Synchronization Risk and the NASDAQ Technology Bubble

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Abstract

We study the role of the synchronization risk in allowing stock prices to rise during the recent technology bubble. In a recent theory by Abreu and Brunnermeier (*Journal of Financial Economics* 2002; *Econometrica* 2003) synchronization risk leads to market timing by arbitrageurs and delays arbitrage. Therefore, in the presence of synchronization risk and the need for coordination in attacking a bubble, asset prices may inflate to an extreme extent. We obtain several results. We show how a measure of preferences toward risk of investors in technology stocks can be used to study the presence of synchronization risk. We show that changes in measured investor risk preferences are closely related to changes in the demand for stocks and affect trading activity. We also show that changes in investor preferences and attitudes were different across different technology stocks. Structural changes in risk preferences took place at different points in time for different stocks in the sample. We infer from this evidence that coordination risk may indeed have been present, making the job of arbitrageurs difficult or impossible. This supports synchronization risk theory. We also observe a dramatic change in aggregate risk preferences across NASDAQ technology stocks during the bubble collapse.

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Abstract

We study the role of the synchronization risk in allowing stock prices to rise during the recent technology bubble. In a recent theory by Abreu and Brunnermeier (*Journal of Financial Economics* 2002; *Econometrica* 2003) synchronization risk leads to market timing by arbitrageurs and delays arbitrage. Therefore, in the presence of synchronization risk and the need for coordination in attacking a bubble, asset prices may inflate to an extreme extent. We obtain several results. We show how a measure of preferences toward risk of investors in technology stocks can be used to study the presence of synchronization risk. We show that changes in measured investor risk preferences are closely related to changes in the demand for stocks and affect trading activity. We also show that changes in investor preferences and attitudes were different across different technology stocks. Structural changes in risk preferences took place at different points in time for different stocks in the sample. We infer from this evidence that coordination risk may indeed have been present, making the job of arbitrageurs difficult or impossible. This supports synchronization risk theory. We also observe a dramatic change in aggregate risk preferences across NASDAQ technology stocks during the bubble collapse.

Introduction

Periods of fast rise in prices, followed by rapid declines—termed "bubbles" and "crashes"—stimulate economic debate on the reasons behind wide swings in asset values. Recent theoretical and empirical work suggests that bubbles can inflate even if there are large numbers of highly capitalized, rational arbitrageurs. Abreu and Brunnermeier (2002, 2003) argue that bubbles can persist in the presence of rational arbitrageurs who experience a synchronization problem or inability to coordinate their trading strategies. This occurs when arbitrageurs lack the power to offset irrational exuberance unless they can coordinate their attacks on the bubble.

Synchronization risk arises from arbitrageur's uncertainty about when other arbitrageurs will start exploiting a common arbitrage opportunity (Abreu and Brunnermeier, 2002 and 2003). The arbitrage opportunity appears when prices move away from fundamental values. In a market populated by rational investors this arbitrage opportunity will be immediately explored. However, the recent literature provides evidence that small noise traders can drive prices significantly further from fundamentals (Barber, Odean and Zhu 2006; Hvidkjaer 2006). The effect of noise traders is driven by market preferences or sentiment (Shleifer and Summers, 1990). If the small investors are optimistic about the stock they will exert buying pressure and move the prices further up from fundamental value. In this situation arbitrage is no longer risk-less. Arbitragers acquire another factor to account for – investor preferences towards a particular stock or a particular type of stocks. If, for example, arbitrager observes that the stock is overpriced and wants to enter a short position he might face the risk that the stock will be even more overpriced in the future. If arbitrager cannot predict investors' preferences towards the stock, or for how long the market is going to be optimistic about the stock, the arbitrage becomes impossible. Synchronization risk, therefore, leads to market timing by arbitrageurs and delays arbitrage.

Understanding the nature of synchronization risk is important for the interpretation of the recent rise and fall in technology stock prices. Empirical evidence on the nature of synchronization risk, however, is difficult to obtain. This is partly because the behavior of investors and their impact on prices is hard to observe simultaneously.[1] Temin and Voth (2004) use trading behavior of an informed investor during the South Sea bubble in 1720's and find support for the synchronization

[1] Brav and Heaton (2002) explore other fundamental reasons for the difficulty of separating competing theories of financial anomalies. They find that "behavioral" theories built on investor irrationality, and "traditional structural uncertainty" theories built on incomplete information about the structure of the economy, have many mathematical and predictive similarities. The theories are difficult to distinguish, in spite of the fact that they relax opposite assumptions of the rational expectations paradigm.

risk hypothesis. They show that the need for coordination in attacking the South Sea bubble was the key to allowing it to inflate.

In this paper we focus on the behavior of the technology stocks during the period from 1996 to 2003.[2] We develop a measure that reflects important characteristic of investors in technology stocks—an estimate of investor risk aversion. Bakshi and Wu (2006) show that information in options on the NASDAQ 100 Index can be used to measure the degree of investor irrationality during NASDAQ bubble. Closely related are the methods developed in Bliss and Panigirtzoglou, (2004) and Jackwerth (2000) that show how equity options on an asset and the returns on this asset can be used jointly to extract preferences toward risk of investors in the asset.[3] We measure preferences toward risk of investors in technology stocks by estimating the value of risk aversion for the stocks in XCI Index for the period from 1996 through 2003. This is a major index of technology stocks. Our estimates capture variation in attitudes of investors in individual stocks.

As suggested by Shleifer and Summers (1990), change in investors' beliefs, investor sentiment, or attitude toward risk affect the demand for risky assets. Therefore, changes in demand associated with change in risk preferences should be reflected in trading activity. We explicitly test this hypothesis. We find that changes in investor risk preferences are an important determinant of the demand for company shares and of the stock trading activity. Changes in risk preferences are closely related to trading activity. In particular, changes in company specific risk preferences are positively and significantly related to turnover. Our results are established at the level of individual technology stocks. This result survives when, in addition to change in risk preferences at the company level, we control for changes in the aggregate, market-level, preferences toward risk.

Our first conclusion is that changes in risk preferences of investors in a stock are closely related to the demand for shares. When this is the case, stocks that experience similar changes in investor risk preferences may be expected to experience similar shifts in demand and therefore exhibit similarities in their patterns of stock returns and other economic variables that capture stock trading activity. We test this and we find that stocks with similar behavior of investor risk aversion also display similarity in other economic characteristics:

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[2] There is another very important difference. Note that the in case of the South Sea bubble *whole bubble* was concentrated in the one asset (The South Sea Company's stock), whereas the NASDAQ technology bubble trading behavior was spread over many assets. This adds an new and important dimension to the notion of synchronization risk. Our study explores this dimension.

[3] This method has been used recently by Blackburn, Goetzmann and Ukhov (2006) to study preferences of value and growth investors.

- Stocks, for which risk aversion changes in a similar way also tend to have similar returns.
- Stocks that have similar changes in investor preferences are also categorized by similar trading behavior (share turnover).
- Stocks with similar changes in risk aversion have similar changes in liquidity.

The results suggest that preferences toward risk on individual stock level are a significant determinant of demand for the stock and of the stock price behavior. This, conclusion is consistent with the literature which argues that individual investors can drive stock prices (Barber, Odean and Zhu (2006), Hvidkjaer (2006)).

Next, we turn to the recent rise and fall of prices of technology stocks. If the technology price bubble was driven by similar changes in investor attitudes (or sentiment) across the technology stocks than we would expect similarities in the behavior of the estimated risk preferences for investors in these stocks. Specifically, the major event of this period--collapse of prices in March 2000--should be observed in all the measures for all stocks approximately at the same point in time. To test for coordination risk we run a test of structural break for each time series of risk aversion. The structural break in risk aversion can be associated with a significant change in market sentiment about the stock. For example the change from optimism to pessimism would result in change in trading behavior, a change from buying to selling. This would lead to significant price decline and eventually be reflected as a structural break in time series of estimated risk preferences. This change in trading strategies was observed during the bubble: hedge funds were riding the bubble till March 2000 and they pooled out before the bubble burst (Brunnermeier and Nagel, 2004). Therefore, the change in market opinion about the stock or the signal of whether to continue or withdraw from investing into the stock should be reflected as a structural break (breaks) in estimated risk aversion.

We first test for one structural break at unknown date using methodology of Bai, Lumsdaine, and Stock (1998). The advantage of this test is that it does not take an a priori stand on the date of a structural change. We, therefore, adopt a flexible approach and let the data determine the date of a structural change for each stock in the sample. We find that different stocks have structural breaks at different times. It means that investors' behavior in each individual stock was independent from other stocks in the same industry (all stocks in the sample are NASDAQ technology stocks and are members of a major technology index). It further suggests that similar stocks had different levels of either optimism or pessimism during the bubble. The arbitrage becomes very difficult in the situation like this. Arbitragers could not predict on average for how long the market optimism about the bubble is going to persist. Shleifer and Summers (1990) argue that this makes arbitrage a risky strategy, and Abreu and Brunnermeier (2002, 2003) suggest that it leads to a synchronization risk.

We further allow for three structural breaks at unknown dates. Three structural breaks in estimated risk preferences are consistent with the interpretation where first, market shifts from a "normal" state into a "bubble period," second, the bubble bursts and a decline begins (a "crash" takes place), and finally the prices enter the stable period again. Our stand here is that if coordination among arbitragers was possible than the second period for each individual stock should come on March or April of 2000. March of 2000 is the last month when prices peaked up and we would expect the structural shift in risk preferences either at this time or in April of 2000 if arbitragers can forecast market optimism and pool out before the prices collapsed.[4] Only one stock out of twenty one we analyze and the *XCI* index has structural breaks associated with our null hypothesis. This provides further support of coordination failure and synchronization risk advocated by Abreu and Brunnermeier (2002, 2003).

Brunnermeier and Nagel (2004), however, report that hedge funds pooled out from the bubble before prices collapsed. It suggests that some coordination was, indeed, possible before the bubble burst. Since individual stocks or the XCI index itself provide no evidence of a coordinating signal, we analyze aggregate risk preferences. The aggregate risk preference is obtained as equally-weighted average preferences in individual stocks. This measure can suggest the general market opinion about the technology stocks. This information is not available at individual stock level, when stocks are considered separately from one another. Also, on the individual stock level we do not know which stock (or a group of stocks) is more influential in driving the technology prices and sustaining the same level of optimism. Thus, the aggregate data can be informative.

As before, we run a test of structural break (breaks) for aggregate time series of risk preferences. The result is remarkable. One-structural break test at an unknown date indicates a break on April 2000. It means that the general market attitude towards technology stocks changes at this time. This is exactly what we observe in the price data. The last month of market optimism is March of 2000, when the prices picked up the last time. The three-structural break test at unknown dates indicates that, on average, market entered the bubble in August 1998, the bubble bursts in April 2000, and stabilization period began in July 2001. This pattern very closely corresponds to the

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[4] Brunnermeier and Nagel (2004) show that hedge-funds pooled out from the market before the prices drop indicating that to some extent they were able to predict the market optimism about technology stocks.

observed price data. Both tests point towards the fact that the average market opinion or market optimism changed in April 2000. Combined with the evidence that hedge-funds quit the bubble earlier (Brunnermeier and Nagel, 2004), this result suggests that arbitragers were able to predict the *aggregate* structural change in market optimism and pooled out before it changed. In aggregate, markets had a predictable change in preference which, as we find, coincides with the time of bubble burst.

