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Investor Attention and Time-varying Comovements

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Abstract

This paper analyses the effect of an increase in market-wide uncertainty on information flow and asset price comovements. We use the daily realised volatility of the 30-year treasury bond futures to assess macroeconomic shocks that affect market-wide uncertainty. We use the ratio of a stock's idiosyncratic realised volatility with respect to the S&P500 futures relative to its total realised volatility to capture the asset price comovement with the market. We find that market volatility and the comovement of individual stocks with the market increase contemporaneously with the arrival of market-wide macroeconomic shocks, but decrease significantly in the following five trading days. This pattern supports the hypothesis that investors shift their (limited) attention to processing market-level information following an increase in market-wide uncertainty and then subsequently divert their attention back to asset-specific information.

Keywords: *limited attention*; *information flow*; *comovement*.

JEL classification: *G*14

1. Introduction

The determinants of asset price fluctuation are one of the central topics in financial economics. In particular, there is now ample empirical evidence that comovement among asset prices varies over time, and also tends to be excessively high during volatile periods, e.g., Hamao *et al.* (1990), Lin *et al.* (1994), and Longin and Solnik (1995). Moreover, studies by French and Roll (1986) and Andersen (1996), among many others, have shown that asset price fluctuations are intimately linked to the amount of information that flows

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to the market. This in turn suggests that the cross-sectional structure of the information flow and the time-series dynamics of that structure are both important for properly understanding asset return comovements. This paper examines the dynamics of such comovements motivated by the idea that investors are faced with limited information processing capabilities and the resulting implications for the structure of the information flow.

Standard asset pricing models assume that investors distill new information with lightning speed and that asset prices incorporate new information instantaneously. However, a large body of psychological research demonstrates that people have limited attention, i.e., they can only process a limited amount of information during a given period.[1] Facing vast amounts of information in the financial markets, investors with limited attention have to be selective in their information processing, i.e., depending on priority and urgency, they allocate attention across either market-level or asset-specific information processing tasks. This attention allocation leads to an endogenous structure of information flow, which directly affects asset return comovement. In particular, with the arrival of a macroeconomic shock that increases the uncertainty at the market-level, attention constrained investors would shift more attention to processing market-level information. As shown in Peng (2005) and Peng and Xiong (2006), the market factor tends to carry more weight in most investors' portfolios and it is in their best interest to quickly resolve the market uncertainty before processing other asset-specific information. This type of attention shift motivates the hypothesis that after a macroeconomic shock, contemporaneous asset comovement tends to rise as investors focus their attention on processing information about the market factor, but subsequently drops as they shift attention back to processing asset-specific information.

We analyse this attention shift hypothesis by focusing on the comovement of the Dow Jones 30 stocks with the S&P500 index in response to macroeconomic shocks. In our analysis, we use innovations in the realised volatility of the 30-year US Treasury Bond futures contract as a proxy for macroeconomic shocks. Following Andersen *et al.* (2003), we construct daily realised volatilities for the S&P500, the 30-year T-Bond, and each of the Dow Jones 30 stocks using 5-minute intraday returns. To measure the comovement of the Dow Jones stocks with the market index, we first regress the 5-minute returns for each of the Dow Jones stocks on the contemporaneous and lagged S&P500 futures. We then compute the realised idiosyncratic return variance for the day and the ratio of the idiosyncratic variance to the total return variance of the stock. The idiosyncratic variance ratio serves as an inverse measure of the comovement of the stock with the market index.

Using VAR analysis, we find that a unit shock to the treasury bond futures volatility results in a same-day increase in the S&P500 volatility of about 0.40, but a decrease over the following five days by an average cumulative amount of 0.47. This result implies that the amount of market information incorporated into stock prices increases contemporaneously with the shock but is then reversed over the following days. Furthermore, the Dow Jones stocks' idiosyncratic variance ratios decrease on average by 0.35 unit on the same day, but increase over the following three trading days by an average cumulative amount of 0.11 unit. These responses of the idiosyncratic variance ratios imply that the comovement of individual stocks with the market index increases contemporaneously with a market-wide shock, but is then reversed over the following three days.

[1] See Kahneman (1973) and Pashler and Johnston (1998) for reviews of these studies.

Our results allow us to sort out several hypotheses about the cross-sectional pattern and the dynamics of the information flow that determines asset return comovement. The first hypothesis stipulates that investors can instantaneously resolve any uncertainty. This hypothesis implies that a macroeconomic shock that increases market wide uncertainty should increase market volatility and asset return comovement instantaneously, with no subsequent impacts.

The second and third hypotheses consider more realistic situations in which investors can only process information and resolve uncertainty at finite speed. The second hypothesis posits that the processed information flow is finite and furthermore, that the cross-sectional structure of the information flow, i.e., the composition of market-level and asset-specific information, stays constant over time. This hypothesis therefore also implies that a fixed fraction of market and asset specific uncertainty is resolved each period. When a macroeconomic shock increases market uncertainty while asset-specific uncertainty remains unchanged, there is a greater rate of uncertainty reduction at the market level, but no change in the rate at the asset-specific level. Since the magnitude of price fluctuation (volatility) is determined by the amount of uncertainty reduction, the increase in market uncertainty would then translate into a higher market volatility and greater contemporaneous asset return comovement. Given the finite speed of uncertainty reduction, the market uncertainty in the following days would remain high. As a result, the shock would also increase market volatility and asset return comovement in the following days, with the magnitude of the increase gradually dying out.

Unlike the second hypothesis, the third hypothesis posits that the cross-sectional structure of information flow changes over time and is determined by the active choice of investors with limited attention. Limited attention implies that investors can only process a finite amount of information per day, thus providing a plausible explanation for the notion of finite information flow. Furthermore, investors can strategically shift their attention in response to changing conditions. In particular, when market-wide uncertainty rises upon the arrival of a macroeconomic shock, investors temporarily shift attention away from processing asset-specific information to processing more market-level information, shifting attention back to asset-specific information over the ensuing days. Consequently, the market volatility and asset return comovement increase contemporaneously in response to the shock, but this pattern reverses over time.

Our finding – that macroeconomic shocks do have lasting effects on market volatility and asset return comovement for up to five days – clearly rejects the first hypothesis. This finding suggests that information flow in financial markets is indeed finite. Furthermore, the finding that the contemporaneous increases in the market volatility and asset return comovement are subsequently reversed is also inconsistent with the prediction of the second hypothesis of a constant cross-sectional structure of information flow over time. The reversal evidence instead supports a time-varying information structure, as consistent with the third hypothesis that investors actively shift more attention to market information when they are faced with a sudden increase in market-wide uncertainty. Moreover, our results are not driven by clustered fundamental shocks because these results are based on the impulse response function of individual shocks estimated from a VAR framework, which separates the impacts of shocks arriving at different times.

The recent theoretical literature in economics and finance has begun to explore the economic implications of agents' active attention allocation. Sims (2003) adopts the concept of channel capacity from information theory to study information-processing constraints in a dynamic consumption choice problem. Peng (2005) models an information capacity constraint in investors' learning processes and analyses the implications on the cross-sectional information structures and return dynamics. Our study is most closely related to Peng and Xiong (2006), who use the same information measure as in Sims and Peng, but focus on analysing investors' category-learning behaviour and its relationship to return comovement and predictability. In addition, Van Nieuwerburgh and Veldkamp (2004) discuss portfolio under-diversification caused by investors' learning constraints, while Gabaix *et al.* (2003) analyse a model of directed attention of economic agents who allocate thinking time to choose a consumption good from several alternatives. Our study adds to this theoretical literature by providing empirical evidence directly linking the dynamics of volatility and comovement to investors' time-varying attention allocation.

Our study is also related to the growing empirical literature that examines the implications of investors' inattention to public information for financial markets. For instance, Huberman and Regev (2001) provide a case study that public information in *The New York Times* about a firm's new product can be ignored by the stock markets for several months. Similarly, Hirshleifer *et al.* (2004) show that investors sometimes ignore useful information in firms' financial statements, while Hong *et al.* (2003) and Hou and Moskowitz (2005) find delays in the responses of a stock's price to useful information reflected by other stocks' prices. Also, Della Vigna and Pollet (2003) show that stock prices do not fully incorporate demographic information that is publicly available. In addition, Della Vigna and Pollet (2005) and Hirshleifer *et al.* (2006) find that earnings announcements made on Fridays or large-event days, during which investors are less attentive to earnings announcements, generate significantly lower price reactions and trading volume than other days. In a related context, Corwin and Coughenour (2006) find that on days when NYSE specialists are fully occupied by trading activities of a subset of securities for which they are responsible for making markets, their attention constraints cause the execution quality (price improvement and transaction cost) of the other securities for which they are responsible to deteriorate.

The literature has also explored several other channels that might affect asset return comovement. In particular, King and Wadhwani (1990) focus on the signal extraction by a group of participants in the UK market from the price movement in US stocks. While their approach also involves an information effect, it treats the information flow as exogenous. Other studies have focused more on the externality effects caused by market participants' trading. For example, Kyle and Xiong (2001) and Boyer *et al.* (2006) analyse mechanisms for fundamentally uncorrelated assets to move together based on the wealth fluctuations of common financial intermediaries.

The rest of the paper is organised as follows. In Section 2, we introduce the three hypotheses that guide our empirical analysis. In Section 3, we describe the data and empirical methodology. Section 4 reports on the actual VAR estimation results. Section 5 concludes the paper.

2. Empirical Hypotheses

In this section, we discuss the theoretical hypotheses concerning the relationship between uncertainty, information flow and asset price fluctuation that motivate our empirical investigations. More specifically, we focus on the implication of attention constraint for the dynamics of asset return comovement.

Investors constantly face uncertainty in financial markets. They resolve uncertainty through information processing and learning. Standard finance theories typically adopt

Bayesian learning frameworks to model investors' learning processes under uncertainty, e.g., Epstein and Turnbull (1980), Detemple (1986), Gennotte (1986), Veronesi (1999), and Brennan and Xia (2001). In these models, a representative investor starts with a prior belief about the distribution of an unobservable fundamental factor, which determines the future payoff of an asset of interest. If the prior belief has a Gaussian distribution, the uncertainty is captured by the variance of the distribution. After the investor receives a noisy signal about the fundamental factor, he uses Bayes rule to update his belief, causing the belief to fluctuate with the information flow in the signal. The greater the amount of information the signal contains, the more uncertainty resolution can be achieved. In equilibrium, the price of the asset fluctuates with both the information flow and the investor's uncertainty resolution process. The dynamics of the asset price volatility in turn is determined by the arrival of shocks, which raise the level of uncertainty about the asset fundamentals and affect the subsequent uncertainty resolution process through investors' learning and information processing.

