The Macroeconomic Determinants of Technology Stock Price Volatility

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Abstract

Stock prices reflect the value of anticipated future profits of companies. Since business cycle conditions impact the future profitability of firms, expectations about the business cycle will affect the current value of firms. This paper uses daily and monthly data from July 1986 to December 2000 to investigate the macroeconomic determinants of US technology stock price conditional volatility. Technology share prices are measured using the Pacific Stock Exchange Technology 100 Index. One of the novel features of this paper is to incorporate a link between technology stock price movements and oil price movements. The empirical results indicate that the conditional volatilities of oil prices, the term premium, and the consumer price index each have a significant impact on the conditional volatility of technology stock prices. Conditional volatilities calculated using daily stock return data display more persistence than conditional volatilities calculated using monthly data. These results further our understanding of the interaction between oil prices and technology share prices and should be of use to investors, hedgers, managers, and policymakers.

JEL classification: G1; E44; Q43
Keywords: Financial markets; Oil prices; Technology stock prices; Volatility

1. Introduction

Currently, there has been much discussion surrounding the high valuations of technology stocks (Tully, 2000; The Economist, 1999a, 1999b). Technology stocks, especially

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Internet stocks, tend to be valued at very high price earnings multiples and stock price movements tend to be linked to expected earnings. These stocks are highly vulnerable to market cycles. The technology sector, which is often referred to as the TMT sector because it is composed of companies from the telecommunications, media, and information technology and software industries, is often singled out for being a very volatile sector to invest in.

When discussing the issue of stock market volatility, the basic question that arises is: What are the determinants of stock market volatility? This question has been tackled in a number of different ways, but the approach that is most relevant for this paper is the one that incorporates various macroeconomic and financial variables.[1] Relevant papers that employ such an approach include, Officer (1973) who examines volatility in business cycle variables, Black (1976) and Christie (1982) who relate stock market volatility to financial leverage, and Schwert (1989) who uses a vector autoregressive approach to study stock market volatility changes across time. Schwert (1989) finds that many key economic variables were more volatile during the 1929–1931 Great Depression than at any other time and that many economic variables are more volatile during recessions. Schwert (1989) also finds some evidence that macroeconomic volatility can help predict stock and bond market volatility. Koutoulas and Kryzanowski (1996) investigate the explanatory power of various macroeconomic variables in an arbitrage pricing model of monthly Canadian stock market returns and find that five macroeconomic factors (industrial production, the Canadian leading economic indicator, the US leading economic indicator, the exchange rate, and the residual market factor) have time-varying and priced risk premia. Kearney and Daly (1998) investigate the explanatory power of various macroeconomic variables in determining Australian stock market volatility and find that the conditional volatilities of inflation and interest rates have large direct impacts on Australian stock market volatility. Other variables like industrial production and money supply have indirect effects. Kearney (2000) investigates the determination and international transmission of stock market volatility and finds that world equity market volatility is caused mostly by volatility in Japanese and US markets and then transmitted to European markets. Kearney (2000) also finds that inflation volatility has a significant impact on stock market volatility. The papers by Kearney (2000), Kearney and Daly (1998), and Koutoulas and Kryzanowski (1996) use a generalised least squares estimator (GLS) that overcomes the generated regressor problem evident in Schwert (1989). In these papers, the basic model for studying the macroeconomic determinants of stock market volatility include variables for the stock market, inflation, industrial production, interest rates, and, possibly, exchange rates.

The purpose of this paper is to examine the macroeconomic determinants of technology stock price volatility. This is a topic that has received very little attention in the academic literature. One of the novel features of this paper is to incorporate a link between technology

[1] Other related questions include: Has stock market volatility increased over time? and Has international financial integration led to faster transmission of volatility across international stock markets?

stock price movements and oil price movements. This link is motivated by the recent interest in investigating the link between oil price shocks and financial markets (Huang, Masulis, & Stoll, 1996; Jones & Kaul, 1996; Sadorsky, 1999).

Jones and Kaul (1996) use quarterly data to test whether the reaction of international stock markets to oil shocks can be justified by current and future changes in real cash flows and/or changes in expected returns. Using a standard cash-flow dividend valuation model discussed in Campbell (1991), they find that the reaction of Canadian and US stock prices to oil price shocks can be completely accounted for by the impact of these shocks on real cash flows. The results for Japan and the United Kingdom are, however, not as strong.