Overall, we infer from this evidence that coordination risk may indeed have been present, making the job of arbitrageurs difficult or impossible. This supports synchronization risk theory. We also observe a dramatic change in aggregate risk preferences across NASDAQ technology stocks during the bubble collapse.

The rest of the paper is organized as follows. Section II describes methodology and data. Section III characterizes the relationship between risk aversion, trading activity and other market variables. Sections IV and V describe the structural break tests and the results. Section VI concludes.

II. Methodology and Data

To assess presence of synchronization risk we build a measure of stock-specific characteristics of the representative investor in this stock—investor risk preferences. In this section we discuss how the marginal investor's risk aversion for a particular stock can be estimated from the data on stock returns and options written on the stock.

Recovering Risk Aversion

An estimate of risk aversion can be obtained from asset prices. There is a relationship between the risk-neutral probability distribution of returns on a stock i, $P(S_{i,T})$, subjective (true) probability distribution $Q(S_{i,T})$, and investor risk aversion. The relation is,[5]

$$Risk\ Aversion = -\frac{U''(S_{i,T})}{U'(S_{i,T})} = \frac{Q'(S_{i,T})}{Q(S_{i,T})} - \frac{P'(S_{i,T})}{P(S_{i,T})},$$

where $U(\bullet)$ is the investor's time–separable utility of wealth. Therefore, knowing the subjective distribution and the risk neutral distribution is sufficient to find risk aversion.

To determine the two distributions, we combine the methodologies of Bliss and Panigirtzoglou (2002, 2004) and Jackwerth (2000). Using option prices for a particular underlying

[5] See, for example, discussion in Jackwerth (2000).

stock, we estimate the risk-neutral probability density function (PDF) according to Bliss and Panigirtzoglou (2002, 2004). We then use five years of past monthly stock returns to determine a risk-adjusted (or, subjective) PDF using a nonparametric kernel density estimator similar to the one used in Jackwerth (2000). Risk aversion is the adjustment required to transform the risk-neutral PDF into the risk-adjusted PDF. Using this method, the risk aversion coefficient can be estimated for every trading day for any asset for which option prices are available.

Risk-neutral probability distribution

To find risk-neutral distribution we use the following approach. It is known from option pricing theory that the risk-neutral PDF is embedded in option prices. Let T be the expiration date of an option. The PDF, $f(S_{i,T})$, for the underlying asset i at time T has been shown to be related to the price of the European call option, $C(S_{i,t}, K, t)$, by Breeden and Litzenberger (1978). Here, K is the option strike price and $S_{i,t}$ is the price of underlying i at time t where $t<T$. This relationship is

$$f(S_{i,T}) = e^{r(T-t)} \left. \frac{\partial^2 C(S_{i,T}, K, t)}{\partial K^2} \right|_{K=S_{i,T}} .$$

For each underlying asset, i, and for each expiration date, however, the function $C(S_{i,t}, K, t)$ is unknown and only a limited set of call options with different strike prices exist. Therefore, in order to calculate the second derivative we estimate a smoothing function using option prices with different strike prices but with the same expiration dates.

Instead of estimating such a smoothing function in option price/strike price space, we follow Bliss and Panigirtzoglou (2002, 2004) by first mapping each option price/strike price pair to the corresponding implied volatility/delta. We fit a curve connecting the implied volatility/delta pairs using a weighted cubic spline where the option's vega is used as the weight. We take 300 points along the curve and transform them back to the option price/strike price space. We thus obtain a smoothed price function, which we numerically differentiate to produce the estimated PDF. Bliss and Panigirtzoglou (2002) find that this method of estimating the implied volatility smile and the implied PDF is "remarkably free of computational problems."

A weighted natural spline is used to fit a smoothing function to the transformed raw data. The natural spline minimizes the following function:

$$\min_{\theta} \sum_{j=1}^{N} w_j \left(IV_j - IV(\Delta_j, \theta) \right)^2 + \lambda \int_{-\infty}^{\infty} g''(x;\theta)^2 dx,$$

where we omit the company-identifying index, i, for brevity; IV_j is the implied volatility of the j^{th} option on stock i in the cross section; $IV(\Delta_j, \theta)$ is the fitted implied volatility which is a function of the j^{th} option delta, Δ_j, and the parameters, θ, that define the smoothing spline, $g(x;\theta)$; and w_j is the weight applied to the j^{th} option's squared fitted implied volatility error. Following Bliss and Panigirtzoglou (2004), we use the option vegas, $v \equiv \partial C / \partial \sigma$, to weight the observations. The parameter λ is a *smoothing parameter* that controls the tradeoff between goodness-of-fit of the fitted spline and its smoothness measured by the integrated squared second derivative of the implied volatility function.

From the estimated cubic spline curve, we take 300 equally spaced deltas and their corresponding implied volatilities and transform them back to option price/strike price space using the Black-Scholes option pricing formula that accounts for dividends paid on the stock. However, although the deltas are equally spaced, the strike prices that are obtained after the conversion are not. We use a cubic spline for a second time to fit a curve connecting the 300 unequally spaced call price/strike price pairs. This allows us to choose 300 equally spaced strike prices with their corresponding call prices. Finally, we use finite differences to estimate the second derivative of the call price with respect to the strike price. This yields the risk-neutral PDF. This procedure does not depend on a specific option pricing model (Bliss and Panigirtzoglou 2004).

Subjective probability distributions

We use a kernel density estimator to estimate the subjective (risk-adjusted) probability density functions. Similar procedure is used in Jackwerth (2000).[6] We use the most recent 60 months of stock return data to estimate the risk-adjusted distribution. To find estimates for January 1996, we use monthly return data from January 1991 to December 1995. All information used in the calculation is part of the investors' information set. Other windows were considered but results were highly correlated. For example, we tried a window of past returns with a lag of one year or six month, and we tried using 72 months of returns instead of 60. Varying our initial choices does not change the results.

[6] This is different from Bliss and Panigirtzoglou (2004) who first hypothesize a utility function (power and exponential utility) for the investor and then use this function to convert the risk-neutral PDF to the subjective PDF. We do not follow this approach because we do not hypothesize a utility function.

We calculate monthly non-overlapping returns from our 5-year sample and compute the kernel density with a Gaussian kernel. The bandwidth

$$h = \hat{\sigma}\left[4/(3n)\right]^{1/5},$$

where *h* is the kernel bandwidth, $\hat{\sigma}$ is the standard deviation of the sample returns, and *n* is the number of observations, is selected by recommendation of Jones, Marron and Sheather (1996).

Data

The data for this study consists of daily closing prices of call options written on the stocks that are included in the XCI Index. This is the index of 30 major technology stocks. The study covers the eight-year period from January 2, 1996 through December 31, 2003, since this is the period when prices of options are available to us. In addition to the daily closing option prices, we use monthly stock returns and daily stock closing prices from CRSP. Table 1 lists the firms in the sample. We include all stocks for which data on exchange-traded options is available. This gives a sample of 21 technology firms. *Microsoft* is the largest firm in our sample, with market capitalization of $295 Billion at the end of the period. The smallest firm in the sample is *Advanced Micro Devices* (AMD) with market capitalization of $5 Billion. The sample includes notable and prominent firms that were at the center of attention during the technology bubble—*Apple*, *Cisco Systems*, *Dell*, *IBM*, *Intel*, *Motorola*, *Sun*, and others.

To estimate risk aversion we need prices of options written on the stocks in the sample. All previous researchers have studied risk aversion using the options on the S&P 500 Index. For index options, a relatively large cross section of strikes exists, all with the same expiration date. Because of this large selection of options, Bliss and Panigirtzoglou (2004) require at least 5 such options in order to do their estimation. We are considering individual stocks. Companies tend to have a smaller cross section of options with different strike prices and their options are comparatively less liquid than index options. Because of this, we require a firm to have options with at least three different strike prices. Similar to Jackwerth (2000), we estimate risk aversion with a constraint on the money-ness. Jackwerth only considers options such that the ratio of the strike price to the stock price is between 0.84 and 1.12. This procedure eliminates far-away-from-the-money observations. This may cause a problem of missing observations, but only when there are large movements in the stock price. Since options with only a few different strikes are traded for each firm (usually five or six strikes), a large enough movement in the stock price causes the money-ness to fall in a window that does not have three option contracts for us to use. We do not estimate risk aversion for such days.

Not surprising, tossing out options that are way in the money or way out of the money affects risk aversion estimates in the tales of the distribution. Our robustness checks indicate that the estimates in the middle of the distribution are generally unaffected by the money-ness constraints. We find our results to be robust to the selection of options.

For our estimation, we use options that expire between one and four months from day *t*. Options on stocks generally exist with expiration dates at three-month intervals. For example, options on Microsoft expire in January, April, July, and October. Therefore, for all days in January, we use options expiring in April. For all days in March, we use those options expiring in July. We use this approach to maintain a relatively constant horizon for our analysis, and at the same time to have a sufficient number of option contracts to obtain reliable risk aversion estimates.

For each of the 21 technology stocks in the sample, for each trading day between January 4, 1996 and December 31, 2003 we calculate estimates of Arrow-Pratt risk aversion coefficient, a computationally intensive process. We use daily estimates to compute a monthly estimate of risk aversion for the stock. Thus, for each stock we have a time series of risk aversion estimates at monthly frequency, from January 1996 through December 2003.

III. Trading Activity and Risk Aversion

As a first step towards understanding the connection between changes in risk preferences and asset prices we study whether changes in risk aversion are related to trading activity. Changes in demand for securities can reflect changes in risk aversion (Shleifer and Summers, 1990; Barberis and Shleifer 2003). If this is the case, then trading activity will be affected by changes in risk preferences. When preferences toward risk change, investors adjust their portfolios accordingly. We conduct several tests to determine whether there is a connection between investor risk aversion and trading activity.

In the first set of tests we perform individual regressions for all companies in the sample. For each firm we estimate a linear model,

$$TRN_t = \alpha + \beta_1 \Delta RA_t + \beta_2 TRN_{t-1} + \beta_3 R_{t-1} + \varepsilon_t .$$

We use turnover, TRN_t, as a measure of trading activity. Turnover is defined as trading volume divided by the number of shares outstanding, for a given firm in a month t. Change of the risk aversion of investors in the stock over the month, $\Delta RA_t = RA_t - RA_{t-1}$, is the variable whose affect on turnover we would like to assess. Past turnover can affect current turnover (Lee and Swaminathan 2000) and we include lag of turnover, TRN_{t-1}, as well as lag of return on the stock, R_{t-1}, in the regression. Table II reports results of these regressions. Change in risk aversion is a significant determinant of the turnover in 12 out of 21 firms in the sample.