To understand asset return comovement, it is important to distinguish the resolution of uncertainty that is common to all assets from that which is asset-specific. Consider a linear model, in which asset fundamentals are determined by a common market factor and an idiosyncratic factor for each asset. Suppose that all of the factors are mutually independent. The price of an asset then fluctuates with the uncertainty resolution processes regarding the market factor and the asset's idiosyncratic factor, respectively. The return comovement between two assets increases when a greater fraction of price fluctuation is caused by the uncertainty resolution of the market factor. Conversely, if the investors increase the rate of uncertainty resolution of the asset specific factors relative to the market factor, the return comovement decreases.

The rate of information flow directly determines the speed of uncertainty resolution and therefore the time-series impact of a shock. We consider three alternative hypotheses concerning the features of the information flow and their corresponding implications for market volatility and asset return comovement. The first hypothesis stipulates that investors can resolve uncertainty instantaneously. The second and the third hypotheses consider more realistic situations, in which investors can only process information and resolve uncertainty at finite speed. We posit that the amount of information processed determines the fraction of uncertainty reduction investors can achieve. The second hypothesis assumes that investors do not change their cross-sectional attention allocation to the market factor versus the asset-specific factors over time. Therefore, the cross-sectional structure of the information flow stays constant and the fraction of uncertainty resolution for the market factor relative to that for the asset-specific factor remains fixed. The third hypothesis posits that investors actively change their cross-sectional attention allocation, depending on the relative importance of the market factor uncertainty and the asset-specific factor uncertainty. When a macroeconomic shock increases the market-factor uncertainty, investors shift more attention to the market factor, away from the asset-specific factor, and achieves greater fraction of uncertainty reduction for this factor. But as the market uncertainty reduces to a certain level, its relative importance with respect to the asset-specific factor decreases. Investors would then shift some attention back to the asset-specific factors. Under this hypothesis, we expect the amount of market factor information processed to increase upon the arrival of the macroeconomic shock, but to decrease subsequently as the investors shift their attention back to the asset-specific factors. In the remaining part of this section, we discuss these hypothesis in detail.

In a perfect world where investors have instantaneous access to information and simultaneously incorporate the information into their beliefs and market prices, the effect of any shock will be instantaneously absorbed and the resulting uncertainty similarly instantaneously resolved. This scenario implies that a shock that raises uncertainty about a fundamental factor would increase the volatility of a related asset only in the contemporaneous period. More specifically, if the shock is to the market factor, the comovement among assets will increase in the contemporaneous period, but not in any future periods. We summarise this prediction in the following hypothesis:

Hypothesis I: *If investors can fully resolve uncertainty instantaneously, a shock that increases market-wide uncertainty, will only increase market volatility and comovement among assets on the day of the shock.*

In contrast to Hypothesis I, if investors can only process a finite amount of information each day, only part of the uncertainty will typically be resolved during the initial day. In this situation, the uncertainty resolution process would continue and affect asset price fluctuations over subsequent days. To facilitate our discussion of this idea, it is useful to adopt an explicit measure of information.

Specifically, we follow Sims (2003) who advocates the use of entropy reduction as a measure of information in economic modelling. Information Theory measures the uncertainty of a random variable Y with a continuous probability density function $f(y)$ by its entropy:

$$H(Y) = -E\log[f(Y)] = -\int (\log f(y))\, f(y)\, dy, \tag{1}$$

that is the negative value of the expectation of the logarithm of the random variable's density function. Intuitively, entropy can be interpreted as the lower bound on the average length of the shortest description of a random variable, as used in data compression.[2]

The amount of information that a noisy signal S contains about Y is defined as the reduction in the entropy of Y due to the knowledge of S:

$$I(Y; S) = H(Y) - H(Y|S), \tag{2}$$

where $H(Y|S)$ refers to the conditional entropy of Y after observing S. As argued by Peng (2005) and Peng and Xiong (2006), a desirable property of this information measure is that it is invariant to any linear transformation of both variables Y and S, and therefore independent of the scale of the underlying variables.[3]

[2] See Cover and Thomas (1991) for a more detailed discussion of Information Theory. Entropy is a widely used concept in many scientific fields, such as statistics, data compression, and computer science.

[3] Other measures of information have, of course, been used in the literature. For example, Verrecchia (1982) uses the precision (the inverse of variance) of noisy signals with Gaussian distributions to measure information in a noisy rational expectations model. However, the precision of a signal is generally not invariant to the scale of the underlying variable. Also, Epstein and Turnbull (1980) use the squared correlation between the noisy signal and the underlying variable to measure the information. This measure is equivalent to the entropy reduction measure when both the signal and the underlying variable are normally distributed.

If the random variable Y has a Gaussian distribution, then its entropy is proportional to the logarithm of its variance σ^2:

$$H(Y) = \frac{1}{2}[\log \sigma^2 + \log(2\pi e)], \tag{3}$$

where $\log(2\pi e)$ is a mathematical constant. If the signal S also has a Gaussian distribution, the posterior distribution of Y after observing S is still Gaussian and the remaining entropy (uncertainty) is proportional to the logarithm of the posterior variance. Thus, if the signal S contains more information about Y, it can reduce the posterior variance by a greater fraction.

Consider a benchmark scenario, in which investors can only process a finite amount of information per day and the cross-sectional structure of the information flow, i.e., the composition of market and asset-specific information, stays constant over time. The constant information flow structure implies that a fixed fraction of uncertainty about each fundamental factor is resolved. Thus, an increase in market-wide uncertainty caused by a macroeconomic shock must lead to higher market volatility on the same day as the shock because volatility captures the amount of uncertainty resolved. Moreover, the market-wide uncertainty would generally remain high for some days as investors can only gradually resolve the impact of the shock. As such, the macroeconomic shock would increase the market volatility over the succeeding days, with the magnitude of the increase gradually dying out. Meanwhile, unaffected by the macroeconomic shock, the dynamics of uncertainty resolution about asset-specific factors and volatility remain unchanged. As a result, asset return comovement would rise contemporaneously in response to a macroeconomic shock and would remain high over subsequent days, only dying out gradually. We summarise these implications in the following hypothesis:

Hypothesis II: *If investors can only process a finite amount of information per period and the cross-sectional structure of the information flow stays constant over time, a shock that increases market-wide uncertainty, would result in an increase in market volatility and asset return comovement on the day of the shock, with the magnitude of the increase in both volatility and comovement gradually dying out over the succeeding days.*

Although the scenario described in Hypothesis II is plausible, investors can change the structure of their information flow over time. In reality of course, investors only have limited attention. As a result, they have to allocate their limited attention to different tasks of information processing based on priority and urgency.[4] Motivated

[4] A large body of psychological research suggests that people's ability to simultaneously perform different tasks depends on whether they involve only perceptual analysis or more central cognitive analysis requiring memory retrieval and action planning. Although people can simultaneously handle multiple perceptual tasks, such as typing while listening to music, psychological evidence shows that overlap in the central cognitive operations of different tasks does not occur successfully, except in a few special cases. Pashler and Johnston (1998) summarise various supporting evidence that the central cognitive-processing capacity of the human brain has its limits. The operation of the human brain is intuitively described by psychologists as similar to that of a single-processor computer. Both deal with multiple tasks by working on one task at a time, alternating between the tasks to respond to inputs in a timely fashion. The rate or efficiency of processing for each task depends on the processing time allocated to the task.

by this idea, Peng and Xiong (2006) explicitly analyse investors' attention allocation decisions. They show that an investor's attention allocation decision across the market and the firm-specific factors is determined by the factors' relative contributions to the total uncertainty of his portfolio. Since the market factor tends to carry more weight in most investors' portfolios, it generally has a higher priority than asset specific factors. Following the intuition developed in their model, upon the arrival of a macroeconomic shock that increases market-wide uncertainty, investors would shift more attention to processing information about the market factor as doing so greatly reduces the total uncertainty of their portfolios. As a result, investors are able to resolve a greater fraction of the market-level uncertainty, and a correspondingly smaller fraction of asset-specific uncertainty. In the extreme case, the investors would only process the market factor information and completely ignore the asset-specific information. But as the market-wide uncertainty reduces to a certain level, the investors would then shift some attention back to processing information about asset-specific factors, causing an increase in the fraction of uncertainty resolution about these factors. The dynamics of investors' attention shift in response to a macroeconomic shock implies that both the market volatility and asset return comovement would rise contemporaneously, but reverse on subsequent days. We summarise these consequences of investors' attention shift in the following hypothesis:

Hypothesis III: *If investors have limited attention and, in response to a shock that increases market-wide uncertainty, shift more attention to the market factor, market volatility and asset return comovement would both increase on the day of the shock, but reverse over subsequent days.*

Hypotheses I–III involve different assumptions about the dynamics of information flow and provide distinct predictions about the response of market volatility and asset return comovement to macroeconomic shocks. If investors can instantaneously resolve any uncertainty by processing an infinite amount of information, the impact of a shock that increases market-wide uncertainty is only limited to the concurrent day. If on the other hand investors can only process a finite amount of information per day, and if the cross-sectional structure of the information flow stays constant over time, the shock causes the market volatility and asset comovement to rise on the concurrent day and then gradually die out over the succeeding days. Finally, if investors have limited attention and if they actively shift their limited attention across different factors, the shock causes both market volatility and asset comovement to rise on the concurrent day, but to reverse over the following days.

3. Data and Methodology

We begin with a brief description of our measures of market volatility and macroeconomic shocks followed by a discussion of our comovement measures that we use in empirically quantifying and discriminating between the three hypotheses discussed in the preceding section.

3.1. *Volatility of S&P500 futures and 30-year T-bond futures*

Following Andersen *et al.* (hereafter ABDL, 2003), we construct daily realised volatility measures on the basis of high-frequency intraday data. Specifically, we use the daily realised volatility constructed from 5-minute returns for the S&P500 futures contract (denoted by SP hereafter) to measure the overall market volatility. The S&P are traded on the Chicago Mercantile Exchange (CME). It is among the most liquid securities traded, so that information is incorporated very quickly into its price. What's more, this also reduces the impact of measurement errors due to non-synchronous trading or bid-ask bounce effects. The data is obtained from Fair's website (http://fairmodel.econ.yale.edu/rayfair/) and from the Institute for Financial Markets. Our sample covers the period from January 1993 to December 2002.