Huang et al. (1996) use a vector autoregression (VAR) approach to investigate the relationship between daily oil futures returns and daily US stock returns. They find that, as expected, oil futures returns do lead some individual oil company stock returns. Oil futures returns do not, however, have much impact on broad-based market indices like the S&P 500. They also find that oil futures volatility leads the petroleum stock index volatility.

Sadorsky (1999) uses a vector autoregressive model with four variables (industrial production, interest rates, real oil prices, and real stock returns) to show that oil prices and oil price volatility both play important roles in affecting real stock returns. There is evidence that oil price dynamics have changed. Comparing the change in forecast errors of real stock returns across two subperiods indicates that after 1986, oil price movements explain a larger fraction of the forecast error variance in real stock returns than do interest rates. There is also evidence that oil price volatility shocks have asymmetric effects on the economy.[2] In particular, positive oil price shocks have a larger impact on real stock returns than do negative oil price shocks.

There are two views on the relationship between oil price movements and technology stock prices. The first view is that oil price changes have very little impact on technology stock prices because technology companies engage in business activities that are not very energy intensive. The second view is that oil price changes do have an impact on technology stock prices because oil price increases fuel inflation and inflation leads to changes in business cycle conditions and economic downturns. High technology companies are very sensitive to the overall business cycle. Both views deserve further discussion.

The basis for the first view is the fact that technology companies produce products or services that are less energy intensive than products produced in other sectors of the economy. For example, it takes less energy per unit of output to produce telecommunications equipment than it does to produce steel beams. Manufacturing, in general, has also become less energy intensive. In the United States, it takes 45% less energy to produce one dollar of GDP today than it did in 1973. The combination of less energy intensive manufacturing and energy

[2] Ferderer (1996) and Lee, Ni, and Ratti (1995) are two recent papers that show the impacts of oil price volatility on the macroeconomy in models without financial variables. In contrast, Darrat, Gilley, and Meyer (1996) present an alternative view that oil price volatility may not play that large of a role in impacting US business cycles.

efficiency suggests that technology stock prices are relatively unaffected by oil price movements.

The second view is that oil price movements have a large impact on technology stock prices. Technology stocks, especially prices of Internet stocks, tend to be valued at very high price earnings multiples and stock price movements tend to be linked to expected earnings. These stocks are highly vulnerable to market cycles. Oil prices are an important component of the business cycle. In the high technology sector, oil price increases can also directly impact technology stock returns by raising the costs of the transportation component of e-business. After all, when a buyer places an order for a product online, the product still needs to be shipped from the warehouse to the buyer's doorstep.

This paper investigates the determinants of technology stock price return volatility over the period 1986–2000. This paper is organized as follows. The econometric methodology and the data are discussed in Sections 2 and 3, respectively. Empirical results (using both monthly and daily technology stock market data) for modeling conditional technology stock price return volatility are presented in Section 4. Section 5 concludes the paper.

2. Econometric methodology

The price of equity at any point in time is equal to the discounted present value of expected future cash flows (including capital gains and dividends) to shareholders.

$$E_{t-1}Q_t^i = \frac{E_{t-1}\sum_{j=1}^{\infty} C_{t+j}^i(Y_{t+j}, O_{t+j}, F_{t+j}, P_{t+j}, E_{t+j})}{(1+R_{t+j})^j} \tag{1}$$

In Eq. (1), Q_t^i is the price of asset i at time t, Q_t^i is the associated cash flow, R_t is the discount rate, and E_{t-1} is the mathematical expectation operator. Asset i's cash flow is affected by business cycle conditions and business cycle conditions can be represented by several key macroeconomic variables, including industrial production (Y), crude oil prices (O), the Federal Funds rate (F), consumer prices (P), and the currency exchange rate (E).