The demand for company shares may be driven by changes in risk preferences of investors in this particular stock as well as by market-wide changes in risk aversion. These are two separate effects. Individual stocks are a part of an industry group and are also a part of the overall U.S. stock market. The demand for stocks there depends on changes in industry-wide and market-wide preferences. In view of this complication we test whether changes in risk aversion at the company level remain significant controlling for market-wide changes in preferences. To test this, we include change of the risk aversion at the market level, $\Delta RA_{Mt} = RA_t - RA_{t-1}$, and estimate the model

$$TRN_t = \alpha + \beta_1 \Delta RA_t + \beta_2 TRN_{t-1} + \beta_3 R_{t-1} + \beta_4 \Delta RA_{Mt} + \varepsilon_t .$$

We use risk aversion for the *XCI Index* for industry-level preferences and risk aversion for the *S&P 500 Index* as the market-wide measure. The results of individual company regressions are not changed. The coefficient of the change in company-specific risk aversion remains significant (Table III).

GLS regressions

In this section we report the results of pooled cross-section time-series regressions of the turnover on risk aversion and the control variables. By estimating simultaneously the coefficient of the risk aversion and the coefficients for control variables, we avoid the potential errors-in-variables problems associated with the traditional Fama and MacBeth (1973) procedure.[7]

We conduct the analysis using the data for 21 technology firms that are members of the *XCI Index* for which estimates of risk aversion are available. The estimation proceeds as follows. Define TRN as the $(21T \times 1)$ vector of individual company turnover (defined as trading volume over a month divided by the number of shares outstanding), where T is the total number of time-series observations. The vector is ordered by month so that the first 21 observations correspond to the turnover in month 1. Define X as the partitioned matrix

[7] Brennan and Subrahmanyam (1996) use this approach in their study of returns and liquidity.

$$X = \begin{bmatrix} W & Z \end{bmatrix},$$

where Z is a $(21T \times 42)$ matrix of control variables. There are two control variables: lagged trading volume and lagged return on the stock. The first 21 columns of Z consist of T stacked (21×21) diagonal matrices with elements $TRN_{i,t-1}$, the lagged turnover for company i in month t; the second 21 columns of Z consist similarly of the lagged return on the stock, $R_{i,t-1}$. The matrix W is a $(21T \times 2)$ matrix, whose first column is a vector of ones and second column is the vector of changes in risk aversion, $\Delta RA_{i,t}$, whose influence on trading activity we wish to assess.

We first perform the OLS pooled cross-section time-series regression

$$TRN = X\beta + \varepsilon, \tag{1}$$

where β is a 44 vector of coefficients, the first element of which is the constant term of the regression, the next element of which is the coefficient of the change in risk aversion variable, and the last 42 elements of which are the coefficients of the two control variables for the stocks ordered by security. ε is a $21T \times 1$ vector of errors. In our application the sample consists of monthly turnover and risk aversion changes from February 1996 to December 2003 so that $T = 95$. To obtain the GLS estimator of β, we estimate Ω, the variance-covariance matrix of errors in (1) assuming that the stock turnover errors are serially independent, but allowing for cross-sectional dependence. Then Ω is a $(21T \times 21T)$ block-diagonal matrix, whose typical element is the 21×21 covariance matrix of errors: it is estimated using the residuals from (1). The GLS estimate of β is given by

$$\hat{\beta} = \left(X'\hat{\Omega}^{-1}X\right)^{-1} X'\hat{\Omega}^{-1}Y,$$

where $\hat{\Omega}$ is the estimate of Ω from the first-stage regressions.

The results of the GLS regression (Table IV) confirm the results from individual company regressions. The constant term is $\alpha = 0.802$ with *t*-statistics of 9.73. The regression coefficient for the change in risk aversion is $\beta_1 = 0.031$ with *t*-statistics of 2.64. For brevity, we do not report the remaining 42 company-specific coefficients for the control variables.

We repeat GLS estimation while controlling for changes in the risk preferences at the market level. To do this we modify the Z matrix to become a $(21T \times 63)$ matrix of control variables. The first 42 columns of Z remain unchanged. We add 21 columns to the right. The new columns consist of T stacked (21×21) diagonal matrices with identical elements ΔRA_{Mt}, the change in the risk aversion at the market level in month $t, t = 1,...,T$. We use two different indices as the market. First, we use risk aversion computed from options on the *XCI Index* to capture changes in risk preferences of investors in the technology sector. Second, we use risk aversion computed from options on *S&P 500 Index* to reflect changes in market-wide attitude toward risk.

Controlling for market-wide changes in risk preferences does not alter our findings. The results are given in Table IV. The coefficient on the change in company-specific risk aversion remains unchanged and retains significance.

We conclude that changes in risk aversion significantly affect turnover at the level of individual firms. This result establishes a connection between risk aversion, trading activity, and demand for securities. This is an important finding. It is a test of a widely discussed (refer to Shleifer and Summers 1990) but previously untested hypotheses that changes in preferences toward risk may affect the demand. We also establish that changes in company-specific risk preferences remain to be a significant determinant of the turnover when we control for market-wide changes in risk aversion. This finding highlights the importance of changes in risk attitude at *a company level* as a determinant of demand.

Additional Evidence

Changes in risk preferences of investors in a stock are closely related to the demand for shares. When this is the case, stocks that experience similar changes in investor risk preferences may be expected to experience similar shifts in demand and therefore exhibit similarities in their patterns of stock returns and other economic variables that capture stock trading activity. We perform several tests to investigate whether stocks with similarities in the behavior of risk aversion also display similarities along other dimensions. To measure the degree of similarity in risk aversion for two stocks i and j we compute correlation between time series changes in risk aversion for two securities,

$$CORR\Delta RA_{i,j} = Corr\lfloor \Delta RA_i, \Delta RA_j \rfloor.$$

This variable measure whether two stocks experienced similar changes in investor risk preferences.

In our first test, we compute correlation between returns on two stocks as a measure of similarity in returns, $CORRRET_{i,j} = Corr\lfloor r_i, r_j \rfloor$. We then regress pair-wise correlation coefficients of returns on pair-wise correlation coefficients of time series of changes in risk aversion,

$$CORRRET_{i,j} = \underset{(0.000)}{0.410} + \underset{(0.08)}{0.128} \cdot CORR\Delta RA_{i,j},$$

where p-values are reported in parentheses. The regression shows that stocks for which investor risk aversion changes in a similar way also tend to have similar returns.

Next, we study the relationship between similarity in trading activity and similarity in investor preferences. We regress pair-wise correlation of turnover on pair-wise correlation coefficients of time series of changes in risk aversion,

$$CORRTURNOVER_{i,j} = \underset{(0.000)}{0.113} + \underset{(0.04)}{0.269} \cdot CORR\Delta RA_{i,j},$$

where p-values are reported in parentheses. Companies that have similar changes in investor preferences are also categorized by similar trading behavior.

Since trading behavior may be connected to stock liquidity, we also investigate the relationship between changes in stock liquidity, measured by effective spread, and similarity in risk preferences. The effective spreads are obtained from TAQ data. Specifically, the effective spread of a particular stock on the k^{th} trade is defined as

$$EFSPREAD_k = 2 \cdot \left|\ln(P_k) - \ln(M_k)\right|$$

where P_k is the price of the k^{th} trade and M_k is the midpoint of the consolidated BBO prevailing at the *time of the* k^{th} *trade*. For a particular stock aggregated over a time interval *i* (either a month or a year), the *EFSPREAD* is the dollar-volume-weighted average of $EFSPRAED_k$ computed over all trades in each month. We regress pair-wise correlation in changes in effective spread on pair-wise correlation coefficients of time series of changes in risk aversion,

$$CORR\Delta EFSPREAD_{i,j} = \underset{(0.000)}{0.226} + \underset{(0.00)}{0.314} \cdot CORR\Delta RA_{i,j},$$

where p-values are reported in parentheses. There is a strong relationship. Companies with similar changes in risk aversion also have similar changes in liquidity.

IV. Testing for a Structural Break

March 2000 is an important month in the recent capital markets history. It is the month when the recent technology burst. All market indices dropped significantly and all aggregate market trading data experienced a structural shift at this date. Of course, the importance of this date and the prevailing interpretation of it as the date when the bubble burst surfaced *after* the events.

We use estimates of risk aversion for investors in different technology stocks to assess these events. In the presence of synchronization (or coordination), the structural change in measured investor risk preferences would occur at the same (or very similar) point in time for all technology stocks. If, however, changes in risk preferences for investors in different stocks occur at different points in time, this evidence would suggest the presence of synchronization risk, or co-ordination risk. In the latter case, synchronization risk comes from inability to predict shifts in investor preferences toward different stocks and the resulting shifts in demand. For example, arbitrageurs can observe that on average noise traders are overly optimistic today and hence on average may be expected to be less optimistic in the future, but the arbitrageurs cannot be certain when this shift in preferences will happen. The coordination becomes even more complicated if arbitragers observe different level of optimism or pessimism across different technology stocks. If the significant change across risk preferences occurs during different times for different stocks than this will provide evidence that it was incredibly difficult to predict for how long the market optimism about technology stocks will persist.

We do not take an *a priori* stand on the date of a structural change. We adopt a flexible approach and let the data determine the date of a structural change for each stock in the sample. We then compare the dates of structural change for different technology stocks. We describe the statistical procedure and empirical results in this section.

Methodology: Wald Test for a Break at an Unknown Date

A test for a structural break at an unknown date has been developed in Bai, Lumsdaine, and Stock (1998). The methodology imposes minimal requirements on the data generation process and allows statistical inference about structural breaks. Non-parametric technique developed in Bai, Lumsdaine, and Stock (1998) searches for a single break in univariate or multivariate time series models. To test for a structural regime shift we specify the relation

$$RA_{it} = \beta_1 + \beta_2 \cdot RA_{it-1} + \beta_3 \cdot t + d_t(k) \cdot [\gamma_1 + \gamma_2 \cdot RA_{it-1} + \gamma_3 \cdot t] + \varepsilon_t .$$

In the above expression, RA_{it} is an estimate of risk aversion for a security i at time t, k is a potential break date, and $d_t(k) = 1$ if $t \geq k$ and zero otherwise. Define vectors $\beta = (\beta_1, \beta_2, \beta_3)'$ and $\gamma = (\gamma_1 . \gamma_2, \gamma_3)'$. This is a model of full structural change.