We use the transaction record for the most liquid contract on each day. The regular trading hours for the S&P are 09:30–16:15 Eastern time. However, to be consistent with the regular trading hours of the NYSE stock market, we only use the 79 5-minute returns from 09:30 to 16:05. We take the price of the last trade in a given 5-minute interval as the price at the end of the interval. The corresponding 5-minute returns are then constructed using the log price difference over each of these intervals. Lastly, the daily realised variances ($RV_t(SP)$) and logarithmic standard deviation ($LV_t(SP)$) are simply defined by:

$$RV_t(SP) = \sum_{i=1}^{79} r_{m,t,i}^2 \tag{4}$$

$$LV_t(SP) = \frac{1}{2} \ln RV_t(SP) \tag{5}$$

where $r_{m,t,i} = 100 \ln (P_i/P_{i-1})$ denotes the ith 5-minute continuously compounded return for day t.

The unconditional distribution of the resulting SP volatilities are summarised in the first two columns of Table 1. The average of the daily realised variances equals 1.739, which implies an annualised standard deviation of 20.9%. The minimum daily realised variance is 0.064, corresponding to an annualised standard deviation of 4%, while the maximum daily realised variance is 10.114, corresponding to an annualised standard deviation of 50.28%. There is also positive skewness and excess kurtosis in the realised variance distribution. Meanwhile, the skewness and kurtosis of the logarithmic standard deviation, $LV(SP)$, are much closer to that of a normal distribution. The top panel of Figure 1 also plots the time series of $LV(SP)$.

We use the realised daily volatility of the 30-year US Treasury Bond futures contract (denoted by TB hereafter) to proxy for macroeconomic shocks that increase market-wide uncertainty. The TB contracts are traded on the Chicago Board of Trade (CBT). They are among the most actively traded Treasury instruments. As documented in Andersen *et al.* (2005), among others, the prices of the T-Bond contracts react very quickly to macroeconomic shocks. This in turn allows us to use the TB realised volatility to indirectly assess the magnitude of market-wide uncertainty. The regular trading hours for the TB contracts are 08:20–15:00 Eastern time. We again obtained the transaction records for the TB contracts from Fair's website (http://fairmodel.econ.yale.edu/rayfair/) and from the Institute for Financial Markets.

Analogous to SP volatilities discussed above, we construct the TB daily realised variance, $RV(TB)$, and logarithmic standard deviation, $LV(TB)$, using the 80 continuously compounded 5-minute returns during the active trading day. Columns 3 and 4 of Table 1 summarise the distribution of the two volatility series. The average of the daily realised variance equals 0.289, implying an annualised standard deviation of 8.5%, or roughly

Table 1

Daily realised volatility distributions: S&P500 futures and T-Bond futures returns

The table summarises the distributions of the daily realised variance and logarithmic realised standard deviations for the S&P500 futures contracts and 30-year Treasury Bond futures contracts. The sample covers the period from 1 January 1993 to 31 December 2002. The first two columns refers to the distribution of the realised variance, *RV*, and the logarithmic standard deviations, *LV*, for the SP500 contract. The third and fourth columns refer to the distribution of *RV* and *LV* for the T-Bond contract. The daily realised variances are constructed from 5-minute squared returns, as detailed in the text. The logarithmic realised standard deviations is defined by $LV = 1/2{\cdot}log(RV)$.

	SP500 futures		T-Bond futures	
	RV	*LV*	*RV*	*LV*
Mean	1.739	−0.268	0.289	−0.734
SD	0.942	0.515	0.234	0.328
Skew	2.007	−0.362	3.172	0.238
Kurt	7.964	2.059	17.022	0.202
Min	0.064	−3.441	0.022	−1.920
Max	10.114	1.621	2.771	0.510
p10	0.816	−0.897	0.102	−1.140
p25	1.077	−0.619	0.148	−0.956
p50	1.554	−0.253	0.225	−0.746
p75	2.126	0.061	0.346	−0.531
p90	2.879	0.364	0.528	−0.319
n	2539	2539	2509	2509

half of the SP volatility. The minimum daily realised variance is 0.022, corresponding to an annualised standard deviation of 2.35%, while the maximum daily realised variance is 2.771, corresponding to an annualised standard deviation of 26.32%. There is also considerable positive skewness and excess kurtosis in the realised variance distribution. However, as for the SP volatilities, the distribution of the logarithmic TB volatilities is fairly closely approximated by a normal distribution. The bottom panel of Figure 1 plots the time series of $LV(TB)$.

3.2. *Comovement of individual stocks with the market index*

Our study of comovement with the market is based on the 30 individual stocks included in the Dow Jones (DJ) index. We focus on these 30 stocks for the same reason that we use the SP500: they are among the most frequently traded stocks and thus have less microstructure related measurement errors. A list of the 30 companies is provided in Table A1 in the appendix. We obtained high frequency transaction data for each of the stocks from the NYSE-TAQ database. The daily transaction record extends from 09:30 to 16:05 Eastern time, resulting in a total of 79 5-minute returns for each day.

We employ the same realised variance measure used to construct the SP and TB volatilities to capture the daily volatilities of the individual stocks. Table 2 summarises the distributions of these realised variances. Consistent with the summary statistics presented in ABDE (2001), the realised variance for the stocks are extremely right-skewed and leptokurtic, yet the log-transformed realised variance series appears fairly close to being normally distributed.

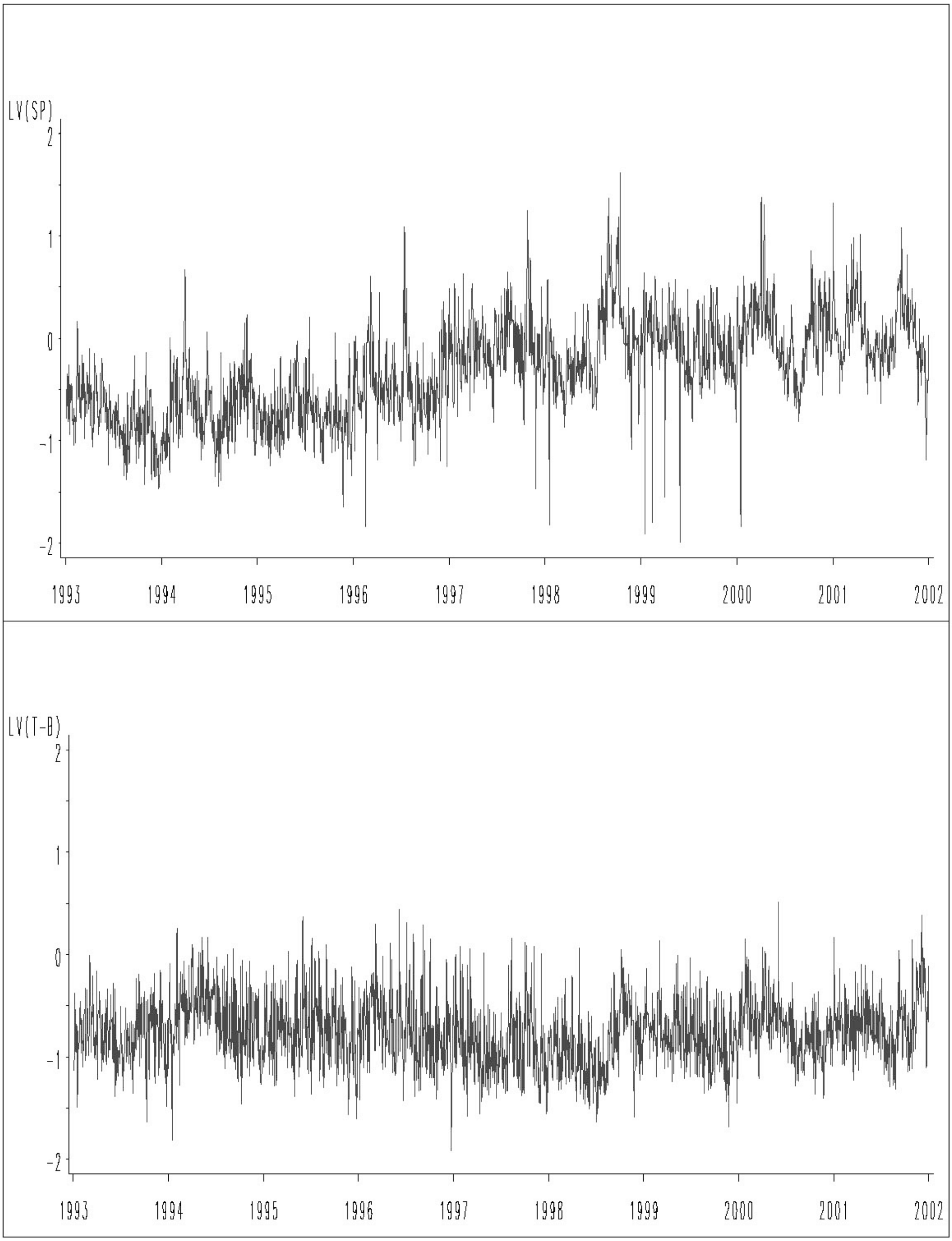

Fig. 1. The time series of $LV(SP)$ and $LV(TB)$

This figure shows the time series of daily logarithmic realised standard deviations for the S&P500 futures contract and the 30-year Treasury Bond futures contract. The sample covers the period from 1 January 1993 to 31 December 2002.

To measure the comovement of the individual stocks with the market index, we decompose the 5-minute returns into a common market component and an asset-specific component. We then construct the realised idiosyncratic volatility from the asset-specific components and compute the ratio of this idiosyncratic variance to the total variance.

Table 2

Daily volatility distribution of Dow Jones 30 stocks

The table summarises the distributions of the daily realised variance for the 30 Dow Jones stocks. The sample covers the period from 1 January 1993 to 31 December 2002. The realised daily variances, *RV*, are calculated from the summation of the squared 5-minute intraday returns. LV denotes the logarithmic realised standard deviations. Further details are described in the main text.

