
β_2			**-.14**	
			(.28E-01)	
β_3			**.13**	
			(.47E-02)	
R^2	.61		.87	
DW	2.04		1.72	
	Equation (24)			
	No $\eta_{F,t}$	With $\eta_{F,t}$	No $\eta_{F,t}$	With $\eta_{F,t}$
ω	**-.20E-01**	-.71E-03	-.75E-02	.12E-02
	(.89E-02)	(.45E-02)	(.74E-02)	(.47E-02)
γ	**5.65**	**2.12**	**4.06**	**3.33**
	(1.77)	**(.86)**	**(1.08)**	**(.86)**
γ_1	-3.57	**-5.42**	-2.33	-2.88
	(2.24)	**(1.10)**	(3.12)	(2.13)
RREL	**-9.26**	**-5.24**	**-9.13**	**-4.03**
	(2.26)	**(1.49)**	**(2.03)**	**(1.62)**
FSDXP	**.50E-02**	.13E-02	.24E-02	.29E-03
	(.22E-02)	(.12E-02)	(.20E-02)	(.13E-02)
δ	-5.77	-1.09	**-9.13**	**-2.20**
	(3.75)	(1.13)	**(2.03)**	**(.36)**
θ		**-.97**		**-.93**
		(.31E-01)		**(.35E-01)**
R^2	.17	.78	.18	.74
DW	2.19	2.14	2.06	2.26

Cases 1, 2 and 3 have the same specifications as cases 2, 3 and 4 in Table 4a, respectively. See footnotes there for more information. We add a recession dummy γ_1 for relative risk aversion in Panel C. Risk aversion is $\gamma + \gamma_1$ during recessions and is γ otherwise.

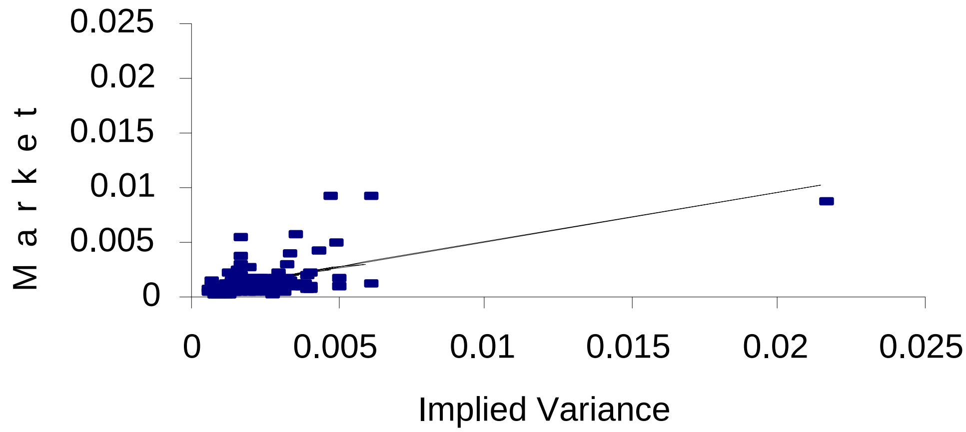

Figure 1: Scatter Plot, Market Variance Against Implied Volatility, Whole Sample

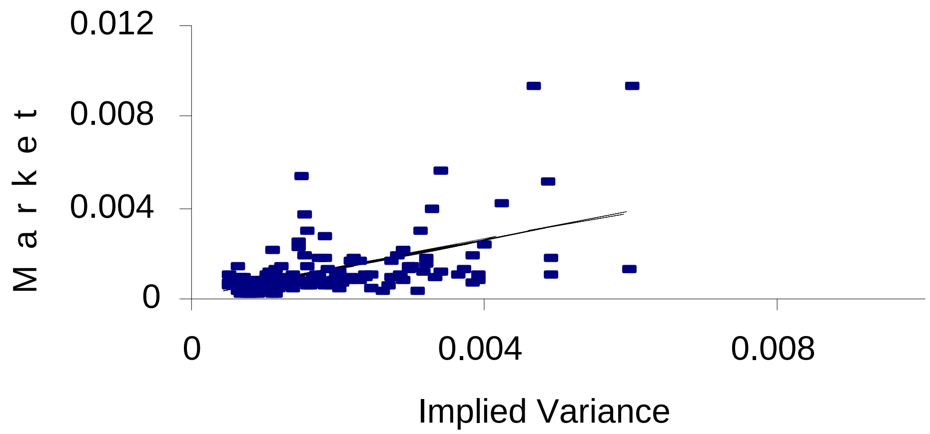

Figure 2: Scatter Plot, Market Variance Against Implied Volatility, October 1987 Excluded.