The tests for a break in the coefficients are based on the sequence of *F*-statistics testing $\gamma = 0$, for $k = k_* + 1, \ldots, T - k_*$, where k_* is some trimming value. Trimming is necessary for the model to be of full rank before and after any potential break date k. The null hypothesis is that no break exists $(\gamma = 0)$. For each k, the estimator $\hat{\beta}(k) = \left(\hat{\beta}', \hat{\gamma}'\right)'$ of the regression parameter is obtained by OLS and the *F*-statistic testing $\gamma = 0$ are computed.

$$\hat{F}(k) = T \cdot \hat{\gamma}' \cdot \left[R \cdot \left(T^{-1} \cdot X'X \cdot \left(\hat{\sigma}^2\right)^{-1} \right)^{-1} \cdot R' \right]^{-1} \cdot \hat{\gamma}.$$

The matrix X contains independent variables, so that the row t is $\left(1, RA_{t-1}, t, d_t(k) \cdot (1, RA_{t-1}, t)\right)$, $\hat{\sigma}^2$ is the estimator of σ^2 based on OLS residuals under the alternative hypothesis given k, and the matrix $R = (0, I)$ so that $R\beta = \gamma$, where I is a 3×3 identity matrix. The estimated break date is the one that gives the highest *F*-statistics, $\hat{k} = \arg\max \hat{F}(k)$. The break date is statistically significant if $\hat{F}(\hat{k})$ is greater than a critical value at the chosen significance level. In our study we use critical values for the test developed in Bekaert, Harvey, and Lumsdaine (2002).

Empirical Evidence

Table V presents the results of the test of a structural break at an unknown date for each individual stock risk aversion from the XCI index and for the index itself. If we assume that the estimates of time varying investor risk aversion should have one structural break associated with bubble collapse, the table clearly demonstrates how coordination failure in arbitrageurs' trading strategies can occur. Risk aversion estimates for different stocks all have different structural break dates. For example, Microsoft has structural break in January, 1999, when some hedge-funds withdraw from the market (Brunnermeier and Nagel, 2004) in expectation of prices to decline. Dell experiences structural break in January, 2001, almost a year after the bubble collapsed. The risk aversion of the XCI index itself was giving a false signal suggesting a bubble burst in June of 1999. Indeed, as reported by Brunnermeier and Nagel (2004), several hedge-funds pull out from the market in the second half of 1999, but there were also many hedge-funds which increased their holdings of technology stocks during this time. Abreu and Brunnermeier (2002), Abreu and Brunnermeier (2003) and Brunnermeier and Nagel (2004) argue that synchronization risk derives from arbitrageurs' uncertainty about when other arbitrageurs will start exploiting a common arbitrage opportunity. This uncertainty is represented by the dispersion of opinion characterized by structural changes in risk preferences in Tables V at different times across different stocks. Therefore, arbitrage was highly risky (if not impossible), and as Brunnermeier and Nagel (2004) report, many hedge-funds chose to ride the technology bubble instead of exerting a price correcting force.

V. Testing for Multiple Structural Breaks

Our study of investor risk preferences covers the period from the beginning of 1996 through the end of 2003. If this was the period when US market shifted from a "normal" state into a "bubble period," then experienced the bubble bursting" and a decline (or a "crash"), and finally stabilized, then there may be three points of structural change in risk preference. The first point reflects the shift from a normal market into the "bubble." The second point of structural change corresponds to the bubble bursting, and to the beginning of the decline. The third point corresponds to the end of the period of decline and to the return to the "normal" state. We address the hypothesis of multiple structural breaks taking place at the same time across different securities using the following test for multiple structural breaks.

Methodology: Wald Test for Multiple Breaks at Unknown Dates

We generalize the test for a structural break at an unknown date of Bai, Lumsdaine, and Stock (1998) to the case of multiple structural breaks, all taking place at unknown dates. Let $\kappa \equiv \{k, l, m\}$ be a triplet containing three possible dates of structural breaks, k, l, m. To test for several structural regime shifts we specify the relation

$$\begin{aligned} RA_{it} &= \beta_1 + \beta_2 \cdot RA_{it-1} + \beta_3 \cdot t + d_{1,t}(k) \cdot [\gamma_1 + \gamma_2 \cdot RA_{it-1} + \gamma_3 \cdot t] \\ &+ d_{2,t}(l) \cdot [\delta_1 + \delta_2 \cdot RA_{it-1} + \delta_3 \cdot t] + d_{3,t}(m) \cdot [\lambda_1 + \lambda_2 \cdot RA_{it-1} + \lambda_3 \cdot t] + \varepsilon_t . \end{aligned}$$

The variables are: an estimate of risk aversion for security i at time t, RA_{it}; the dummy variables are $d_{\{1,2,3\},t}(x) = 1$ if $t \geq x$ and zero otherwise for $x \in \{k, l, m\}$. Define $\beta = (\beta_1, \beta_2, \beta_3)'$, $\gamma = (\gamma_1, \gamma_2, \gamma_3)'$, $\delta = (\delta_1, \delta_2, \delta_3)'$, and $\lambda = (\lambda_1, \lambda_2, \lambda_3)'$. The tests for structural breaks in the coefficients are based on the value of *F*-statistics computed for all possible triplets $\kappa \equiv \{k, l, m\}$ of structural break dates. The null hypothesis is that no break exists ($\gamma = \delta = \lambda = 0$). For each κ, the estimator $\hat{\beta}(\kappa) = \left(\hat{\beta}', \hat{\gamma}', \hat{\delta}', \hat{\lambda}'\right)'$ of the regression parameter is obtained by OLS and the *F*-statistics are computed,

$$\hat{F}(\kappa) = T \cdot \hat{\beta}' \cdot \left[R \cdot \left(T^{-1} \cdot X'X \cdot \left(\hat{\sigma}^2\right)^{-1} \right)^{-1} \cdot R' \right]^{-1} \cdot \hat{\beta}.$$

The matrix X contains independent variables, so that the row t is

$$\left(1, RA_{t-1}, t, d_{1,t}(k) \cdot (1, RA_{t-1}, t), d_{2,t}(l) \cdot (1, RA_{t-1}, t), d_{3,t} \cdot (1, RA_{t-1}, t)\right),$$

$\hat{\sigma}^2$ is the estimator of σ^2 based on OLS residuals under the alternative hypothesis given κ. The estimated triplet of break dates is the one that gives the highest *F*-statistics. The break date is statistically significant if $\hat{F}\left(\hat{k}\right)$ is greater than a critical value at the chosen significance level.

Empirical Evidence

The results of the test are presented in Table VI. Technology stocks experience different structural breaks corresponding to the three periods in the life cycle of the firm during the bubble: entering the bubble, the bubble burst and subsequent stabilization. Similarly to evidence reported in Table V, we find that different stocks experienced structural changes at different dates. We find no evidence that the bubble burst at individual firm level occurs in March 2000 for all stocks. We do find a stock which fits the expected pattern. This is Sun Microsystems (SUNW). It enters the bubble in June 1998. In April 2000, right after the bubble burst, the risk preferences of investors in this stock experience the second structural break. Finally, the stock enters the normal path in July 2001.

The other stocks either exit the bubble and stabilize before March 2000 (for example IBM Corp (IBM), and Hewlett Packard (HPQ)) or experience the structural break associated with bubble collapse and stabilization after March 2000 (for example, Dell Computer (DELL), Apple Computer (AAPL)). These findings support the hypothesis of synchronization risk as a barrier to arbitrage. By looking at individual stocks it was impossible to predict for how long the same attitudes towards the technology stocks will persist, or for how long the market optimism will last. The challenges in predicting investor preferences result in difficulties in forecasting demand for these stocks. Different stocks can be sending very different signals to an arbitrageur who is attempting to forecast appetite for risk and the demand for stocks in the technology sector. When investor risk preferences in each of the technology stocks differ, an arbitrageur may infer from one stock that sentiment toward these securities worsens, while a very similar can signal strong optimism. In the absence of a strong coordination signal, attacking the technology bubble becomes a risky proposition. This finding is in line with recent theoretical work by Abreu and Brunnermeier (2003) and with the empirical findings in Temin and Voth (2004) who study the trading by Hoare's Bank during the 1720 South Sea bubble and find evidence consistent with synchronization risk.

Evidence from Aggregate Behavior

The evidence reported above indicates that it was difficult to predict the movements of active investors on the individual stock level. The level of the XCI index itself does not provide any indication of when the bubble can burst. The presence of coordination risk is evident from this data. Brunnermeier and Nagel (2004), however, report that hedge funds had some success in exiting the bubble before prices collapsed. This indicates that hedge-fund managers had some ability to mitigate some of the coordination risk by predicting on average when changes in preference may occur or had the ability to forecast investors' sentiment (Shleifer and Summers, 1990).

Can we observe a change in risk preference in our data during the bubble collapse? Was there a signal, albeit a weak one, for hedge funds to pool out? To address these questions we analyze an aggregate risk aversion obtained as equally-weighted average of risk aversion estimates for individual stocks. The motivation for looking at aggregate data is that on individual stock level the marginal investors in different stocks are different and we do not know which one leads the market. On the aggregate level, however, we can observe and measure a general trend in risk preferences of a marginal investor in the whole market. This represents a general opinion about stocks in the bubble market.

We analyze aggregate risk aversion. Table VII presents a test of one and three structural breaks for the aggregate time series. One structural break test indicates that the break occurred in April 2000 (Panel A). The test for three structural breaks suggests that on *aggregate,* the market entered the bubble in August 1998, the bubble bursts in April 2000, and stabilization period began in July 2001. This finding is remarkable. March 2000 is the last month when the prices peaked during the bubble. Right after this, in April 2000, we observe a significant change in risk preferences at the aggregate level.

A structural change in aggregate risk aversion in April 2000 is informative in light of the high persistence of aggregate risk aversion. Autocorrelation coefficients for one, two, and three lags are 0.93, 0.90, and 0.87, respectively (p-values in all cases are below 0.0001). Because of the high persistence, the best predictor for the future value is based on the recent past. An abrupt change in preferences, therefore, can serve as a signal. If, on average, hedge funds were able to predict the structural change in the markets in April 2000, then they would be able to withdraw from the market before prices fell. Our finding of a major structural change in April 2000 is consistent with the hypothesis where hedge funds were able to forecast the future change in market-level optimism of market sentiment and quit the market before the collapse.

VI. Conclusion

Asset price bubbles may inflate when rational arbitrage forces do not prevent prices from deviating from fundamental values. One of the reasons for arbitrageurs not to attempt actions that force prices to fundamentals may be synchronization risk. This risk arises when arbitrageurs lack the power to offset irrational exuberance unless they can coordinate, or *synchronize*, their actions. If synchronization is difficult or risky, and when individual arbitrageurs are not large enough to bring down the market on their own, prices may deviate from fundamental values. This approach has been used recently to interpret the rise and fall in prices of technology stocks.

We use a novel approach to study whether synchronization risk was present in the recent NASDAQ technology bubble. First, we develop a measure that reflects an important characteristic of investors in individual technology stocks--an estimate of investor risk aversion. Change in demand associated with change in preferences should cause portfolio rebalancing and subsequently affect trading activity. We then show that this prediction holds and that changes in estimated risk preferences of investors in a stock are closely related to changes in demand for the stock, and to the trading activity in the stock. After demonstrating the robustness of this result, we expect and find the following:

- Stocks, for which risk aversion changes in a similar way also tend to have similar returns.
- Stocks that have similar changes in investor preferences are also categorized by similar trading behavior (share turnover).
- Stocks with similar changes in risk aversion have similar changes in liquidity.