	RV				*LV*			
Stock	Mean	SD	Skew	Kurt	Mean	SD	Skew	Kurt
AA	3.812	3.511	2.935	13.116	0.520	0.379	0.168	0.121
AXP	5.582	4.600	3.983	25.492	0.750	0.324	0.055	0.777
BA	4.274	3.954	10.064	225.284	0.619	0.315	0.209	0.827
C	5.343	6.512	10.537	168.465	0.716	0.313	0.727	2.064
CAT	3.784	3.390	4.670	45.078	0.543	0.337	0.299	0.387
DD	3.845	3.045	3.679	22.253	0.577	0.294	0.544	0.665
DIS	4.851	4.994	9.809	187.395	0.674	0.318	0.436	1.135
EK	3.375	3.235	5.544	47.419	0.499	0.302	0.710	1.622
GE	3.310	3.540	7.333	99.795	0.468	0.335	0.579	0.885
GM	3.580	2.728	4.076	29.687	0.543	0.301	0.107	0.834
HD	5.069	4.969	7.312	102.689	0.703	0.305	0.564	1.671
HON	4.955	5.716	7.055	87.029	0.648	0.366	0.407	0.699
HPQ	6.014	7.519	8.805	140.917	0.729	0.382	0.510	0.377
IBM	3.733	3.518	4.796	41.246	0.532	0.338	0.390	0.563
INTC	7.588	7.713	5.578	57.860	0.870	0.362	0.333	0.230
IP	4.444	3.646	3.459	24.601	0.625	0.344	0.078	0.102
JNJ	3.123	2.418	5.070	53.283	0.472	0.307	0.066	0.573
JPM	5.364	7.041	10.080	182.762	0.687	0.354	0.601	1.371
KO	3.362	2.505	4.757	45.429	0.518	0.291	0.125	0.753
MCD	4.251	3.428	6.829	101.577	0.633	0.288	0.368	0.824
MMM	2.765	2.303	3.505	20.941	0.390	0.339	0.065	0.484
MO	3.990	5.827	12.601	228.611	0.538	0.355	0.541	1.414
MRK	3.735	3.258	6.005	73.719	0.547	0.325	0.169	0.613
MSFT	5.420	5.522	7.499	112.295	0.711	0.350	0.274	0.463
PG	3.166	2.778	5.377	48.752	0.475	0.298	0.490	1.226
SBC	4.203	3.699	4.752	37.823	0.613	0.304	0.465	1.348
T	4.315	4.454	5.098	39.938	0.601	0.328	0.811	0.943
UTX	3.185	3.547	5.415	50.949	0.410	0.394	0.323	0.114
WMT	7.009	5.661	8.660	188.967	0.859	0.350	−0.353	0.075
XOM	2.598	2.371	5.767	54.738	0.378	0.286	0.855	1.694
Mean	4.335	4.247	6.368	85.270	0.598	0.328	0.371	0.853
SD	1.194	1.565	2.454	64.930	0.126	0.029	0.269	0.522

This variance ratio in turn serves as our (inverse) measure of the stock's comovement with the market index.

To extract the idiosyncratic component we first filter out the influence of the market return. Although the 30 Dow Jones stocks are among the most liquid, their prices might still react to market information with a delay. Hence, to fully filter out the market movement, we regress the 5-minute returns for each of the individual stocks on the contemporaneous and lagged 5-minute S&P500 returns on a day-by-day basis:

$$r_{i,t,\tau} = \beta_{i,t} r_{m,t,\tau} + \sum_{j=1}^{J} \beta_{i,t,j}\, r_{m,t,\tau-j} + \epsilon_{i,t,\tau}, \tag{6}$$

where $\tau = J + 1, J + 2, \ldots, 79$. Inclusion of more lagged market returns helps to form a cleaner decomposition of the market and idiosyncratic return components. However, the inclusion of more lags also reduces the number of observations. Thus, to keep a reasonable balance, we choose to include four lags, of $J = 4$, as all of the S&P500 returns beyond 20 minutes generally were insignificant. The resulting average beta estimates for each of the 30 stocks are summarised in Table A2 in the appendix.

To capture the comovement of an individual stock with the market index, we next compute the ratio of idiosyncratic realised variance to total realised variance:

$$Ratio(i)_t^o = \frac{\sum_{\tau=5}^{79} \epsilon_{i,t,\tau}^2}{\sum_{\tau=5}^{79} r_{i,t,\tau}^2}. \tag{7}$$

This ratio is inversely related to the comovement of the stock's return with the SP return. The distribution of the idiosyncratic variance ratios, $Ratio^o$, are summarised in the first four columns of Table 3. The unconditional mean ranges from 0.721 to 0.853, with an average of 0.804. This indicates that the idiosyncratic variance accounts for about 80% of the total daily variances, or 90% of the daily standard deviation. The time series of the idiosyncratic variance ratios are plotted in Figure 2. As immediately evident from the figure, the values of the $Ratio(i)_t^o$'s are bounded between zero and one by construction.

To facilitate our empirical analysis, we therefore transform the idiosyncratic variance ratio according to the monotone transformation:

$$Ratio(i)_t = -\ln\left(\frac{1}{Ratio(i)_t^o} - 1\right) \tag{8}$$

which changes the support from [0, 1] to $(-\infty, \infty)$. The unconditional distributions of the $Ratio(i)$ series are summarised in the last four columns of Table 3. In contrast to the pronounced negative skewness of the raw ratio series cause by the boundary at unity, the transformed ratio series are close to symmetrically distributed, and as such, much more amenable to standard time series analysis. Comparing the time series plots for each of the 30 transformed ratios in Figure 3 to those for the raw ratios in Figure 2 further underscores this point.[5]

4. Empirical Analysis

Our analysis in this section focuses on the responses of both market volatility and the comovement of the individual stocks to macroeconomic shocks. To assess these responses, we formulate and estimate a series of bivariate VAR's.

[5] It appears from Figure 3 that for some of the stocks there is a slight downward trend in the transformed idiosyncratic variance ratio over the sample. To guard against this, we repeated all of the model estimates reported below with time trends included. The main results were all the same. Further details regarding these robustness checks are available upon request.

Table 3

Daily idiosyncratic variance ratio of Dow Jones 30 stocks

The table summarises the distributions of the daily idiosyncratic variance ratios for the 30 Dow Jones stocks. The sample covers the period from 1 January 1993 to 31 December 2002. The daily idiosyncratic variance ratios, *Ratio*, refer to the ratio of the daily idiosyncratic realised variance to the daily total realised variance. The daily idiosyncratic realised variances are constructed on the basis of the residuals from a regression of the 5-minute stock returns on the contemporaneous and four lagged 5-minute S&P500 Futures returns. The daily total realised variances are constructed from the summation of the squared 5-minute returns. The transformed idiosyncratic variance ratios are calculated as $-\ln(1/Ratio - 1)$. Further details are described in the main text.

	Ratio				*Ratio (transformed)*			
Stock	Mean	SD	Skew	Kurt	Mean	SD	Skew	Kurt
AA	0.834	0.101	−1.190	1.855	1.797	0.779	0.227	0.397
AXP	0.796	0.138	−0.903	0.453	1.612	0.982	0.285	−0.028
BA	0.840	0.109	−1.315	1.872	1.889	0.862	0.146	0.219
C	0.778	0.149	−0.903	0.177	1.490	0.965	0.077	−0.385
CAT	0.813	0.117	−1.127	1.394	1.663	0.827	0.169	0.352
DD	0.805	0.120	−1.072	1.198	1.605	0.828	0.142	0.132
DIS	0.831	0.114	−1.218	1.497	1.813	0.863	0.135	0.097
EK	0.839	0.099	−1.232	2.200	1.839	0.792	0.297	0.520
GE	0.731	0.154	−0.668	−0.116	1.166	0.891	0.217	−0.058
GM	0.827	0.110	−1.140	1.290	1.773	0.829	0.149	0.022
HD	0.817	0.123	−1.191	1.391	1.718	0.881	0.078	0.001
HON	0.830	0.113	−1.324	2.097	1.800	0.842	0.013	0.067
HPQ	0.793	0.106	−0.779	0.680	1.477	0.711	0.346	0.479
IBM	0.750	0.141	−0.717	0.002	1.262	0.851	0.266	0.118
INTC	0.721	0.175	−0.487	−0.803	1.169	1.035	0.298	−0.454
IP	0.837	0.109	−1.387	2.083	1.842	0.815	−0.051	0.063
JNJ	0.809	0.114	−0.909	0.656	1.634	0.824	0.344	0.229
JPM	0.793	0.128	−0.877	0.391	1.545	0.878	0.294	0.122
KO	0.802	0.123	−0.994	0.961	1.604	0.869	0.339	0.415
MCD	0.853	0.095	−1.238	1.707	1.965	0.799	0.202	0.326
MMM	0.797	0.129	−1.010	0.657	1.574	0.877	0.191	0.172
MO	0.841	0.105	−1.274	1.739	1.884	0.832	0.130	0.150
MRK	0.802	0.125	−0.919	0.518	1.620	0.903	0.442	0.800
MSFT	0.723	0.172	−0.507	−0.623	1.177	1.034	0.333	−0.350
PG	0.787	0.123	−0.751	0.152	1.486	0.829	0.328	0.015
SBC	0.821	0.120	−1.099	0.984	1.753	0.896	0.225	0.146
T	0.831	0.105	−1.022	0.973	1.795	0.822	0.288	0.140
UTX	0.827	0.109	−1.148	1.393	1.763	0.819	0.206	0.311
WMT	0.798	0.156	−1.071	0.461	1.678	1.073	0.024	−0.337
XOM	0.782	0.137	−1.006	0.742	1.475	0.881	0.116	0.103
Mean	0.804	0.124	−1.016	0.933	1.629	0.870	0.208	0.126
SD	0.035	0.021	0.234	0.792	0.218	0.080	0.115	0.274