The actual return on asset i is q_t^i and the expected return conditional on the available information set at time $t-1$ is $\hat{q}_t^i = E_t(q_t^i \backslash I_{t-1})$. The unconditional standard deviation of q_t^i is σ_t^{qi} and the conditional standard deviation of q_t^i is $\hat{\sigma}_t^{qi} = E_t(\sigma_t^{qi}/I_{t-1})$. Using Eq. (1), the conditional expected returns on asset i can be written as:

$$E_t(q_t^i/I_{t-1}) = f(E_t[C_t^i(Y_t, O_t, F_t, P_t, E_t)]/I_{t-1}) \tag{2}$$

The conditional standard deviation of returns can be written as:

$$E_t(\sigma_t^{qi}/I_{t-1}) = g(E_t[\sigma_t^Y, \sigma_t^o, \sigma_t^F, \sigma_t^P, \sigma_t^E]/I_{t-1}) \tag{3}$$

Macroeconomic factors are observed monthly. Consequently, their conditional standard deviations are estimated using the methodology of Davidian and Carroll (1987). This modeling approach has recently been used by Kearney (2000), Kearny and Daly (1998), and Koutoulas and Kryzanowski (1996).

Let $X=X(Q,Y,O,P,F,E)$ denote the vector of macroeconomic variables, σ_t^X denote the unconditional standard deviation of these variables and $\hat{\sigma}_t^X=E_t(\sigma_t^{Xi}/I_{t-1})$ denote the conditional standard deviations of these variables. The conditional standard deviations are estimated as $\hat{\sigma}_t^X=\sigma_t^X-\varepsilon_{2,t}^X$ from the following ordinary least squares (OLS) regression.

$$\sigma_t^X = \beta_1(L)\sigma_t^X + \sum_{j=1}^{12}\beta_{s,j}\mathrm{DUM}_{j,t} + \varepsilon_{2,t}^X \tag{4}$$

where $\beta_1(L)$ is a 12th order polynomial in the lag operator L and DUM are monthly seasonal dummy variables. The variables $\sigma_t^X=|\varepsilon_{1,t}^X|$ are computed as the residuals from the following equation.

$$\varepsilon_{1,t}^X = \Delta\log(X_t) - E_t(\Delta\log(X_t)|I_{t-1}) = \Delta\log(X_t) - \delta_1(L)\Delta\log(X_t) - \sum_{j=1}^{12}\delta_{s,j}\mathrm{DUM}_{j,t} \tag{5}$$

In Eq. (5), $\delta_1(L)$ is a 12th order polynomial in the lag operator L and DUM are monthly seasonal dummy variables. Davidian and Carroll (1987) suggest that standard deviations based on the absolute value of the prediction errors are more robust than a measure based on the squared residuals.

The equation for the conditional volatility of the technology stock price index is given by:

$$\hat{\sigma}_t^Q = \lambda_0 + \lambda_1(L)\hat{\sigma}_t^X + \varepsilon_{3,t} \tag{6}$$

where $X=X(Q,Y,O,P,F,E)$ and $\lambda_1(L)$ is a fourth order polynomial in the lag operator. In order to take into account the possibility of cross equation correlations among the time series, Eq. (6) is estimated jointly as a system with the six equations from Eq. (4) and the six equations from Eq. (5).

The conditional volatility measure generated from Eq. (4) is a generalization of the twelve-month rolling standard deviation estimator used by Fama (1976), Merton (1980), and Officer (1973). This measure allows the conditional mean to vary over time in Eq. (5) and allows different weights on the lagged absolute unpredicted changes in stock market returns in Eq. (4). This measure of conditional standard deviations, which is similar to the autoregressive conditional heteroskedasticity (ARCH) model of Engle (1982, 1993), has been widely used in finance. See, for example, Kearney (2000), Kearney and Daly (1998), Koutoulas and Kryzanowski (1996), and Schwert (1989).

In the econometric estimation, robustness of the results is checked in two ways. First, daily stock market data is used to estimate monthly unconditional standard deviations. Second, the Federal Funds rate is replaced with a term premium (TP) variable calculated as the difference between the yield on the 10-year Government bond and the yield on the three month Government treasury bill. The term premium is a widely used variable in equations that explain stock price returns (Chen, 1991; Chen, Roll, & Ross, 1986; Darrat & Brocato, 1994; Fama & French, 1989; Ferson & Harvey, 1991).[3]

3. Data

The data are monthly and cover the period January 1984 to December 2000. Market data on the PSE Technology 100 Index comes from Reuters. Monthly technology stock market close data are denoted by Q. Daily technology stock market close data are denoted by D. A monthly unconditional standard deviation is computed from daily data by replacing Eq. (5) with the standard deviation of daily returns. A nonoverlapping sample of daily data is used to estimate the unconditional monthly variances. This should create estimation error that is uncorrelated across time.