We therefore establish that preferences toward risk on individual stock level are a significant determinant of demand for the stock and of the stock price behavior.

Next, we turn to the recent rise and fall in prices of technology stocks. If the technology price bubble was driven by similar changes in investor attitudes (or sentiment) across the technology stocks than we would expect similarities in the behavior of the estimated risk preferences for investors in these stocks. Specifically, the major event of this period--collapse of prices in March 2000--should be observed in all the measures for all stocks approximately at the same point in time.

In the presence of synchronization risk, however, this will not be the case. Estimated preferences for investors in different stocks will experience changes in *different* points in time. This will be source of synchronization risk.

We study structural changes in estimates of investor risk preferences. Structural changes do take place in our sample, but they occur at very different points in time for different stocks. This means that similar stocks have different levels of optimism or pessimism and may be exposed to different trading strategies at the same time. This finding is consistent with the presence of synchronization risk. We also find that significant changes in individual risk preferences do not occur during the time of bubble collapse, but rather either before or after the burst. This is not surprising, given the finding of Bakshi and Wu (2006) who report that volatility of the NASDAQ 100 index spiked after the bubble burst, not before. Taking all the results together, we conclude that coordination uncertainty or synchronization risk was very high and the arbitrage was highly risky, if not impossible.

This evidence stimulates the discussion of what has become a signal for market participants to pool out from the market before the prices dropped (Brunnermeier and Nagel, 2004). It means that some coordination may have become possible right before the markets collapsed. The analysis of individual stocks and the XCI index does not provide a clear answer.

We also find that our measures contain important information about the burst of the bubble in March 2000. The aggregate market preference is obtained as equally-weighted average of the preferences for individual stocks. The advantage of using an aggregate data is that on individual level we do not know which stock (or group of stocks) is more influential in driving the technology prices and sustaining the same level of optimism. The aggregate risk preference experiences a structural shift in April 2000, right after the March of 2000 when the prices peaked for the last time. This is a strong and astonishing result. It suggests that change in aggregate market opinion, the change from market optimism to pessimism, was expected to occur in April. Hedge-funds started withdrawing from the bubble before this happened (Brunnermeier and Nagel, 2004). We infer that overall, changes in investor preferences and sentiment, and the presence of synchronization risk, made the job of rational arbitrageurs very difficult, risky, or virtually impossible.

References

Abreu, Dilip and Markus K. Brunnermeier, 2002, "Synchronization Risk and Delayed Arbitrage," *Journal of Financial Economics* 66, 341-360.

Abreu, Dilip and Markus K. Brunnermeier, 2003, "Bubbles and Crashes," *Econometrica* 71, 173—204.

Bai, Jushan, Robin L. Lumsdaine, and James H. Stock, 1998, Testing For and Dating Common Breaks in Multivariate Time Series, *Review of Economic Studies* 65, 395—432.

Bakshi, Gurdip. and Liuren. Wu, 2006, Investor Irrationality and the NASDAQ Bubble, working paper.

Barber, B., T. Odean and N. Zhu, 2006, Do Noise Traders Move Markets? Working paper

Barberis, Nicholas and Andrei Shleifer, 2003, "Style investing," *Journal of Financial Economics* 68, 161—199.

Bekaert, G., C. Harvey, and R. Lumsdaine, 2002, Dating the Integration of World Equity Markets, *Journal of Financial Economics* 65, 203—247.

Blackburn, Douglas W., William N. Goetzmann, and Andrey D. Ukhov, 2006, Risk Aversion and Clientele Effects, Working paper.

Bliss, Robert R., and Nikolaos Panigirtzoglou, 2002, Testing the stability of implied probability density functions, *Journal of Banking and Finance* 26, 381—422.

Bliss, Robert R., and Nikolaos Panigirtzoglou, 2004, Option-Implied Risk Aversion Estimates, *Journal of Finance* 59, 407—446.

Brav, Alon and J. B. Heaton, 2002, "Competing Theories of Financial Anomalies," *Review of Financial Studies* 15, 575—606.

Breeden, Douglas T., and Robert H. Litzenberger, 1978, "Prices of state-contingent claims implicit in options prices," *Journal of Business* 51, 621—651.

Brennan, Michael J., and Avanidhar Subrahmanyam, 1996, Market microstructure and asset pricing: On the compensation for illiquidity in stock returns, *Journal of Financial Economics* 41, 441-464.

Brunnermeier, Markus K., and Stefan Nagel, 2003, Hedge Funds and the Technology Bubble, *Journal of Finance* 59, pp. 2013—2040.

De Long, Bradford, Andrei Shleifer, Lawrence Summers, Robert Waldmann, 1990, Positive-Feedback Investment Strategies and Destabilizing Rational Speculation, *Journal of Finance* 45, pp. 374—97.

Harrison, J. Michael and David M. Kreps, 1978, Speculative Investor Behavior in a Stock Market with Heterogeneous Expectations, *Quarterly Journal of Economics* 92, pp. 323—36.

Hvidkjaer, S., 2006, Small Trades and the Cross-Section of Stock Returns, working paper

Shleifer, Andrei and Lawrence H. Summers, 1990, A Noise Trader Approach to Finance, *Journal of Economic Perspectives* 4, 19—33.

Fama, Eugene and James MacBeth, 1973, "Risk, return, and equilibrium: Empirical tests," *Joural of Political Economy* 71, 607—636.

Jackwerth, Jens Carsten, 2000, Recovering risk aversion from option prices and realized returns, *Review of Financial Studies* 13, 433-467.

Jones, M.C., Marron, J.S., Sheather, S.J. (1996), "A Brief Survey of Bandwidth Selection for Density Estimation," *Journal of the American Statistical Association*, 91, 401-407.

Lee, C. M. C. and B. Swaminathan, 2000, "Price Momentum and Trading Volume." *Journal of Finance* 55, 2017-2069.

Santos, Manuel S. and Michael Woodford, 1997, Rational Asset Pricing Bubbles, *Econometrica* 65, pp. 19—57.

Temin, Peter and Hans-Joachim Voth, 2004, Riding the South Sea Bubble, *American Economic Review* 94, 1654—1668.

Table I
Descriptive Statistics for Sample Stocks

The table reports descriptive statistics for the technology stocks in our sample, from the beginning of the sample period (2_Jan-1996) through the end of the sample period (31-Dec-2003). All selected stocks are members of the Computer Technology Index (XCI). This index trades on American Stock Exchange and contains 30 largest technology companies. To be included in the study, we require that a stock has options traded on it for the sample period. The companies in the table satisfy this requirement. We report market capitalization (in millions of US Dollars) and per share price at the beginning and the end of the sample period. We also report holding period return (HPR) and the minimum and maximum per share prices achieved during this period. All data is adjusted for stock splits.

	Ticker	Market Cap 2-Jan-96 ($MM)	Market Cap 31-Dec-03 ($MM)	Price 2-Jan-96 ($)	Price 31-Dec-03 ($)	HPR 2-Jan-96 to 31-Dec-03	Max Price 96-03 ($)	Min Price 96-03 ($)
Apple Computer Inc	AAPL	3,955.17	7,880.42	16.06	21.37	33.04%	72.09	6.47
Adobe Systems Inc	ADBE	4,670.48	9,312.76	16.03	39.08	143.77%	83.25	6.11
Automatic Data Processing Inc	ADP	10,548.15	23,545.69	18.31	39.61	116.30%	68.88	18.19
Applied Materials Inc	AMAT	7,417.63	37,732.19	5.17	22.44	333.89%	57.44	2.81
Advanced Micro Devices Inc	AMD	1,798.66	5,194.01	8.63	14.90	72.75%	47.28	3.20
Computer Associates Intl Inc	CA	13,622.85	15,832.10	25.06	27.34	9.12%	74.69	7.61
Computer Sciences Corp	CSC	3,901.90	8,284.99	35.06	44.23	26.15%	96.56	24.56
Cisco Systems Inc	CSCO	21,107.38	167,267.88	4.24	24.23	471.05%	80.06	3.63
Dell Computer Corp	DELL	3,260.47	87,003.28	1.11	33.98	2952.24%	58.13	0.65
EMC Corp	EMC	3,856.76	31,081.53	2.13	12.92	508.00%	103.94	1.94
Hewlett Packard Co	HPQ	42,735.30	70,038.75	20.88	22.97	10.04%	77.25	11.16
International Bus Machines Corp	IBM	50,736.88	159,448.80	22.72	92.68	307.94%	137.88	20.78
Intel Corp	INTC	48,142.85	207,908.35	7.33	32.05	337.36%	74.88	6.27
Motorola Inc	MOT	34,866.82	32,588.74	19.67	14.00	-28.81%	60.21	7.71
Microsoft Corp	MSFT	52,952.50	295,294.93	5.61	27.37	387.93%	59.56	5.01
Micron Technology Inc	MU	8,567.18	8,205.16	20.75	13.47	-35.08%	96.56	6.76
National Semiconductor Corp	NSM	2,807.10	7,305.94	22.75	39.41	73.23%	84.44	8.00
Oracle Corp	ORCL	18,826.90	69,160.98	3.20	13.23	312.96%	46.31	2.96
Storage Technology Corp	STK	1,269.10	222,349.28	11.94	34.04	185.15%	50.19	9.00
Sun Microsystems Inc	SUNW	8,202.94	14,692.43	2.80	4.47	59.82%	64.31	2.34
Texas Instruments Inc	TXN	9,157.38	50,845.76	6.06	29.38	384.62%	93.81	5.22

Table II
Changes in Risk Preferences and Turnover

This table reports the results of OLS regressions by firm that relate turnover to the changes in risk aversion,

$$TRN_t = \alpha + \beta_1 \Delta RA_t + \beta_2 TRN_{t-1} + \beta_3 R_{t-1} + \varepsilon_t .$$

The turnover TRN_t is trading volume divided by the number of shares outstanding, for a given firm in a month t. The independent variables are: change of the risk aversion over the month, $\Delta RA_t = RA_t - RA_{t-1}$; lag of turnover, TRN_{t-1}; and lag of return on the stock, R_{t-1}. The *t*-statistics based on bootstrap standard errors from 1,000 simulations are in parentheses below the coefficients. The data covers the period from February 1996 to December 2003. The cases where the variable of interest (ΔRA_t) is statistically significant are in bold.