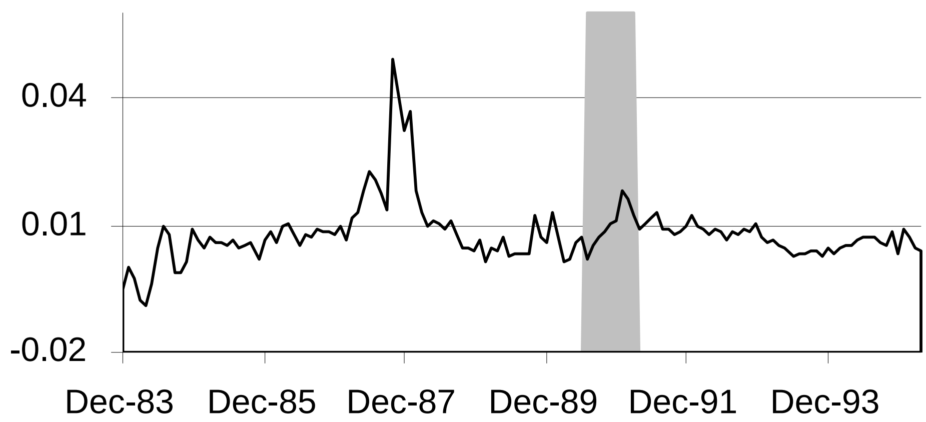

Figure 3: Expected Market Return, Case 4 of Table 4b

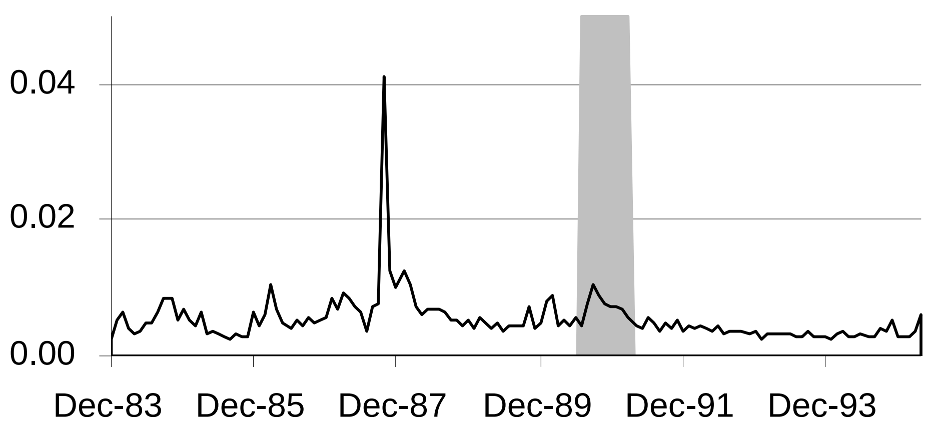

Figure 4: Risk Component, Case 4 of Table 4b

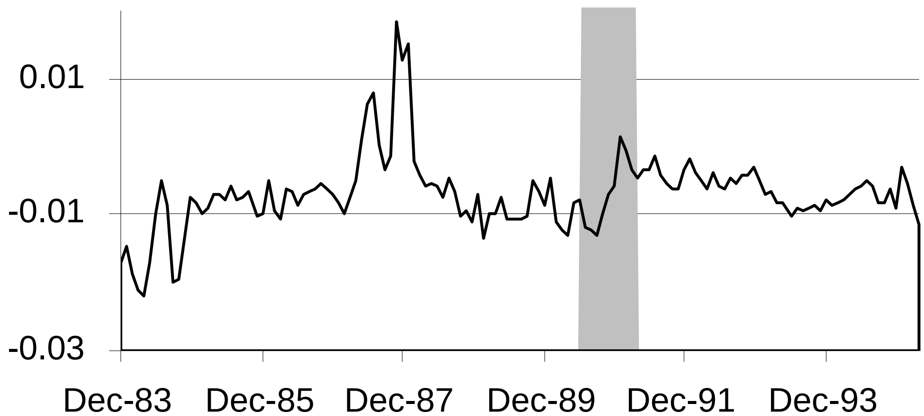

Figure 5: Hedging Component, Case 4 of Table 4b