The economic variables come from the Federal Reserve Bank of Saint Louis economic database (www.stls.frb.org). Allowing for various data transformations and lags, econometric models are built over the period July 1986 to December 2000. US industrial production (a measure of output) is denoted by Y. Industrial production is a strong indicator of real output and current economic conditions. Industrial production is widely used in empirical studies of the stock market (Chen, 1991; Fama, 1990, Kearney, 2000; Kearney & Daly, 1998; Lee, 1992; Sadorsky, 1999, 2001; Thorbecke, 1997). Oil prices are measured using oil futures prices on West Texas Intermediate crude oil. Futures prices are used rather than spot prices because spot prices are more affected by short-run price fluctuations due to temporary shortages or surpluses. The oil futures price data are from Datastream. The continuous oil price futures series is denoted by O. Interest rates are measured using the Federal Funds rate and denoted by F. The importance of the Federal Funds rate is indicated by the fact that since 1983 the Federal Reserve has targeted the Federal Funds rate (Patelis, 1997; Thorbecke, 1997). The consumer price index (P) is included as a general indicator of inflationary conditions (Lee, 1992; Sadorsky, 2001; Thorbecke, 1997). The foreign currency exchange rate variable (E) is the trade weighted US dollar against its major trading partners. The currency exchange rate is an important variable for some sectors of the economy but overall results are mixed (Kearney & Daly, 1998).

Technology share price movements can be measured in a number of different ways but one way to look at a pure play on technology is to follow the Pacific Stock Exchange (PSE) Technology 100 Index. The PSE Technology 100 Index is a price-weighted index composed

[3] In August of 2000, the term premium variable turned negative. Consequently, for this variable, the first difference of the natural logarithm was replaced with discrete returns.

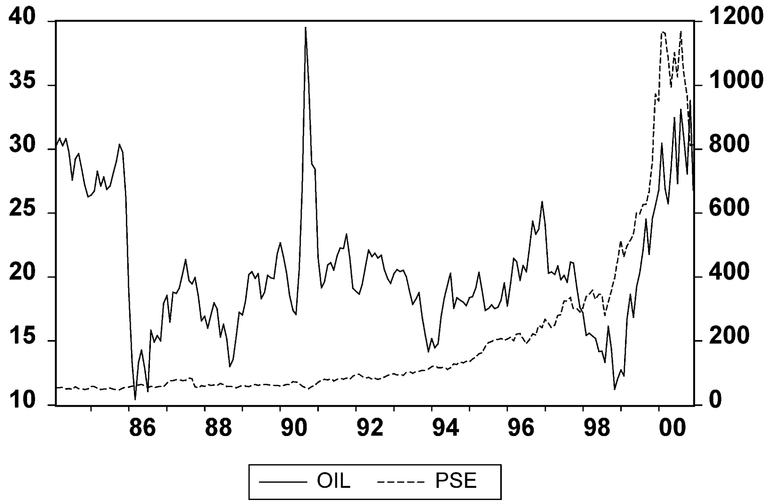

Fig. 1. Oil prices and technology stock prices.

of 100 listed and over the counter stocks from 15 different industries (www.pacificex.com). As of January 1999, the index had a market capitalization of US$1.2 trillion. This index is the most widely cited technology benchmark and also the index with the longest historical record. Share prices of large technology stocks were fairly constant up to 1990 (Fig. 1). After the 1990–1991 recession, technology share prices began what appears to be an exponential increase (with large drops in 1997 and 1998 due to the various global economic and financial crises in Asia, Russia, and the United States). There are periods in which oil prices, measured using futures prices on the West Texas Intermediate crude oil contract, and technology stock prices appear to move in opposite directions from each other (Fig. 1). The period June 1990 to November 1990 is one period over which large oil price increases were matched by large technology stock price decreases. During this period oil prices increased 69% while technology prices fell 20%. The period December 1996 to November 1998 is a period over which oil prices fell and technology stock prices increased. During this period, oil prices fell 57% while technology stock prices increased 63%.