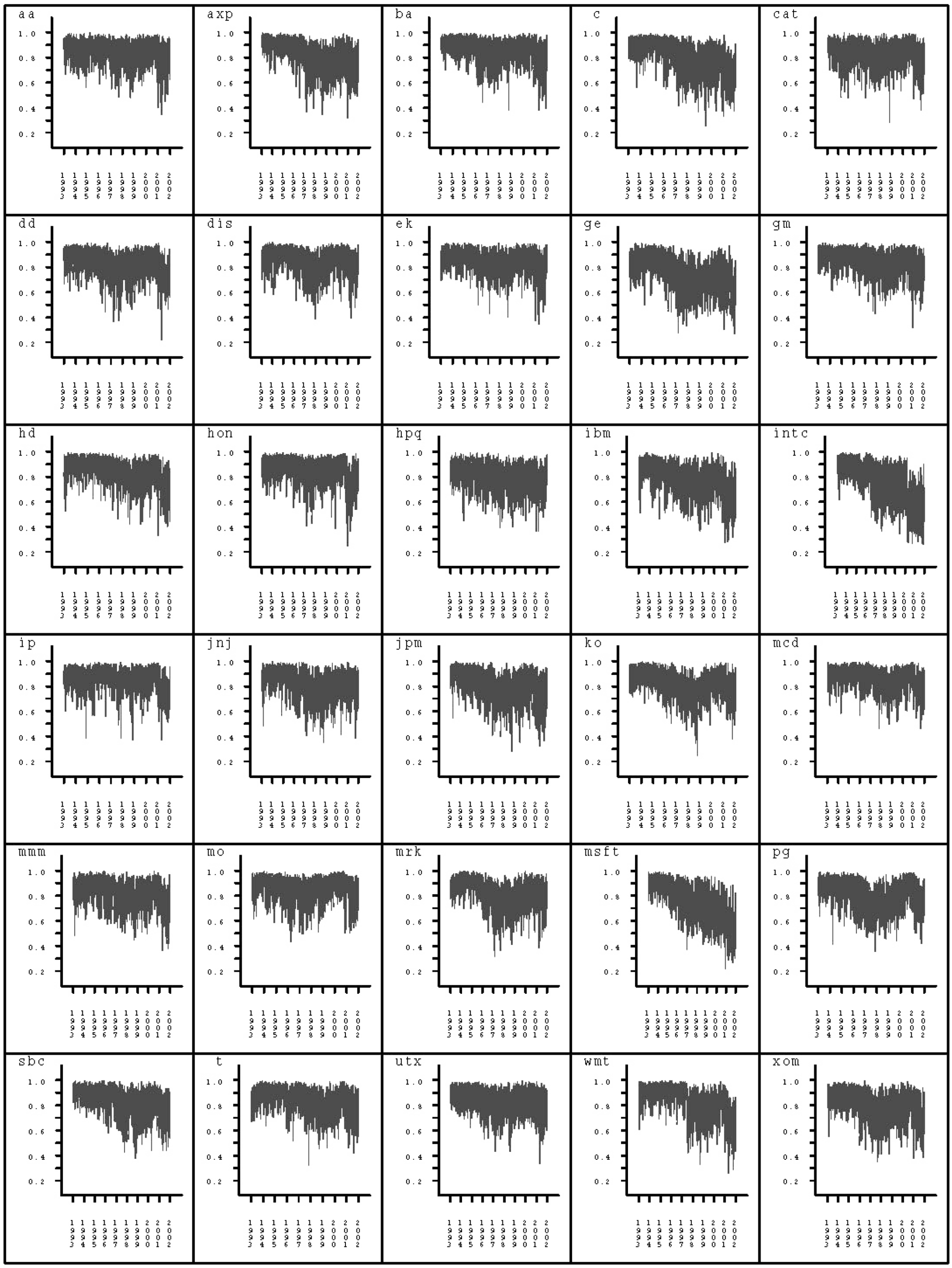

Fig. 2. The time series of idiosyncratic variance ratios

This figure shows the time series of the daily idiosyncratic variance ratios for the 30 Dow Jones stocks. The sample covers the period from 1 January 1993 to 31 December 2002.

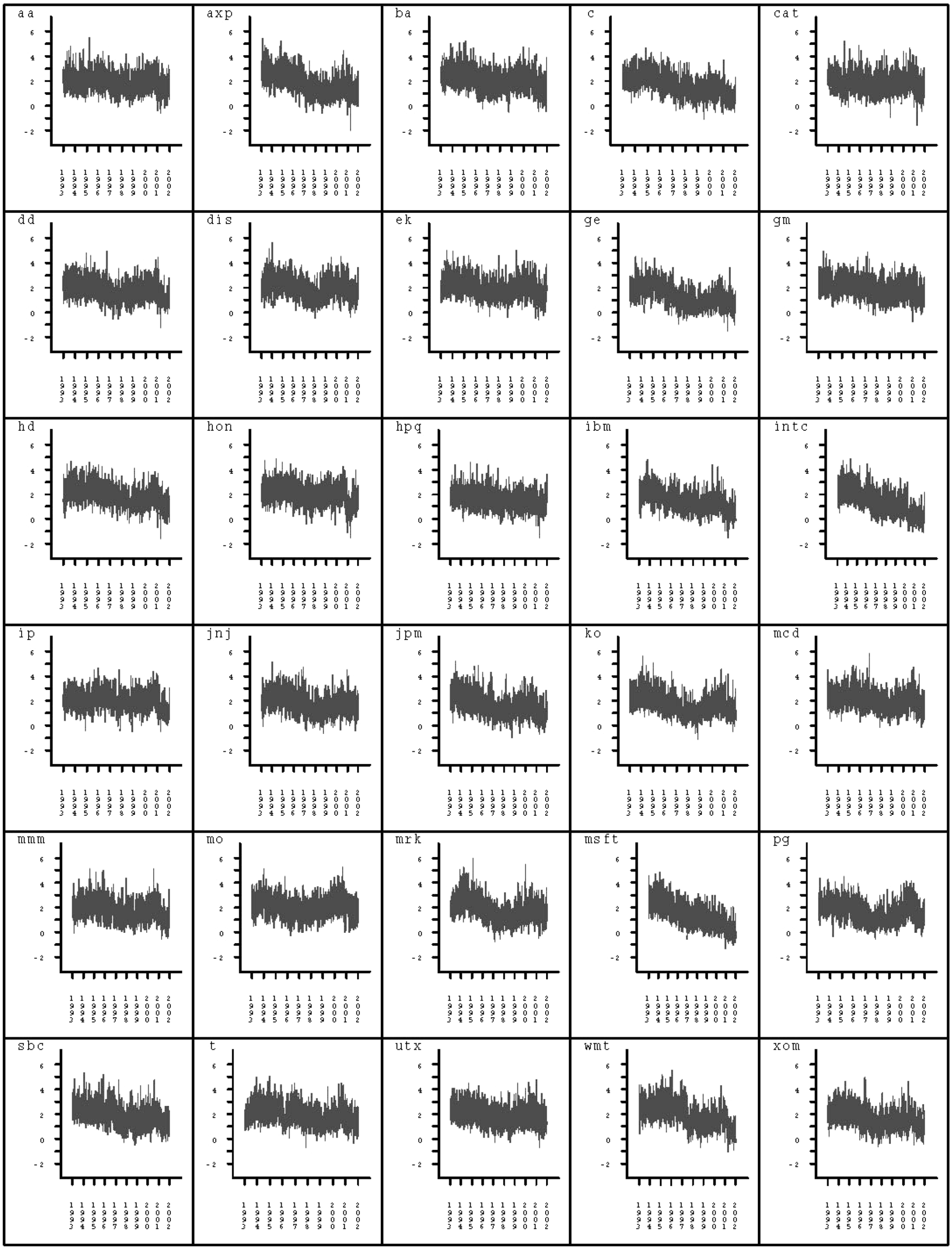

Fig. 3. The time series of transformed idiosyncratic variance ratios

This figure shows the time series of the daily transformed idiosyncratic variance ratios for the 30 Dow Jones stocks. The sample spans 1 January 1993 to 31 December 2002.

4.1. *The response of the market volatility to macroeconomic shocks*

Our analysis of the response of market volatility to macroeconomic shocks is based on the following VAR for the logarithmic SP and TB volatilities:

$$Y_t^{SP} = \begin{bmatrix} LV(SP) \\ \\ LV(TB) \end{bmatrix}_t = C^{SP} + \sum_{p=1}^{P} \Phi_p^{SP} Y_{t-p}^{SP} + \epsilon_t \tag{9}$$

where[6]

$$\epsilon_t \sim \text{i.i.d. } N(0, \Omega_{SP}) \qquad \Omega_{SP} = \begin{bmatrix} Var_{SP} & Cov_{SP,TB} \\ Cov_{SP,TB} & Var_{TB} \end{bmatrix}. \tag{10}$$

Equation 9 allows us to directly examine the dynamic relationship between the market volatility and macro shocks, as proxied by shocks to the TB volatility.

The estimation results are summarised in Table 4.[7] Panel A in the table gives the estimates for the contemporaneous variance-covariance matrix. The innovations in $LV(SP)$ and $LV(TB)$ have a contemporaneous covariance of 0.031, and a correlation of 0.429. The following Wald-type test statistic (see Hamilton (1994) for details):

$$\frac{\sqrt{T}\hat{\sigma}_{12}}{\left(\hat{\sigma}_{11}\hat{\sigma}_{22} + \hat{\sigma}_{12}^2\right)^{1/2}} \sim N(0, 1) \tag{11}$$

provide a simple way of assessing the statistical significance of the comovements. Evaluating this statistic at the point estimates reported in the table results in value of 5.75, with a corresponding p-value of zero to the first three decimal points. Hence, the innovations to two daily volatility series are clearly contemporaneously correlated.

To further assess the economic significance of this contemporaneous relationship among the two series, it is useful to consider the average change in $LV(SP)$ associated with a contemporaneous one-unit shock to $LV(TB)$. We denote this value as $\Delta LV(SP) = Cov_{SP,TB})/Var(TB)$. The corresponding point estimate, reported in the last column of Panel A of Table 4, suggests that on days in which there is one-unit shock to LV(TB), there is typically a contemporaneous increase of 0.395 in LV(SP). In other words, consistent with all three Hypotheses I, II and III, on days when there is a macroeconomic shock to the treasury bond markets that causes the volatility of the TB futures to rise, the volatility of the S&P also increases.

Panel B of Table 4 lists the impulse response and cumulative impulse response coefficients of $LV(SP)$ with respect to $LV(TB)$ shocks. The impulse response function is also plotted in Figure 4. In contrast to the positive and significant contemporaneous relationship between SP and TB volatilities, shocks to $LV(TB)$ have a significantly *negative* impact on $LV(SP)$ on subsequent days. The magnitude of this effect decreases over time, but it remains significant for up to seven days. Also, a one-time positive unit

[6] The assumption of i.i.d. normally distributed errors is merely for convenience. The resulting maximum likelihood estimates are readily interpreted as robust least squares estimates more generally.

[7] All of the results reported below are based on an unrestricted VAR with a lag of 25 days, or $P = 25$.

Table 4
VAR analysis of LV(SP) and LV(TB)

This table reports the estimates of the VAR(25) model for the logarithmic daily realised standard deviation of the S&P500 futures contract, *LV*(SP), and the 30-year Treasury Bond futures contract, *LV*(TB). The sample covers the period from 1 January 1993 to 31 December 2002. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

A. Contemporaneous relationship
The first three numbers report the estimates for each of the elements in the variance-covariance matrix for the innovations. The fourth number gives the corresponding correlation. The final number reported under $\Delta LV(SP) = Cov_{SP,TB}/Var_{TB}$ corresponds to the average contemporaneous shock to *LV(SP)* associated with a unit shock to *LV(TB)*.

Var_{SP}	Var_{TB}	$Cov_{SP,TB}$	$Corr_{SP,TB}$	$\Delta LV(SP)$
0.067	0.079	0.031	0.429	0.395

B. Response of LV(SP) to LV(TB) shocks
This panel reports the impulse response and cumulative impulse response coefficients, along with their standard errors, for *LV(SP)* with respect to innovations in *LV(TB),* at lags ranging from 1 to 8 days.

Lag	Impulse response coefficients		Cumulative impulse response coefficients	
	Coefficients	SE	Coefficients	SE
1	−0.138***	0.021	−0.138***	0.021
2	−0.126***	0.022	−0.264***	0.043
3	−0.089***	0.023	−0.353***	0.071
4	−0.053**	0.024	−0.406***	0.105
5	−0.065***	0.024	−0.471***	0.145
6	−0.078***	0.025	−0.549***	0.194
7	−0.061**	0.025	−0.609**	0.249
8	−0.035	0.025	−0.644**	0.313

shock to $LV(TB)$ decreases $LV(SP)$ over the following week, or five trading days, by an average cumulative amount of 0.471.