Symbol	α	β_1	β_2	β_3	R^2
AAPL	2.53	**0.35**	0.44	-0.098	0.21
	(2.80)	**(1.71)**	(4.74)	(-0.08)	
ADBE	2.77	**0.049**	0.26	-0.48	0.12
	(8.37)	**(1.98)**	(7.23)	(-2.24)	
ADP	0.26	**0.011**	0.55	-0.41	0.34
	(3.73)	**(1.75)**	(7.97)	(-2.11)	
AMAT	2.21	-0.02	0.53	-0.96	0.30
	(5.01)	(-0.39)	(7.92)	(-2.17)	
AMD	1.45	0.13	0.67	1.21	0.50
	(1.20)	(0.94)	(6.71)	(1.32)	
CA	0.72	**0.04**	0.37	-0.48	0.21
	(3.55)	**(2.70)**	(7.20)	(-3.84)	
CSC	0.78	-0.008	0.42	-0.009	0.17
	(3.86)	(-0.45)	(6.62)	(-0.05)	
CSCO	0.91	**0.12**	0.59	-1.14	0.48
	(2.13)	**(2.91)**	(7.91)	(-2.55)	
DELL	0.49	0.13	0.84	1.07	0.77
	(0.29)	(0.45)	(6.55)	(0.60)	
EMC	0.73	**0.064**	0.52	-0.68	0.37
	(3.88)	**(3.08)**	(7.10)	(-3.91)	
HPQ	0.51	**0.025**	0.37	-0.13	0.16
	(6.88)	**(3.06)**	(7.96)	(-2.00)	
IBM	0.62	**0.034**	0.42	-0.85	0.26
	(2.79)	**(2.04)**	(3.81)	(-2.74)	
INTC	0.83	0.047	0.59	-0.56	0.38
	(2.54)	(0.89)	(6.97)	(-1.66)	
MOT	0.98	**0.062**	0.19	-0.44	0.12
	(7.78)	**(3.86)**	(3.60)	(-2.83)	
MSFT	0.93	0.005	0.35	-0.31	0.13
	(2.93)	(0.30)	(3.55)	(-1.06)	
MU	1.67	-0.07	0.58	0.54	0.40
	(2.86)	(-0.76)	(8.01)	(1.14)	
NSM	1.21	0.04	0.59	0.28	0.36
	(2.18)	(0.58)	(5.96)	(0.63)	
ORCL	1.37	**0.07**	0.30	-0.62	0.16
	(5.56)	**(2.76)**	(3.75)	(-2.58)	
STK	0.45	-0.01	0.69	-0.19	0.48
	(1.93)	(-0.44)	(8.43)	(-0.53)	
SUNW	1.96	**0.06**	0.44	-0.32	0.25
	(6.54)	**(1.98)**	(7.93)	(-1.00)	
TXN	0.67	**0.075**	0.58	-0.38	0.47
	(1.89)	**(2.59)**	(8.06)	(-1.45)	

Table III
Changes in Risk Preferences and Turnover:
Controlling for Market-Wide Changes in Risk Preferences

This table reports the results of OLS regressions by firm that relate turnover to the changes in risk aversion. To control for market-wide changes in risk preferences we include the change in risk aversion estimated for the market index, $\Delta RA_{Mt} = RA_{Mt} - RA_{Mt-1}$, and estimate the regression equation

$$TRN_{it} = \alpha + \beta_1 \Delta RA_{it} + \beta_{i2} TRN_{it-1} + \beta_{i3} R_{it-1} + \beta_{i4} \Delta RA_{Mt} + \varepsilon_t .$$

We use risk aversion for the *XCI Index* (Panel A) and *S&P 500 Index* (Panel B). The turnover variable TRN_t is trading volume divided by the number of shares outstanding, for a given firm in a month t. The independent variables are: change of the risk aversion over the month, $\Delta RA_t = RA_t - RA_{t-1}$; lag of turnover, TRN_{t-1}; and lag of return on the stock, R_{t-1}. The *t*-statistics based on bootstrap standard errors from 1,000 simulations are in parentheses below the coefficients. The data covers the period from February 1996 to December 2003. The cases where the variable of interest (ΔRA_t) is statistically significant are in bold.

Panel A: Risk Aversion for *XCI Index*						
Symbol	α	β_1	β_2	β_3	β_4	R^2
AAPL	2.53	**0.35**	0.44	-0.08	0.01	0.21
	(1.83)	**(2.04)**	(5.99)	(-0.07)	(0.16)	
ADBE	2.77	**0.05**	0.26	-0.49	-0.01	0.12
	(8.73)	**(1.91)**	(7.25)	(-2.07)	(-0.45)	
ADP	0.26	**0.01**	0.55	-0.41	0.0004	0.34
	(1.63)	**(1.78)**	(8.76)	(-2.36)	(0.07)	
AMAT	1.42	-0.03	0.53	-0.94	-0.04	0.30
	(1.29)	(-0.42)	(5.42)	(-1.36)	(-0.69)	
AMD	1.42	0.10	0.67	1.29	-0.12	0.52
	(1.29)	(0.76)	(5.86)	(1.46)	(-1.31)	
CA	0.72	**0.04**	0.37	-0.48	0.01	0.21
	(2.96)	**(2.43)**	(6.98)	(-3.25)	(1.14)	
CSC	0.79	-0.01	0.42	0.01	**0.03**	0.19
	(2.86)	(-0.36)	(5.53)	(0.03)	**(1.76)**	
CSCO	0.89	**0.13**	0.60	-1.21	-0.04	0.49
	(1.99)	**(2.69)**	(7.03)	(-2.46)	(-1.23)	
DELL	0.48	0.13	0.85	1.04	-0.03	0.77
	(0.40)	(0.63)	(8.82)	(0.85)	(-0.28)	
EMC	0.73	**0.06**	0.51	-0.67	0.01	0.37
	(2.53)	**(2.99)**	(6.81)	(-3.44)	(0.43)	

Table III—*Continued*

HPQ	0.50 (4.24)	**0.02** **(1.72)**	0.38 (6.61)	-0.10 (-1.07)	**0.02** **(3.53)**	0.20
IBM	0.59 (2.60)	**0.03** **(2.12)**	0.44 (4.37)	-0.85 (-3.15)	-0.02 (-1.07)	0.27
INTC	0.76 (2.51)	0.06 (1.14)	0.62 (6.77)	-0.60 (-2.11)	-0.04 (-1.62)	0.40
MOT	0.98 (5.24)	**0.06** **(3.33)**	0.19 (2.65)	-0.44 (-2.02)	0.002 (0.20)	0.12
MSFT	0.92 (4.93)	0.01 (0.52)	0.35 (4.37)	-0.31 (-1.45)	-0.01 (-0.43)	0.13
MU	1.67 (1.81)	-0.07 (-0.60)	0.59 (5.64)	0.55 (0.89)	0.01 (0.23)	0.40
NSM	1.20 (1.57)	0.04 (0.81)	0.59 (6.29)	0.29 (0.67)	0.02 (0.49)	0.36
ORCL	1.34 (3.00)	**0.07** **(1.92)**	0.31 (2.91)	-0.67 (-1.93)	-0.03 (-1.04)	0.17
STK	0.45 (1.77)	-0.02 (-0.47)	0.69 (7.35)	-0.17 (-0.49)	**0.05** **(2.07)**	0.51
SUNW	1.99 (5.29)	**0.07** **(1.84)**	0.44 (8.75)	-0.30 (-0.87)	0.04 (1.07)	0.26
TXN	0.66 (3.64)	**0.07** **(2.58)**	0.58 (7.59)	-0.37 (-1.62)	-0.03 (-1.56)	0.47

Table III—*Continued*

Panel B: Risk Aversion for *S&P 500 Index*						
Symbol	α	β_1	β_2	β_3	β_4	R^2
AAPL	2.53	**0.34**	0.44	-0.08	-0.02	0.21
	(1.95)	**(2.07)**	(6.19)	(-0.08)	(-0.49)	
ADBE	2.80	**0.04**	0.25	-0.45	**0.02**	0.13
	(8.90)	**(1.73)**	(8.69)	(-2.20)	**(2.03)**	
ADP	0.26	**0.01**	0.55	-0.41	-0.0003	0.34
	(3.64)	**(1.71)**	(9.05)	(-2.33)	(-0.10)	
AMAT	2.20	-0.02	0.53	-0.97	-0.01	0.30
	(2.38)	(-0.30)	(6.02)	(-1.52)	(-0.54)	
AMD	1.45	0.13	0.67	1.20	0.003	0.50
	(1.35)	(1.31)	(7.73)	(1.81)	(0.08)	
CA	0.72	**0.04**	0.37	-0.48	-0.0002	0.21
	(3.60)	**(2.52)**	(7.16)	(-3.34)	(-0.02)	
CSC	0.77	-0.01	0.43	-0.02	**0.01**	0.18
	(5.97)	(-0.61)	(7.85)	(-0.12)	**(1.76)**	
CSCO	0.93	**0.12**	0.58	-1.19	0.01	0.48
	(1.55)	**(2.47)**	(6.82)	(-2.49)	(0.67)	
DELL	0.50	0.13	0.84	1.07	0.003	0.77
	(0.34)	(0.54)	(7.48)	(0.72)	(0.05)	
EMC	0.74	**0.07**	0.51	-0.68	0.01	0.38
	(3.48)	**(2.85)**	(6.90)	(-3.28)	(1.27)	
HPQ	0.51	**0.02**	0.37	-0.13	0.002	0.16
	(7.86)	**(2.17)**	(6.93)	(-1.65)	(0.71)	
IBM	0.62	**0.03**	0.41	-0.85	0.002	0.26
	(2.94)	**(2.94)**	(5.02)	(-4.03)	(0.47)	
INTC	0.79	0.04	0.61	-0.52	-0.02	0.39
	(2.18)	(0.67)	(6.63)	(-1.39)	(-1.08)	
MOT	0.98	**0.07**	0.19	-0.43	-0.012	0.14
	(5.43)	**(2.87)**	(2.14)	(-1.76)	(-1.55)	
MSFT	0.94	0.004	0.34	-0.35	0.01	0.14
	(3.62)	(0.31)	(3.86)	(-1.55)	(1.10)	
MU	1.64	-0.07	0.59	0.56	-0.01	0.40
	(2.87)	(-0.75)	(8.13)	(1.21)	(-0.44)	
NSM	1.21	0.04	0.59	0.29	-0.01	0.36
	(1.86)	(0.92)	(7.47)	(0.83)	(-0.72)	
ORCL	1.31	**0.09**	0.32	-0.53	**-0.04**	0.24
	(4.10)	**(3.28)**	(3.85)	(-2.17)	**(-2.98)**	
STK	0.48	-0.01	0.67	-0.23	0.02	0.49
	(1.71)	(-0.48)	(6.41)	(-0.84)	(1.14)	
SUNW	2.00	**0.06**	0.44	-0.36	0.01	0.26
	(4.47)	**(1.85)**	(8.93)	(-0.94)	(0.66)	
TXN	0.62	**0.08**	0.61	-0.40	-0.01	0.47
	(2.22)	**(2.43)**	(6.85)	(-1.61)	(-1.22)	

Table IV
GLS Regressions
Changes in Risk Preferences and Turnover

This table reports the results of GLS regressions of turnover on the change in risk aversion and control variables. The first regression equation is

$$TRN_{it} = \alpha + \beta_1 \Delta RA_{it} + \beta_{i2} TRN_{it-1} + \beta_{i3} R_{it-1} + \varepsilon_t ,$$

where TRN_{it} denotes the turnover of stock i in month t, the turnover variable TRN_{it} is trading volume divided by the number of shares outstanding, for a given firm in a month t. The independent variables are: change of the risk aversion of investors in stock i over the month, $\Delta RA_{it} = RA_{it} - RA_{it-1}$; lag of turnover, TRN_{it-1}; and lag of return on the stock, R_{it-1}. To control for market-wide changes in risk preferences we include the change in risk aversion estimated for the market index, $\Delta RA_{Mt} = RA_{Mt} - RA_{Mt-1}$, and estimate the regression equation

$$TRN_{it} = \alpha + \beta_1 \Delta RA_{it} + \beta_{i2} TRN_{it-1} + \beta_{i3} R_{it-1} + \beta_{i4} \Delta RA_{Mt} + \varepsilon_t .$$

We use risk aversion for the *XCI Index* and *S&P 500 Index*. The data covers the period from February 1996 to December 2003. The *t*-statistics are in parentheses.