4. Estimation results

Estimation results for the autoregressive Eqs. (4) and (5) are presented in Table 1. Estimation results for Eq. (5) reveal that the explanatory power of these regressions varies between 13% and 31%. These values are fairly large given that the regressions are modeling predictive power in the growth rates of the variables in the vector X. The Ljung–Box Q statistics indicate serial correlation is not present in any of these equations. SUM is a hypothesis test that tests whether or not the sum of the coefficients on the lagged dependent variables is equal to zero. This hypothesis can be rejected at conventional levels for the industrial production, exchange rate, federal funds rate, and consumer price equations. A joint

Table 1
Estimation results for the autoregressions

Variables	R^2	$Q(36)$	SUM	F_1	F_2
Eq. (5)					
Y	.13	0.68	0.01	0.14	0.44
O	.16	0.91	0.44	0.24	0.16
Q	.16	0.94	0.75	0.17	0.02
E	.22	0.97	0.03	0.00	0.52
F	.25	0.94	0.00	0.00	0.48
P	.31	0.99	0.00	0.00	0.05
TP	.19	0.99	0.74	0.01	0.21
Eq. (4)					
Y	.09	0.99	0.67	0.81	0.32
O	.31	0.99	0.00	0.00	0.01
Q	.15	0.89	0.04	0.13	0.15
D	.48	0.99	0.00	0.00	0.01
E	.12	0.84	0.35	0.35	0.01
F	.21	0.96	0.00	0.07	0.01
P	.18	0.97	0.05	0.22	0.01
TP	.20	0.91	0.18	0.03	0.05

$Q(36)$ is a Ljung–Box Q statistic, with 36 *df*, for serial correlation. SUM refers to a test that the sums of the coefficients of the lagged dependent variable in each equation equal zero. F_1 is a F statistic for the joint exclusion of all lagged dependent variables in each equation. F_2 is a F statistic for the joint exclusion of all seasonal dummy variables in each equation. Probability values are reported for the test statistics.

hypothesis test for excluding the lagged values of the dependent variable can be rejected in the equations for the exchange rate, federal funds rate, consumer price, and term premium equations (F_1). A joint hypothesis test for excluding all of the seasonal dummy variables can be rejected in the equations for the stock prices and consumer prices (F_2).[4] This finding of seasonality in the PSE Technology Index is consistent with the large body of research that finds seasonality in stock market data. For example, Gultekin and Gultekin (1983) found evidence of seasonality in 14 out of the 17 countries that they studied and Kramer (1994) found that stock market seasonality in the United States tended to be linked with seasonality in the macroeconomy.

The unconditional standard deviation regression equation results are presented in the lower panel of Table 1. The reported R^2 values vary between 9% and 48% indicating the combination of the lag dependent variables and seasonal dummy variables do contain predictive content. None of these equations contain serial correlation. Lagged dependent variables are statistically significant in the equations for oil prices, daily stock prices, the Federal Funds rate, and the term premium. Seasonal dummy variables are important

[4] The raw data for the industrial production index is seasonally adjusted, while the raw data for the consumer price index is seasonally unadjusted.

explanatory variables in all of the unconditional standard deviation equations except for the industrial production index and the monthly stock returns equation.

Summary statistics for the conditional standard deviations are reported in Table 2. The term premium has the greatest conditional volatility on average with a mean conditional standard deviation of 0.204. Crude oil futures prices and technology stock prices have the next largest mean conditional standard deviations with values of 0.071 and 0.060 (*D*) and 0.055 (*Q*), respectively. By comparison, the consumer price index has the lowest conditional volatility on average with a mean conditional standard deviation of 0.001. As indicated by the reported probability values, each of the means is statistically significant at the 0% level. These series display considerable variability from a variance low of 7.23e − 7 for the industrial production variable to a variance high of 1.99e − 2 for the term premium variable. The conditional standard deviations for industrial production and the Federal Funds rate display evidence of normality (no significant evidence of either skewness or kurtosis), while the conditional standard deviations for the other variables display evidence of nonnormality (some significant evidence of either skewness or kurtosis).