The existence of significant responses in SP volatility to past macroeconomic shocks is clearly inconsistent with the hypothesis that investors can instantaneously resolve the associated uncertainty, thus contradicting Hypothesis I. Furthermore, the negative sign of the responses is also at odds with Hypothesis II, which posits that investors can only process a finite amount of information per day and that the cross-sectional structure of the information flow is constant over time. On the other hand, the information flow dynamics is entirely consistent with that predicted by the attention shift Hypothesis III: when investors are capacity constrained, they would temporarily shift more attention to processing information about the market after a macroeconomic shock that increases market-wide uncertainty, and then shift their attention back to asset specific information on subsequent days. As a result, the SP volatility should increase in response to the

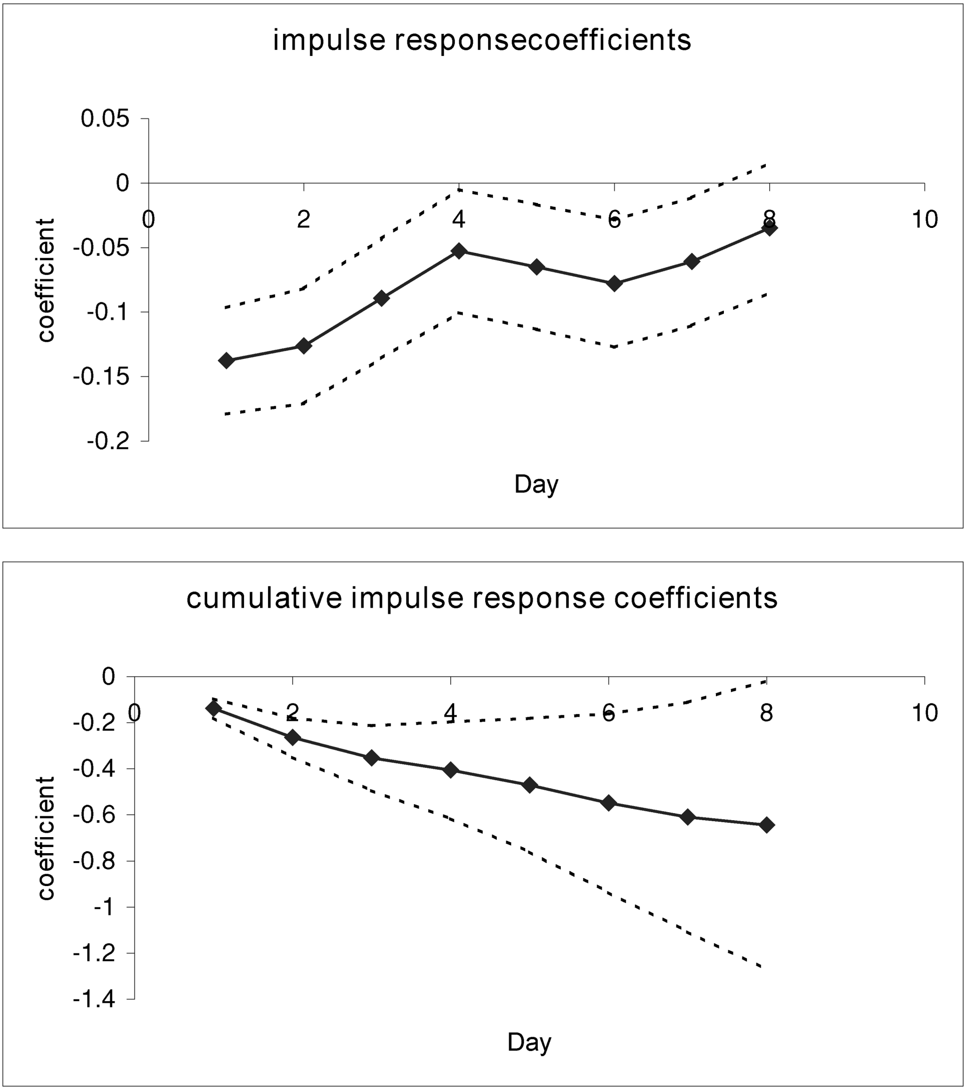

Fig. 4. Impulse response of *LV*(*SP*) to *LV*(*TB*) shocks

This figure shows the impulse and cumulative impulse response functions of *LV*(*SP*) with respect to *LV*(*TB*) shocks. The estimates are based on a VAR(25) model.

TB volatility shock contemporaneously, but reverse on the following days, as directly implied by the VAR estimates.

4.2. *The response of individual stocks' idiosyncratic variance ratio to macroeconomic shocks*

To further analyse the impact of macroeconomic shocks on the comovement of the individual stocks with the market, we estimate the following VAR for the logarithmic T-Bond volatility and the (transformed) idiosyncratic variance ratios for each of the

30 stocks:

$$Y_t^i = \begin{bmatrix} Ratio^i \\ LV(TB) \end{bmatrix}_t = C^i + \sum_{p=1}^{P} \Phi_p^i Y_{t-p}^i + \eta_t^i \tag{12}$$

where $i = 1, 2, 3, \ldots, 30$ represents each of the Dow Jones 30 stocks, and

$$\eta_t^i \sim \text{i.i.d. } N(0, \Omega^i) \qquad \Omega^i = \begin{bmatrix} Var_i & Cov_{Ratio^i,TB} \\ Cov_{Ratio^i,TB} & Var_{TB} \end{bmatrix}. \tag{13}$$

We summarise the estimation results in the form of two tables – one for the contemporaneous relationship between the $LV(TB)$ shocks and the transformed idiosyncratic variance ratios, and another for the impulse and cumulative response functions.

Turning to Table 5 and the contemporaneous relationship, it follows that the covariances between $LV(TB)$ and *Ratio* are negative, and according to the Wald test discussed above significantly so, for all of the 30 stocks. Further, calculating the typical change in *Ratio* associated with a positive unit shock to $LV(TB)$, the average value across the 30 stocks is -0.349, with maximum of -0.258 for INTC and a minimum of -0.460 for JPM. Given the inverse relationship of *Ratio* and the comovement of the individual stock's return with the market index, these results therefore suggest that comovement increases contemporaneously with the arrival of macroeconomic shocks. This finding is consistent with all three Hypotheses I, II, and III.

Turning to Table 6 and the lagged responses of $Ratio(i)$ to a shock in $LV(TB)$, Panel A describes the impulse response coefficients, while Panel B describes the cumulative impulse response coefficients. As seen from Panel A, a unit shock to $LV(TB)$ has an average positive effect of 0.039 on $Ratio(i)$ on the following day, an effect of 0.051 two days after the initial shock, and an effect of 0.021 three days later. For the first three lags, 16 of the 30 stocks have at least one positive and significant coefficient. Overall there are also very few negative coefficients for the first three days, and none of them are statistically significant. These findings are also visually evident from the plots of the impulse response coefficients in Figure 5.[8]

The cumulative impulse response coefficients in Panel B tell a similar story. The average cumulative impact of a unit shock to $LV(TB)$ on the value of $Ratio^o$ over the following three days equal 0.039, 0.089, and 0.110, respectively. Also, 11 out of the 30 stocks have at least one significant cumulative impulse response coefficient within a one-week horizon, and for none of the stocks is the effect significantly negative. Again, the graphical representation of all 30 cumulative impulse response coefficients in Figure 6 further underscore this systematic finding.

Our finding of significant reactions in the individual stocks' idiosyncratic variance ratios to past macroeconomic shocks is again inconsistent with the hypothesis that investors can instantaneously resolve the associated uncertainty, thus rejecting Hypothesis I. The positive sign of the responses is also inconsistent with Hypothesis II, which states that investors can only process a finite amount of information and that the

[8] The two dashed lines included in Figures 5 and 6, represent the usual $\pm$ 1.96 standard error bands.

Table 5

Contemporaneous relationship of *Ratio*(i) and $LV(TB)$

This table reports the estimates of the VAR(25) model for the daily transformed idiosyncratic variance ratio for each of the 30 Dow Jones stocks, *Ratio*, and the 30 year Treasury Bond futures contract, $LV(TB)$. The first two columns give the estimated variance and covariance for the contemporaneous innovations. The third and fourth columns report the Wald statistic for testing the covariance equal to zero along with the corresponding P-value. The fifth column gives the correlation. $\Delta Ratio$ refers to the contemporaneous shock to *Ratio* associated with a positive unit shock to $LV(TB)$. It is calculated as $Cov_{Ratio,TB}/Var_{TB}$. The sample covers the period from 1 January 1993 to 31 December 2002.

Firm	Var(Ratio)	Cov	Stats	P-value	Corr	ΔRatio
AA	0.466	−0.025	−6.436	0.000	−0.130	−0.317
AXP	0.442	−0.030	−7.993	0.000	−0.162	−0.385
BA	0.499	−0.031	−7.735	0.000	−0.157	−0.396
C	0.413	−0.032	−8.673	0.000	−0.176	−0.405
CAT	0.465	−0.029	−7.540	0.000	−0.153	−0.373
DD	0.432	−0.030	−7.993	0.000	−0.162	−0.383
DIS	0.457	−0.022	−5.897	0.000	−0.119	−0.287
EK	0.465	−0.027	−6.925	0.000	−0.140	−0.341
GE	0.373	−0.030	−8.710	0.000	−0.177	−0.387
GM	0.458	−0.026	−6.919	0.000	−0.140	−0.339
HD	0.438	−0.032	−8.419	0.000	−0.171	−0.405
HON	0.469	−0.023	−5.969	0.000	−0.120	−0.295
HPQ	0.414	−0.034	−9.355	0.000	−0.190	−0.440
IBM	0.366	−0.025	−7.398	0.000	−0.150	−0.324
INTC	0.376	−0.020	−5.812	0.000	−0.117	−0.258
IP	0.435	−0.028	−7.591	0.000	−0.154	−0.363
JNJ	0.441	−0.024	−6.417	0.000	−0.129	−0.307
JPM	0.453	−0.036	−9.351	0.000	−0.190	−0.460
KO	0.435	−0.028	−7.594	0.000	−0.154	−0.364
MCD	0.462	−0.021	−5.488	0.000	−0.110	−0.270
MMM	0.447	−0.026	−6.783	0.000	−0.137	−0.328
MO	0.490	−0.030	−7.529	0.000	−0.152	−0.381
MRK	0.450	−0.026	−6.871	0.000	−0.139	−0.333
MSFT	0.358	−0.021	−6.252	0.000	−0.126	−0.270
PG	0.415	−0.027	−7.532	0.000	−0.152	−0.352
SBC	0.476	−0.028	−7.245	0.000	−0.146	−0.362
T	0.461	−0.028	−7.366	0.000	−0.149	−0.362
UTX	0.463	−0.026	−6.723	0.000	−0.136	−0.331
WMT	0.436	−0.023	−6.227	0.000	−0.125	−0.298
XOM	0.410	−0.030	−8.333	0.000	−0.169	−0.387
Mean	0.440	−0.027	−7.267	0.000	−0.147	−0.349
SD	0.036	0.004	1.020	0.000	0.021	0.050

cross-sectional structure of the information flow stays constant over time. On the other hand, the documented time-varying cross-sectional structure of the information flow is directly in line with the patterns predicted by the attention shift Hypothesis III: when investors are constrained by their information processing capacity, they would