	α	β_1	β_1 With *XCI Index*	β_1 With *S&P 500 Index*
Turnover and risk aversion	0.802	0.031		
	(9.73)	(2.64)		
Controlling for ΔRA_M using *XCI Index*	0.795		0.030	
	(9.63)		(2.55)	
Controlling for ΔRA_M using *S&P 500*	0.798			0.030
	(9.61)			(2.61)

Table V
Wald Test for a Break at an Unknown Date

To test for a structural regime shift in estimated risk aversion coefficient RA_{it} for firm i at time t. We specify the relation

$$RA_{it} = \beta_1 + \beta_2 \cdot RA_{it-1} + \beta_3 \cdot t + d_t(k) \cdot [\gamma_1 + \gamma_2 \cdot RA_{it-1} + \gamma_3 \cdot t] + \varepsilon_t .$$

All coefficients are allowed to change. The relation is estimated for all possible break dates, k. The variable $d_t(k) = 1$ if $t \geq k$ and zero otherwise. For each potential structural break date k we compute $F(k)$ statistic as

$$\hat{F}(k) = T \cdot \hat{\gamma}' \cdot \left[R \cdot \left(T^{-1} \cdot X'X \cdot \left(\hat{\sigma}^2\right)^{-1} \right)^{-1} \cdot R' \right]^{-1} \cdot \hat{\gamma}.$$

The matrix X contains independent variables, so that the row t is $(1, RA_{t-1}, t, d_t(k) \cdot (1, RA_{t-1}, t))$, $\hat{\sigma}^2$ is the estimator of σ^2 based on OLS residuals under the alternative hypothesis given k, and the matrix $R = (0, I)$ so that $R\beta = \gamma$, where I is a 3×3 identity matrix.

Company	β_1	β_2	β_3	γ_1	γ_2	γ_3	Adj R^2	*F(k)*
AAPL	-0.07	0.82	-0.003	-25.43	-0.43	0.27	0.85	20.14
K = Oct,02	(-0.37)	(12.12)	(-0.65)	(-4.41)	(-2.71)	(4.32)		
ADBE	-3.41	0.33	0.07	8.11	0.11	-0.14	0.79	35.23
K=Sept,99	(-4.93)	(2.94)	(3.73)	(5.22)	(0.53)	(-5.06)		
ADP	14.02	-0.12	-0.24	-12.18	0.95	0.21	0.94	20.81
K=Apr,97	(5.09)	(-0.60)	(-2.06)	(-4.15)	(4.56)	(1.73)		
AMAT	-2.24	0.45	-0.002	6.04	-0.09	-0.07	0.85	20.32
K=Dec,99	(-4.33)	(4.72)	(-0.15)	(3.64)	(-0.37)	(-2.17)		
AMD	-2.24	-0.03	0.11	3.84	0.46	-0.15	0.67	23.87
K=Mar,97	(-2.56)	(-0.14)	(1.26)	(3.96)	(1.91)	(-1.67)		
CA	0.21	0.14	0.19	10.39	0.21	-0.37	0.94	45.24
K=Apr,98	(0.40)	(0.90)	(3.95)	(4.95)	(1.04)	(-6.26)		
CSCO	1.00	0.65	-0.04	3.89	-0.28	-0.03	0.70	15.59
K=Dec,98	(1.86)	(7.06)	(-1.56)	(2.88)	(-1.56)	(-1.05)		
DELL	0.18	0.59	0.002	0.96	0.001	-0.05	0.94	23.31
K=Jan,01	(0.69)	(6.16)	(0.27)	(0.69)	(0.01)	(-1.92)		
HPQ	2.74	0.46	-0.10	0.26	0.16	0.04	0.90	19.44
K=Apr,99	(4.18)	(4.23)	(-4.20)	(0.23)	(0.99)	(1.52)		
IBM	1.42	-0.26	-0.74	1.37	0.73	0.64	0.93	30.52
K=Dec,96	(1.06)	(-0.66)	(-2.70)	(0.94)	(1.84)	(2.35)		
INTC	0.19	0.91	-0.02	2.48	-0.35	-0.03	0.88	26.58
K=Nov,98	(0.66)	(11.60)	(-1.34)	(4.08)	(-3.13)	(-1.76)		
MSFT	1.39	0.13	-0.06	0.74	0.64	0.01	0.85	21.54
K=Jan,99	(1.88)	(0.89)	(-1.75)	(0.46)	(3.67)	(0.28)		
MOT	-0.29	0.82	-0.01	-18.31	-0.74	0.18	0.92	18.92
K=Sep,01	(-0.93)	(12.16)	(-1.10)	(-4.27)	(-3.69)	(4.15)		

Table V – *Continued*

Company	β_1	β_2	β_3	γ_1	γ_2	γ_3	Adj R^2	*F(k)*
EMC	-2.01	0.08	-0.28	2.63	0.29	0.26	0.65	33.96
K=Dec,96	(-1.68)	(0.32)	(-2.15)	(2.13)	(1.09)	(2.02)		
CSC	6.17	0.36	-0.13	-11.03	0.15	0.18	0.89	28.30
K=Nov,00	(5.40)	(3.25)	(-5.29)	(-4.43)	(0.70)	(5.16)		
MU	1.06	0.49	-0.03	121.33	-1.19	-1.34	0.80	19.45
K=Aug,03	(3.90)	(5.40)	(-4.45)	(3.77)	(-2.66)	(-3.81)		
XCI	1.20	0.78	-0.01	0.56	-0.54	-0.03	0.76	14.53
K=Jun,99	(1.58)	(8.70)	(-0.38)	(0.40)	(-3.32)	(-0.86)		
ORCL	0.20	0.52	-0.05	2.62	-0.11	-0.001	0.65	19.93
K=Dec,98	(0.40)	(3.64)	(-1.92)	(2.88)	(-0.64)	(-0.04)		
STK	0.77	0.84	-0.02	-287.83	-1.42	2.93	0.87	70.82
K=Aug,03	(2.43)	(15.01)	(-2.81)	(-6.81)	(-7.50)	(6.63)		
NSM	5.74	-0.51	-1.20	-4.56	0.92	1.17	0.63	23.28
K=Oct,96	(3.14)	(-1.40)	(-3.62)	(-2.46)	(2.45)	(3.52)		
SUNW	-0.53	0.36	0.002	-10.56	0.54	0.16	0.98	49.21
K=Apr,00	(-1.24)	(3.06)	(0.14)	(-4.25)	(4.34)	(4.36)		
TXN	-0.36	0.59	-0.04	1.67	0.03	0.01	0.81	17.59
K=Dec,98	(-0.73)	(6.70)	(-1.94)	(2.22)	(0.22)	(0.50)		

Table VI
Wald Test for Three Breaks at Unknown Dates

To test for a structural regime shift in estimated risk aversion coefficient RA_{it} for firm i at time t we specify the relation

$$RA_{it} = \beta_1 + \beta_2 \cdot RA_{it-1} + \beta_3 \cdot t + d_{1,t}(k)\cdot[\gamma_1 + \gamma_2 \cdot RA_{it-1} + \gamma_3 \cdot t] + d_{2,t}(l)\cdot[\delta_1 + \delta_2 \cdot RA_{it-1} + \delta_3 \cdot t] + d_{3,t}(m)\cdot[\lambda_1 + \lambda_2 \cdot RA_{it-1} + \lambda_3 \cdot t] + \varepsilon_t .$$

All coefficients are allowed to change. The relation is estimated for all possible break dates, *k*, *l* and *m*. The variable $d_{1,t}(k)=1$ if $t \geq k$ and zero otherwise, $d_{2,t}(l)=1$ if $t \geq l$ and zero otherwise, $d_{3,t}(m)=1$ if $t \geq m$ and zero otherwise. The matrix X contains independent variables, so that the row t is $(1, RA_{t-1}, t, d_{1,t}(k)\cdot(1, RA_{t-1}, t), d_{2,t}(l)\cdot(1, RA_{t-1}, t), d_{3,t}\cdot(1, RA_{t-1}, t))$, $\hat{\sigma}^2$ is the estimator of σ^2 based on OLS residuals under the alternative hypothesis given κ. For each potential structural break date triplet *k*, *l* and *m* we compute $F(\kappa)$ statistic as

$$\hat{F}(\kappa) = T \cdot \hat{\beta}' \cdot \left[R \cdot \left(T^{-1} \cdot X'X \cdot \left(\hat{\sigma}^2\right)^{-1}\right)^{-1} \cdot R' \right]^{-1} \cdot \hat{\beta}.$$