It is useful to compare the summary statistics of the conditional standard deviations computed using monthly and daily technology stock market data. The mean values of the conditional standard deviations computed using the monthly and daily data are 0.055 and 0.060, respectively. The variances of the conditional standard deviations computed using the monthly and daily data are 2.89e − 4 and 5.28e − 4, respectively. While the two variables have approximately the same mean values, the daily data has a variance that is almost twice as large. The first four estimated autocorrelations for the monthly data are .515, .111, .014, and .053. Only the first of these is statistically significant at the 5% level of significance. The first four autocorrelations for the daily data are .624, .375, .324, and .252. All four of these are statistically significant at the 5% level of significance. The autocorrelations for the monthly data have a significant coefficient at lag 1 and the partial autocorrelations smoothly decay to zero. This is indicative of an MA(1) process. In comparison, no clear time series pattern emerges for the conditional stock market volatility measure computed from the daily returns. These results, which indicate that the daily data has more persistence than the monthly data, are similar to the findings of Schwert (1989). A plot of the conditional standard deviations,

Table 2
Summary statistics for the conditional volatilities

Variable	Mean	Variance	Skewness	Kurtosis
Y	0.004 (.00)	7.23e − 7	− 0.18 (.33)	− 0.41 (.28)
O	0.071 (.00)	1.10e − 3	0.74 (.00)	0.46 (.00)
Q	0.055 (.00)	2.89e − 4	1.14 (.00)	1.52 (.00)
D	0.060 (.00)	5.28e − 4	1.64 (.00)	4.42 (.00)
E	0.011 (.00)	1.03e − 5	0.12 (.51)	0.99 (.01)
F	0.023 (.00)	1.07e − 4	0.20 (.27)	− 0.44 (.24)
P	0.001 (.00)	1.81e − 7	0.47 (.01)	0.23 (.53)
TP	0.204 (.00)	1.99e − 2	1.82 (.00)	4.80 (.00)

Probability values are shown beside parameter estimates.

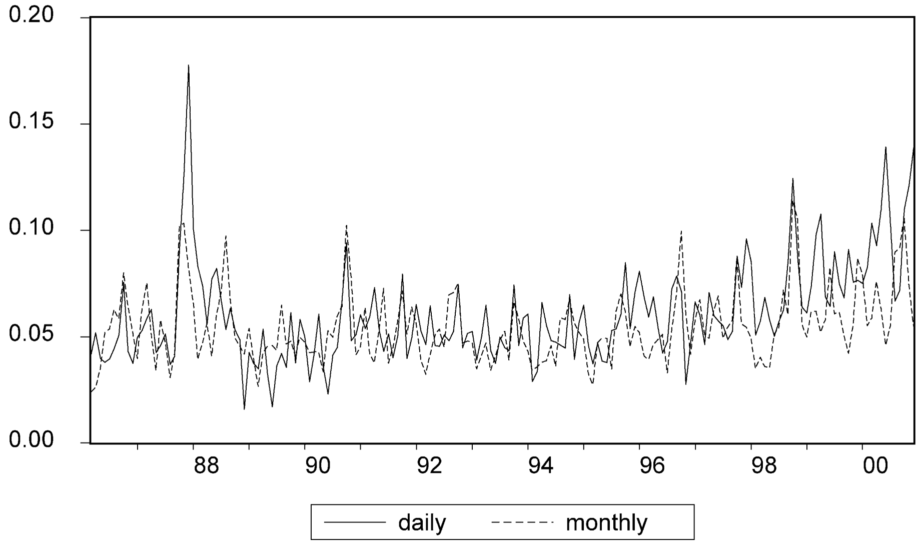

Fig. 2. Conditional volatilities of PSE returns.

computed using monthly and daily technology stock market data show that the two series do tend to move together but the conditional standard deviations computed using daily data display more persistence (Fig. 2).

Augmented Dickey and Fuller (1979) and Phillips and Perron (1988) unit root tests are reported in Table 3. All test regressions include intercepts. The Phillips and Perron's (1988) test results indicate that each variable is stationary in first differences at the 1% level of significance.