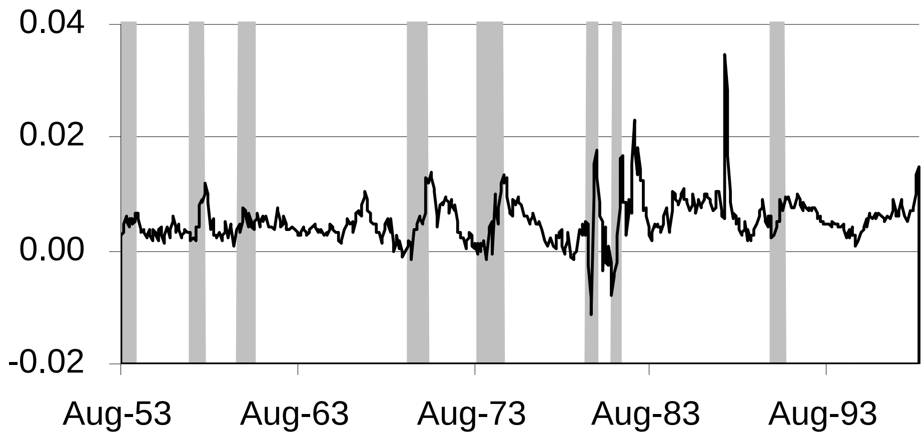

Figure 6: Expected Market Return, Case 4 of Table 5c

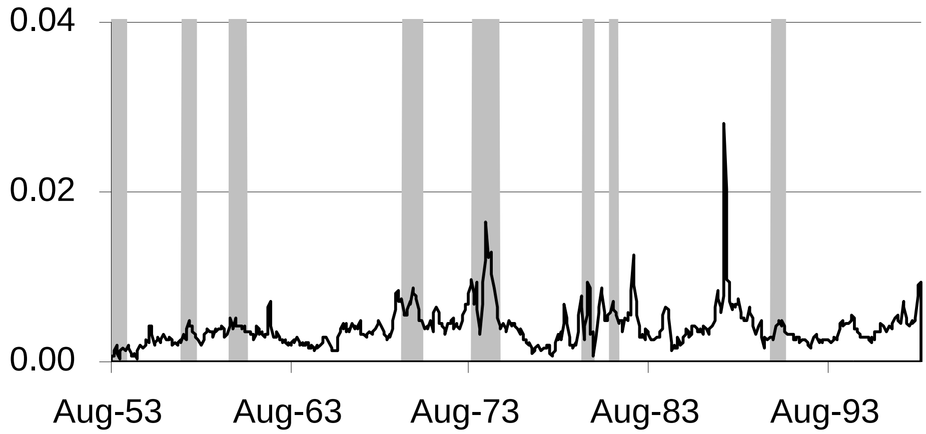

Figure 7: Risk Component, Case 4 of Table 5c

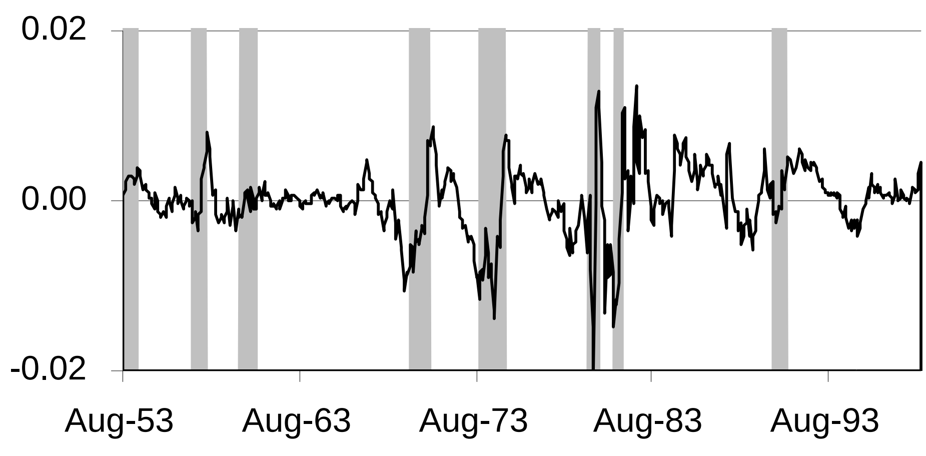

Figure 8: Hedging Component, Case 4 of Table 5c