Company	β_1	β_2	β_3	γ_1	γ_2	γ_3	δ_1	δ_2	δ_3	λ_1	λ_2	λ_3	Adj R^2	*F(k)*
AAPL														
k=Dec,99	-1.17	0.25	0.002	7.60	0.31	-0.14	30.14	-0.32	-0.37	-57.68	0.001	0.69	0.89	73.57
l=Jun,02	(-3.86)	(1.72)	(2.71)	(3.86)	(1.54)	(-3.99)	(3.66)	(-1.52)	(-3.46)	(-3.75)	(0.04)	(4.06)		
m=Apr,03														
ADBE														
k=Oct,96	-4.07	-0.34	-0.21	-7.55	0.007	0.62	-28.97	0.74	0.93	41.05	0.34	-1.35	0.83	83.35
l=Mar,98	(-2.81)	(-1.05)	(-1.28)	(-3.18)	(0.20)	(3.46)	(-3.66)	(2.57)	(3.51)	(5.32)	(1.42)	(-5.30)		
m=Sep,98														
ADP														
k=May,96	4.76	-0.005	2.86	20.20	-0.25	-4.58	3.12	-0.05	0.59	-25.54	1.17	1.08	0.96	66.15
l=Oct,96	(0.66)	(-0.10)	(2.90)	(0.98)	(-0.25)	(-2.65)	(0.16)	(-0.06)	(0.41)	(-6.32)	(5.91)	(6.07)		
m=Sep,97														
AMAT														
k=Sep,98	-1.94	0.51	-0.003	-164.30	-0.61	4.71	144.70	0.30	-4.28	26.04	0.08	-0.51	0.90	87.33
l=Dec,98	(-3.83)	(5.37)	(-0.14)	(-6.18)	(-2.09)	(6.10)	(5.38)	(0.92)	(-5.51)	(5.91)	(0.27)	(-5.87)		
m=Apr,00														
AMD														
k=Sep,96	-2.54	-1.55	-0.52	10.33	0.97	-0.23	-0.96	0.54	0.52	-5.57	0.66	0.20	0.78	89.23
l=Mar,97	(-2.71)	(-3.09)	(-2.03)	(3.16)	(1.58)	(-0.62)	(-0.29)	(1.45)	(1.87)	(-4.70)	(3.91)	(5.28)		
m=Jan,99														
CA														
k=Jul,96	-8.40	-0.57	2.41	5.56	0.39	-1.76	-0.65	0.20	-0.26	13.81	0.33	-0.57	0.95	95.19
l=Feb,97	(-4.46)	(-2.17)	(5.11)	(2.01)	(0.85)	(-3.36)	(-0.28)	(0.45)	(-1.08)	(6.34)	(1.39)	(-6.23)		
m=Sep,98														
CSCO														
k=May,97	0.45	0.07	0.18	32.82	-0.08	-1.78	-22.40	-0.32	1.08	-8.13	0.91	0.49	0.78	68.77
l=Dec,97	(0.70)	(0.36)	(2.61)	(3.11)	(-0.18)	(-3.63)	(-1.79)	(-0.70)	(1.96)	(-1.20)	(3.22)	(1.87)		
m=Jun,98														

Table VI – *Continued*

Company	β_1	β_2	β_3	γ_1	γ_2	γ_3	δ_1	δ_2	δ_3	λ_1	λ_2	λ_3	Adj R^2	$F(k)$
DELL														
k=Feb,99	0.71	0.53	-0.03	-0.63	-0.34	0.04	-13.59	0.15	0.16	11.71	0.26	-0.19	0.95	55.59
l=Jan,01	(1.94)	(4.75)	(-1.92)	(-0.45)	(-1.29)	(1.32)	(-1.79)	(0.43)	(1.33)	(1.53)	(0.94)	(-1.53)		
m=Oct,01														
HPQ														
k=Apr,98	3.59	0.19	-0.09	-56.03	-0.45	1.82	41.37	0.46	-1.45	13.12	0.50	-0.31	0.93	71.96
l=Aug,98	(4.96)	(1.26)	(-3.96)	(-5.03)	(-1.48)	(4.90)	(3.64)	(1.47)	(-3.87)	(5.02)	(2.30)	(-5.22)		
m=Jan,00														
IBM														
k=Dec,96	1.42	-0.26	-0.74	3.30	0.82	0.53	13.36	-0.30	-0.25	-13.58	0.25	0.34	0.94	72.94
l=Dec,98	(1.23)	(-0.76)	(-3.12)	(2.10)	(2.28)	(2.23)	(2.68)	(-1.64)	(-2.03)	(-2.66)	(1.30)	(2.82)		
m=Dec,99														
INTC														
k=Sep,96	-1.74	-0.09	-0.03	3.80	0.78	-0.07	35.72	0.02	-0.90	-36.05	0.01	0.97	0.92	87.57
l=Nov,98	(-2.51)	(-0.25)	(-0.25)	(4.51)	(2.06)	(-0.50)	(2.88)	(0.09)	(-2.66)	(-2.90)	(0.05)	(2.87)		
m=Jul,99														
MSFT														
k=Oct,97	0.61	-0.02	0.06	-5.68	0.12	0.07	14.14	0.25	-0.31	-15.57	-0.003	0.19	0.88	63.58
l=Dec,98	(0.74)	(-0.11)	(1.02)	(-1.69)	(0.42)	(0.54)	(3.51)	(0.97)	(-2.54)	(-4.53)	(-0.02)	(3.52)		
m=Mar,01														
MOT														
k=Jul,97	-2.14	0.37	0.09	10.17	0.12	-0.42	-10.82	0.02	0.34	-15.80	-0.43	0.16	0.94	58.06
l=Mar,99	(-3.12)	(2.01)	(1.79)	(4.61)	(0.52)	(-4.37)	(-3.95)	(0.08)	(4.00)	(-3.87)	(-1.87)	(3.66)		
m=Sep,01														
EMC														
k=Dec,96	-2.01	0.08	-0.28	4.60	-0.11	0.17	-3.82	0.12	0.13	15.54	0.14	-0.20	0.76	105.15
l=Dec,98	(-2.09)	(0.40)	(-2.68)	(3.94)	(-0.49)	(1.54)	(-3.85)	(0.60)	(4.50)	(2.05)	(0.34)	(-2.15)		
m=Jun,02														
CSC														
k=Jul,96	4.49	-0.25	1.70	2.77	0.43	-1.82	-64.77	-0.60	2.36	57.31	1.22	-2.24	0.92	87.35
l=Feb,98	(2.28)	(-1.03)	(4.07)	(0.92)	(1.32)	(-4.31)	(-5.61)	(-2.00)	(5.61)	(5.06)	(5.55)	(-5.38)		
m=Jul,98														
MU														
k=Jun,98	2.19	0.28	-0.09	0.27	0.08	0.04	13.74	-0.78	-0.17	106.19	-0.28	-1.14	0.83	53.45
l=Jun,02	(3.20)	(1.51)	(-3.06)	(0.29)	(0.35)	(1.16)	(2.76)	(-2.58)	(-2.63)	(3.71)	(-0.59)	(-3.64)		
m=Aug,03														
XCI														
k=Nov,97	2.80	0.43	0.04	-21.74	-0.31	0.64	88.95	-0.70	-2.24	-68.05	0.82	1.52	0.82	57.21
l=Jan,99	(2.78)	(2.12)	(0.63)	(-5.28)	(-1.11)	(4.13)	(4.70)	(-1.55)	(-5.17)	(-3.67)	(1.93)	(3.70)		
m=Nov,99														

Table VI – *Continued*

Company	β_1	β_2	β_3	γ_1	γ_2	γ_3	δ_1	δ_2	δ_3	λ_1	λ_2	λ_3	Adj R^2	*F(k)*
ORCL														
k=Sep,97	1.31	0.45	-0.18	-0.22	-0.65	0.07	0.41	0.34	0.09	-2.27	-0.09	-0.01	0.72	58.38
l=Jan,99	(1.81)	(2.44)	(-2.51)	(-0.11)	(-2.17)	(0.68)	(0.21)	(1.21)	(1.34)	(-0.39)	(-0.32)	(-0.09)		
m=Sep,02														
STK														
k=Jul,99	0.05	0.44	0.04	7.46	0.13	-0.17	25.76	-0.50	-0.31	-320.34	-0.64	3.34	0.91	144.67
l=May,02	(0.15)	(3.20)	(2.20)	(3.08)	(0.68)	(-3.83)	(3.39)	(-2.13)	(-3.10)	(-8.93)	(-2..60)	(8.85)		
m=Aug,03														
NSM														
k=Oct,96	5.74	-0.51	-1.20	-4.53	0.59	1.16	-13.19	0.16	0.31	16.78	-0.16	-0.36	0.72	71.62
l=Jan,99	(3.74)	(-1.66)	(-4.30)	(-2.74)	(1.73)	(4.15)	(-3.79)	(0.62)	(3.82)	(4.58)	(-0.61)	(-4.57)		
m=May,00														
SUNW														
k=Jun,98	1.43	-0.03	-0.17	-0.93	0.07	0.15	7.49	0.46	-0.19	-45.71	0.17	0.73	0.98	105.54
l=Apr,00	(2.54)	(-0.22)	(-4.28)	(-0.52)	(0.26)	(2.64)	(1.13)	(1.81)	(-1.51)	(-1.95)	(0.68)	(2.27)		
m=Jul,01														
TXN														
k=May,97	-4.03	0.24	0.28	-6.95	-0.39	0.09	0.34	0.34	-0.13	12.03	0.45	-0.26	0.85	54.94
l=Apr,98	(-2.55)	(1.28)	(2.28)	(-2.09)	(-1.15)	(0.54)	(0.10)	(1.05)	(-1.08)	(5.42)	(2.29)	(-5.67)		
m=Apr,00														

Table VII

Wald Test for Breaks at Unknown Dates for the Aggregate Risk Aversion

Panel A reports the results for a test of *one* structural regime shift in aggregate risk aversion coefficient RA_t at time t. We specify the relation

$$RA_t = \beta_1 + \beta_2 \cdot RA_{t-1} + \beta_3 \cdot t + d_t(k) \cdot [\gamma_1 + \gamma_2 \cdot RA_{t-1} + \gamma_3 \cdot t] + \varepsilon_t$$

All coefficients are allowed to change. The relation is estimated for all possible break dates, k. The variable $d_t(k) = 1$ if $t \geq k$ and zero otherwise.

Panel B reports the results for a test of *three* structural regime shifts in aggregate risk aversion coefficient RA_t at time t. We specify the relation

$$RA_{it} = \beta_1 + \beta_2 \cdot RA_{it-1} + \beta_3 \cdot t + d_{1,t}(k) \cdot [\gamma_1 + \gamma_2 \cdot RA_{it-1} + \gamma_3 \cdot t] + d_{2,t}(l) \cdot [\delta_1 + \delta_2 \cdot RA_{it-1} + \delta_3 \cdot t] + d_{3,t}(m) \cdot [\lambda_1 + \lambda_2 \cdot RA_{it-1} + \lambda_3 \cdot t] + \varepsilon_t$$

where the variable $d_{1,t}(k) = 1$ if $t \geq k$ and zero otherwise, $d_{2,t}(l) = 1$ if $t \geq l$ and zero otherwise, $d_{3,t}(m) = 1$ if $t \geq m$ and zero otherwise.

	β_1	β_2	β_3	γ_1	γ_2	γ_3	δ_1	δ_2	δ_3	λ_1	λ_2	λ_3	Adj R^2	*F(k)*
Panel A. Wald Test for a Break at an Unknown Date														
K=Apr,00	-0.53	0.36	0.002	-10.56	0.54	0.16							0.98	49.21
	(-1.24)	(3.06)	(0.14)	(-4.25)	(4.34)	(4.36)								
Panel B. Wald Test for Three Breaks at Unknown Dates														
k=Aug,98	1.06	0.01	-0.13	1.92	-0.30	0.06	5.01	0.78	-0.14	-45.71	0.17	0.73	0.98	105.29
l=Apr,00	(1.99)	(0.08)	(-3.81)	(0.91)	(-0.95)	(0.93)	(0.75)	(2.53)	(-1.03)	(-1.95)	(0.68)	(2.27)		
m=Jul,01														