Table 3
Unit root tests

Variable	ADF	*l*	PP	*k*
Y	– 7.26***	4	– 12.88***	4
O	– 4.03***	4	– 6.37***	4
Q	– 6.57***	4	– 7.59***	4
D	– 2.47	4	– 5.12***	4
E	– 5.89***	4	– 19.38***	4
F	– 3.86***	4	– 9.67***	4
P	– 4.72***	4	– 12.65***	4
TP	– 2.23	4	– 11.52***	4

ADF denotes the augmented Dickey–Fuller unit root test and PP denotes the Phillips and Perron unit root test. Critical values are from Hamilton (1994). The parameter *l* is a truncated lag parameter used in the nonparametric correction for serial correlation and is set according to the sample size. The parameter *k* is set using Perron's (1997) *t*-sig criterion.

*** Denotes a statistic is significant at the 1% level of significance.

Table 4 reports regression results obtained from fitting a constant and a linear trend to each of the conditional volatilities. These results are useful for determining whether or not the conditional volatilities follow a linear trend. For each volatility series, the constant term is positive and statistically significant at conventional levels. The conditional volatilities of technology stock price returns, exchange rate returns, and the term premium each have positive and statistically significant trend coefficients. These results indicate that technology stock price return volatility, exchange rate volatility, and the term premium volatility each have a slight positive trend over the sample period. The conditional volatilities of the Federal Funds rate, and consumer prices each have negative and statistically significant trend coefficients. These results indicate that the conditional volatilities of the Federal Funds rate and consumer prices do have trends and that these trends are downward.

In order to take into account cross equation correlations, Eqs. (4)–(6) were estimated as a system of equations with four lags on the variables in Eq. (6). A dummy variable to account for the October 1987 crash was also included in Eq. (6). Table 5 reports the empirical results from four models.

The R^2 values range from .503 to .583 indicating relatively little difference in explanatory power between the four models. The standard error of the estimate (S.E.E.) is also fairly similar across the four models. In the two models using monthly stock return data, the standard error of the estimate is approximately 21% of the mean of the dependent variable. In the two models using daily stock return data, the standard error of the estimate is approximately 29% of the mean of the dependent variable. In each of the four models, the estimated coefficient on the dummy variable for the October 1987 stock market crash is positively signed and significant at the 0% level. As expected, the October 1987 stock market crash increased the volatility in the technology stock price index. The Durbin–Watson statistics indicates no evidence of first order serial correlation. The Ljung–Box Q statistics indicate evidence of higher order serial correlation in the residuals in the two models using daily stock market return data. This is probably due to the autocorrelations of the regression residuals at lags two and three being larger than they should for a random process. Lagrange multiplier (LM) tests (Greene, 1990) indicate evidence of ARCH effects in the two models

Table 4
Estimation results from fitting a linear trend to the conditional volatilities

Variable	Constant	Trend	R^2
Y	0.0038 (0.00)	− 7.86e − 7 (0.53)	.0023
O	0.0771 (0.00)	− 7.29e − 5 (0.14)	.0124
Q	0.0489 (0.00)	6.40e − 5 (0.01)	.0376
D	0.0443 (0.00)	1.87e − 4 (0.00)	.1589
E	0.0107 (0.00)	8.19e − 5 (0.08)	.0173
F	0.0279 (0.00)	− 5.02e − 5 (0.00)	.0625
P	0.0013 (0.00)	− 1.64e − 6 (0.01)	.0394
TP	0.1637 (0.00)	4.53e − 4 (0.03)	.0273

Regression results from fitting each conditional volatility to a constant and a linear time trend. P-values shown above coefficient estimates.

Table 5
Estimation results for the conditional volatility of technology stock price returns

	Monthly		Daily	
	Fed funds	Term premium	Fed funds	Term premium
R^2	.5776	.5830	.5030	.5360
Adjusted R^2	.5060	.5126	.4196	.4576
S.E.E.	0.0118	0.0117	0.0180	0.0174
Durbin Watson	2.08	2.05	2.00	2.00
Crash dummy	0.0417 (.00)	0.0217 (.00)	0.0860 (.00)	0.0840 (.00)
Constant	0.0166 (.26)	0.0130 (.36)	0.0105 (.42)	− 0.0030 (.81)
Exclusion tests				
Y	0.086	0.068	0.495	0.475
O	0.006	0.003	0.005	0.001
Q	0.000	0.000	–	–
D	–	–	0.000	0.000
E	0.000	0.000	0.122	0.132
F	0.049	–	0.312	–
P	0.006	0.001	0.077	0.056
TP	–	0.029	–	0.011
Q(12)	0.295	0.440	0.000	0.000
ARCH(12)	0.258	0.304	0.000	0.000