Table 6

Impulse response of *Ratio*(i) to shocks in $LV(TB)$

This table reports the impulse and cumulative impulse response coefficients of the VAR(25) model for the daily transformed idiosyncratic variance ratio for each of the 30 Dow Jones stocks, *Ratio*, and the 30 year Treasury Bond futures contract, $LV(TB)$. The lags range from 1 to 5 days. The sample covers the period from 1 January 1993 to 31 December 2002. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

A. Impulse response coefficients

Firm	lag1	lag2	lag3	lag4	lag5
AA	−0.047	0.001	0.087*	−0.041	−0.031
AXP	0.046	0.064	0.024	−0.041	−0.032
BA	0.004	0.018	−0.041	−0.074	0.036
C	0.008	0.041	0.049	−0.046	0.065
CAT	−0.049	0.022	−0.045	0.010	−0.014
DD	0.105**	−0.077	−0.004	−0.132***	−0.087*
DIS	0.114**	0.091*	0.108**	0.005	0.061
EK	0.041	0.016	0.028	−0.026	−0.046
GE	0.001	0.069	0.071	−0.046	0.046
GM	0.024	0.073	0.020	−0.063	0.077
HD	0.001	0.009	0.120**	−0.104**	0.055
HON	−0.071	0.111**	0.065	0.106**	−0.062
HPQ	−0.038	0.056	0.005	−0.050	−0.061
IBM	0.061	0.092**	−0.005	−0.009	−0.002
INTC	0.086*	0.096**	−0.022	0.022	0.050
IP	0.015	0.096**	−0.007	−0.013	−0.035
JNJ	−0.007	0.112**	0.028	−0.070	0.097**
JPM	0.041	0.036	−0.016	−0.063	0.018
KO	0.056	0.012	0.011	−0.015	−0.007
MCD	0.052	0.009	−0.005	0.065	0.003
MMM	0.020	0.135***	0.023	0.016	−0.018
MO	0.141***	0.072	0.009	0.079	0.008
MRK	0.066	0.034	0.052	0.063	0.030
MSFT	0.108**	0.017	0.001	0.043	−0.017
PG	0.094**	0.035	0.065	0.018	−0.023
SBC	0.100**	−0.013	0.066	−0.035	0.063
T	0.063	0.116**	−0.045	−0.024	0.024
UTX	0.005	0.005	−0.050	0.005	−0.109**
WMT	0.013	0.064	−0.007	−0.013	−0.029
XOM	0.112**	0.104**	0.038	0.045	−0.016
Mean	0.039	0.051	0.021	−0.013	0.001
SD	0.054	0.048	0.045	0.054	0.050

temporarily shift more attention to processing information about the market factor after a macroeconomic shock that increases market-wide uncertainty, and then subsequently shift their attention back to asset specific information on subsequent days. As a result, comovement between individual assets and the market index should increase in response

Table 6
Continued.

B. Cumulative Impulse response coefficients					
Firm	lag1	lag2	lag3	lag4	lag5
AA	−0.047	−0.046	0.041	0.000	−0.031
AXP	0.046	0.110	0.135	0.093	0.062
BA	0.004	0.022	−0.020	−0.094	−0.058
C	0.008	0.049	0.098	0.051	0.116
CAT	−0.049	−0.027	−0.072	−0.062	−0.076
DD	0.105**	0.028	0.024	−0.108	−0.194
DIS	0.114**	0.205**	0.313***	0.318**	0.380*
EK	0.041	0.057	0.084	0.058	0.013
GE	0.001	0.070	0.141	0.095	0.141
GM	0.024	0.097	0.117	0.054	0.131
HD	0.001	0.009	0.130	0.026	0.081
HON	−0.071	0.040	0.105	0.211	0.149
HPQ	−0.038	0.018	0.023	−0.027	−0.088
IBM	0.061	0.153**	0.148	0.139	0.137
INTC	0.086*	0.181**	0.160	0.182	0.232
IP	0.015	0.111	0.105	0.092	0.056
JNJ	−0.007	0.105	0.133	0.063	0.160
JPM	0.041	0.077	0.061	−0.002	0.016
KO	0.056	0.068	0.079	0.064	0.057
MCD	0.052	0.061	0.057	0.121	0.125
MMM	0.020	0.155**	0.178*	0.194	0.176
MO	0.141***	0.214**	0.223*	0.302*	0.310
MRK	0.066	0.101	0.153	0.215	0.245
MSFT	0.108**	0.125*	0.126	0.169	0.151
PG	0.094**	0.129*	0.193*	0.211	0.188
SBC	0.100**	0.087	0.153	0.118	0.181
T	0.063	0.179**	0.135	0.111	0.135
UTX	0.005	0.010	−0.040	−0.035	−0.145
WMT	0.013	0.077	0.070	0.058	0.029
XOM	0.112**	0.216***	0.254**	0.299**	0.283
Mean	0.039	0.089	0.110	0.097	0.099
SD	0.054	0.069	0.083	0.112	0.133

to macroeconomic shocks contemporaneously, but then reverse over longer horizons. This, of course, is entirely consistent with the VAR estimates for the daily TB volatility and *Ratio*(i) series discussed above.

5. Conclusion

This paper analyses the effect on investors attention allocation and asset price co-movements of macroeconomic shocks that increase market-wide uncertainty. We use the daily realised volatility of the 30-year Treasury Bond futures contract to measure macroeconomic shocks and the daily realised volatility of the S& P to capture market-wide information. We also use the ratio of idiosyncratic realised volatility to the total

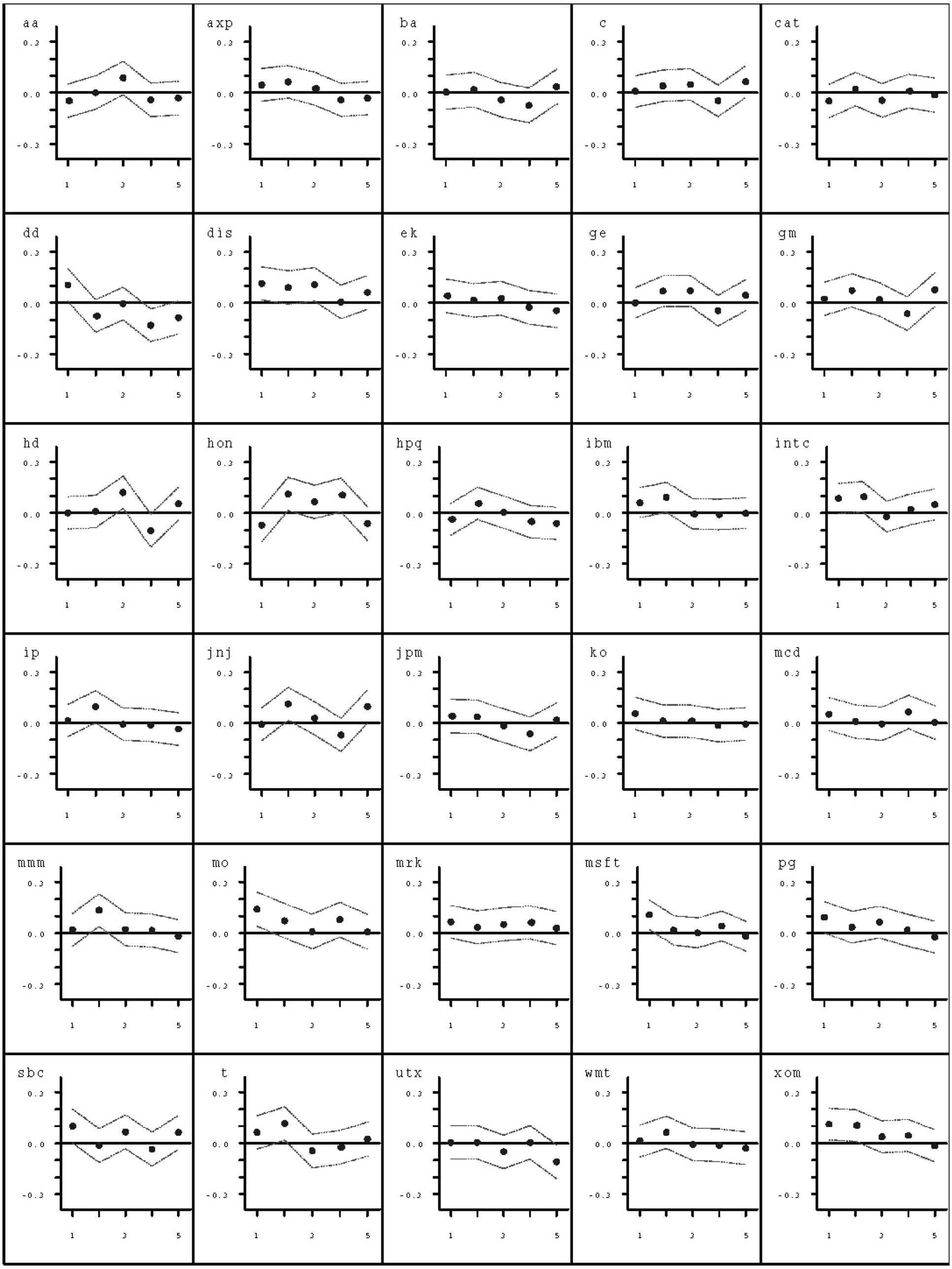

Fig. 5. Impulse response of *Ratio* to *LV*(*TB*) shocks

This figure shows the impulse response functions of the transformed idiosyncratic volatility ratio, *Ratio*, with respect to *LV*(*TB*) shocks for Dow Jones 30 stocks. The estimates are based on a VAR(25) model.