Probability values are shown beside crash dummy coefficient and constant estimates. Probability values are shown for exclusion tests. *Q*(12) is a Ljung–Box *Q* statistics for residual serial correlation at lag 12 (Greene, 1990). ARCH(12) is an Engle (1982) LM test statistics for residual ARCH effects at lag 12.

using daily stock market return data. Residual plots (not shown but available upon request), for the four models with associated upper and lower confidence bounds, from Eq. (6) indicate no evidence of structural stability problems. Consequently, the regression models using monthly stock price return data to estimate Eq. (6) appear to be better specified than the models estimated using daily stock return data. The adjusted R^2 statistics indicate that the best model using monthly data is the model that includes the term premium. Similarly, the best model using daily data is also the model that includes the term premium.

The exclusion tests report probability values from restricting the four lags of each variable equal to zero in Eq. (6). Oil prices, the consumer price index, and the term premium are the most important variables in explaining current stock return volatility. The results that lagged oil price volatility helps to determine current stock return volatility is particularly important because it establishes a link between the old economy (bricks and mortar) and the new economy (information technology). As expected, lagged stock return volatility helps predict current stock return volatility.

Lagged industrial production helps to predict stock return volatility in the models using monthly stock return data but this result does not hold for the models where stock return volatility is calculated from daily stock return data. Similarly, lagged exchange rate volatility helps to predict current stock return volatility in the models estimated using monthly stock return data. Lagged values of the Federal Funds rate volatility are important determinants of stock return volatility where stock return volatility is calculated from monthly stock return data. Some of these results can be attributed to the fact that conditional stock market volatility estimated from monthly data (rather than daily data) tends to be more highly correlated with the conditional volatilities of the macroeconomic factors. This is somewhat expected since conditional stock market volatility estimated from daily data tends to be noisier than conditional stock market volatility estimated from monthly data (Table 2 and Fig. 2).

The estimated coefficient on the constant term is statistically insignificant in each of the four regression models reported in Table 5. This suggests that volatility in the US technology stock price returns probably does not occur from other factors not explicitly included in the model.

The results in this paper are consistent with other papers that show macroeconomic volatility can help to predict conditional stock market volatility (Kearney, 2000; Kearney & Daly, 1998; Koutoulas & Kryzanowski, 1996; Schwert, 1989). Collectively, these papers provide results on the interaction between macroeconomic variables and conditional stock market volatility for Australia, Canada, Britain, France, Germany, Japan, and the United States. All of these papers find inflation volatility has a significant impact on stock market volatility. The volatility of industrial production, interest rates, and exchange rates impact stock market conditional volatility in different ways across the countries studied by these authors. In general, interest rates and industrial production impact an important influence on stock market volatility but exchange rates have a lesser impact. None of these papers, however, include an oil price factor nor do they explicitly look at technology stock returns.

5. Concluding remarks

Stock prices reflect the value of anticipated future profits of companies. Since business cycle conditions impact the future profitability of firms, expectations about the business cycle will affect the current value of firms. This paper investigates the macroeconomic determinants of United States technology stock price conditional volatility. Technology stock prices are measured using the Pacific Stock Exchange (PSE) Technology 100 Index. The empirical results suggest that the conditional volatilities of oil prices, the term premium, and the consumer price index each have significant impacts on the conditional volatility of technology stock prices. Conditional volatilities calculated using daily stock return data display more persistence than conditional volatilities calculated using monthly data. These results should be of use to investors, managers, hedgers, and policymakers.

One of the novel features of this paper is to incorporate a link between technology stock price movements and oil price movements. Evidence is presented to show that oil price volatility is important in explaining technology stock return volatility. Oil price volatility is a major source of business cycle uncertainty, and stock prices (especially technology stock prices) do not perform well in periods of uncertainty. These results help to further our understanding of how oil price movements impact technology stock returns. This suggests that managers of new technology companies must be aware of oil price risk and take this risk into consideration when performing their financial engineering calculations.

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