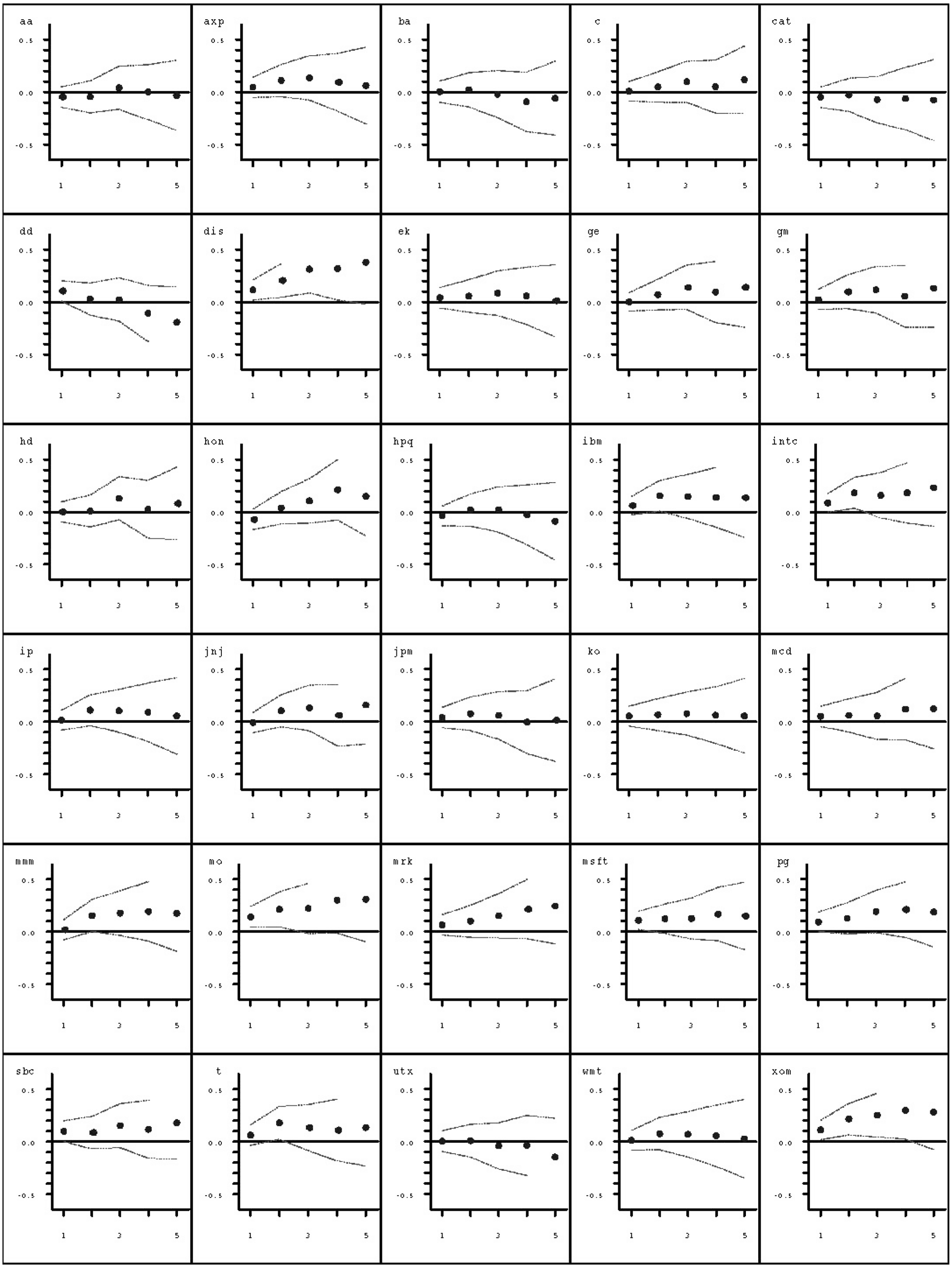

Fig. 6. Cumulative impulse response of *Ratio* to $LV(TB)$ shocks

This figure shows the cumulative impulse response functions of the transformed idiosyncratic volatility ratio, *Ratio*, to $LV(TB)$ shocks for each of the 30 Dow Jones stocks. The estimates are based on a VAR(25) model.

realised volatility of the 30 Dow Jones stocks to capture asset price comovement with the market factor.

We find that market volatility and individual stocks' comovement with the market increases contemporaneously with the arrival of macroeconomic shocks, but decreases significantly in the following five trading days. This pattern contradicts hypotheses that investors can instantaneously resolve any uncertainty and that the cross-sectional composition of investors' information flow remains constant over time. Instead, our result supports the hypothesis that investors attention allocation is time-varying: investors shift their limited mental attention to processing more market information when market-wide uncertainty rises and later divert attention back to processing asset-specific information.

Appendix

Table A1
Dow Jones 30 companies

Ticker	Name
AA	Alcoa INC
AXP	American Express Co
BA	Boeing Co
C	Citigroup Inc
CAT	Caterpillar Inc
DD	Du Pont e i De Nemours
DIS	Disney Walt Co
EK	Eastman Kodak Co
GE	General Electric Co
GM	General Motors Corp
HD	Home Depot Inc
HON	Honeywell Internationa
HPQ	Hewlett Packard Co
IBM	International Business
INTC	Intel Corp
IP	International Paper Co
JNJ	Johnson & Johnson
JPM	Morgan J P & Co Inc
KO	Coca Cola Co
MCD	Mcdonalds Corp
MMM	Minnesota Mining & Mfg
MO	Philip Morris Cos Inc
MRK	Merck & Co Inc
MSFT	Microsoft Corp
PG	Procter & Gamble Co
SBC	S B C Communications I
T	A T & T Corp
UTX	United Technologies Co
WMT	Wal Mart Stores Inc
XOM	Exxon Mobil Corp

Table A2

Time series average of daily betas

This table summarises the daily regression estimates of the 5-minute individual stock returns on a constant and the 5-minute returns on the S&P500 Futures contract. Each of the regressions include the contemporaneous and four lagged values of the S&P500 returns. We compute the time series mean and the t-statistics of the mean for the estimated coefficients, as well as the average R^2. The sample covers the period from 1 January 1993 to 31 December 2002. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Ticker	beta	beta1	beta2	beta3	beta4	R^2
AA	0.43	0.33	0.07	0.01	0.00	0.09
	(53.74)	(45.63)	(10.48)	(1.54)	(0.73)	
AXP	0.60	0.36	0.06	0.03	0.01	0.14
	(53.34)	(36.82)	(6.42)	(2.85)	(1.54)	
BA	0.45	0.27	0.03	0.01	0.01	0.09
	(53.65)	(32.26)	(4.37)	(1.81)	(0.83)	
C	0.66	0.35	0.09	0.03	0.03	0.16
	(59.82)	(38.95)	(11.05)	(3.67)	(4.02)	
CAT	0.49	0.39	0.07	0.00	0.01	0.12
	(64.45)	(50.98)	(9.89)	(0.63)	(1.16)	
DD	0.56	0.36	0.01	−0.01	−0.02	0.13
	(73.58)	(44.79)	(1.44)	(−1.09)	(−2.73)	
DIS	0.51	0.37	0.04	0.01	−0.01	0.10
	(56.96)	(42.06)	(5.15)	(0.73)	(−1.45)	
EK	0.40	0.30	0.05	0.01	0.01	0.09
	(50.79)	(38.77)	(7.76)	(1.80)	(0.82)	
GE	0.71	0.37	0.01	0.00	−0.01	0.21
	(92.00)	(53.20)	(2.56)	(0.02)	(−2.23)	
GM	0.42	0.37	0.09	0.03	0.01	0.10
	(52.63)	(46.10)	(12.54)	(4.06)	(1.30)	
HD	0.51	0.40	0.10	0.02	0.01	0.12
	(51.85)	(42.95)	(12.46)	(2.46)	(1.30)	
HON	0.50	0.35	0.05	0.03	0.00	0.10
	(55.22)	(40.55)	(7.30)	(4.78)	(0.49)	
HPQ	0.72	0.51	0.05	0.01	0.01	0.14
	(74.68)	(52.88)	(7.33)	(1.77)	(0.75)	
IBM	0.70	0.39	0.01	0.00	0.00	0.19
	(85.51)	(48.56)	(1.27)	(0.28)	(−0.20)	
INTC	0.99	0.44	0.12	0.03	0.02	0.22
	(61.68)	(39.00)	(11.13)	(3.37)	(1.56)	
IP	0.46	0.32	0.04	0.00	−0.01	0.09
	(58.05)	(40.09)	(5.92)	(0.10)	(−1.67)	
JNJ	0.47	0.36	0.04	0.00	0.00	0.13
	(61.19)	(42.32)	(6.20)	(−0.18)	(0.56)	
JPM	0.63	0.40	0.08	0.02	0.00	0.14
	(62.84)	(46.82)	(10.88)	(2.93)	(0.61)	
KO	0.54	0.32	0.03	−0.02	−0.01	0.13
	(72.41)	(40.24)	(4.13)	(−2.64)	(−0.92)	
MCD	0.40	0.29	0.05	0.02	0.00	0.08
	(46.72)	(32.34)	(6.23)	(1.96)	(0.08)	
MMM	0.47	0.32	0.04	0.01	−0.01	0.14

Table A2
Continued.

Ticker	beta	beta1	beta2	beta3	beta4	R^2
	(67.58)	(44.97)	(6.80)	(1.54)	(−1.50)	
MO	0.43	0.29	0.03	0.00	−0.01	0.09
	(55.15)	(34.53)	(4.65)	(−0.33)	(−1.70)	
MRK	0.51	0.32	0.03	0.02	0.01	0.13
	(59.56)	(35.13)	(3.83)	(2.26)	(1.18)	
MSFT	0.78	0.40	0.11	0.04	0.00	0.22
	(62.72)	(38.77)	(12.71)	(5.03)	(−0.22)	
PG	0.56	0.33	0.01	−0.02	−0.01	0.15
	(79.75)	(39.58)	(2.27)	(−2.63)	(−1.25)	
SBC	0.48	0.34	0.08	0.02	0.02	0.11
	(51.15)	(41.30)	(10.87)	(2.35)	(2.28)	
T	0.48	0.35	0.03	0.02	−0.01	0.10
	(60.35)	(46.97)	(4.43)	(3.60)	(−1.99)	
UTX	0.41	0.29	0.05	0.02	0.00	0.10
	(60.64)	(42.22)	(8.77)	(2.87)	(0.81)	
WMT	0.59	0.36	0.07	0.03	0.00	0.14
	(48.06)	(31.17)	(6.53)	(2.65)	(0.03)	
XOM	0.52	0.28	−0.01	−0.02	−0.01	0.16
	(75.21)	(40.62)	(−2.72)	(−3.64)	(−1.89)	
Number firms with t-stats >1.96						
	30	30	27	14	2	
Average beta	0.546	0.351	0.052	0.012	0.001	0.131

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