Price Formation in
Multi-Asset Securities Markets

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Price Formation in Multi-Asset Securities Markets

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Introduction

This thesis examines the information aggregation within a financial market where many individual securities are traded. The first two chapters are based on a theoretical model, while the third chapter presents empirical evidence that relates returns on individual securities to those of stock indices. Each chapter is fully self-contained, and chapters can therefore be read in any order.

The first chapter, "Lead-Lag Effects in a Competitive REE Market," introduces a theoretical model of cross-security information aggregation. The model is an extension of the model of Chan (1993)[1] to the case of simultaneous auction markets. The model also provides a richer stochastic structure, allowing revealed information or trading to be correlated across securities.

The information aggregation is manifested in lead-lag effects, or cross-autocorrelations, between securities returns. The model generates a number of testable hypotheses, and the empirical section provides support for several of these hypotheses, using data from the Paris Bourse.

For example, it is demonstrated that cross-autocorrelation is stronger between closely related companies, and that securities with less noisy prices tend to lead other securities. The empirical tests also reject several alternate specifications of cross-security price formation, including nonsynchronous trading and the Chan (1993) model, in favour of the model of cross-security information aggregation.

[1] Full references are found at the end of the relevant chapters.

The model is also used to derive empirical predictions of the lead-lag relation between stock returns and stock option returns, and shows that option returns are unlikely to lead returns on the underlying stock.

In the second chapter, "Learning the True Index Level," the model of cross-security information aggregation is further developed, exploring the implications for index return autocorrelation. Autocorrelation will be high when there is much noise in the index level prior, for example, when opening on Monday morning or after a night of high volatility. Autocorrelation will be low if there is high cross-security autocorrelation in the information revealed in trading, for example, when there is heavy index arbitrage trading. It is shown that the model can explain the finding of McInish and Wood (1991), that is, that autocorrelation may *increase* when trading is active, contrary to the predictions of the nonsynchronous trading hypothesis.

Empirical tests are carried out using opening and closing prices from the Paris Bourse. Most of the model's predictions are supported by the empirical observations. In some cases, the results are at odds with the model's predictions; a discussion follows on how testable hypotheses of investor behaviour can be generated from these results.

In the third and last chapter, "An Empirical Study of Index Return Autocorrelation," the relation between index returns and individual stock returns is studied in-depth. Using data from the Stockholm Stock Exchange, it is demonstrated that individual stock returns and index returns share several important time series properties, including return dependence and day-of-the-week dependence. Therefore, it is concluded that the factors that cause autocorrelation in individual stock returns also cause autocorrelation in index returns. The most probable explanation is a combination of short-term profit taking and long-term time-varying expected returns. For index returns, nonsynchronous trading or cross-security information aggregation add to the autocorrelation in short-term returns.

1

Lead-Lag Effects in a Competitive REE Market

Abstract:
This paper introduces and analyses a model of cross-security information aggregation in a rational expectations equilibrium (REE). The model predicts a well-defined lead-lag structure between securities returns as a result of Bayesian information extraction from realised securities prices. Both leads and lags will be strongest between securities with highly correlated return processes, but only weakly correlated return innovations. Securities whose prices reveal highly precise signals will tend to lead other securities.

The model has important implications for empirical testing of lead-lag effects between financial markets and instruments. As an application of the model, it is demonstrated that stock option returns will tend to lag the corresponding stock prices.

Direct empirical tests of the lead-lag effects between individual stocks on the Paris Bourse provided strong support for the model. In addition to confirming the predicted pattern of leads and lags, the paper demonstrates that the cross-security correlation is higher for short-term returns than for long-term returns for about a third of securities pairs traded on the Paris Bourse. This result is interpreted as strong cross-security correlation of revealed information, which gives the model strong support over alternative specifications of multi-asset securities markets, such as the nonsynchronous trading hypothesis or the Chan (1993) model.

1 Introduction

Although stocks are traded individually, their returns are strongly correlated. This implies the existence of an informational link between the different securities. If the price of one security moves "out of line" relative to other securities, relative prices are corrected in subsequent trading.

While such a mechanism is highly intuitive, its implications for measured stock returns are not well understood. In partial remedy, this paper derives and tests a model of lead-lag effects, or equivalently cross-autocorrelations, between individual securities that trade simultaneously. In the model, information revealed in the price of one security affects the valuation of all other securities. The resulting price adjustments generate a well-defined pattern of cross-autocorrelation in security returns.

The theoretical analysis of the lead-lag relation is basically a study of relative informativeness. If the price of a security is informative for prices of other securities, its returns will lead those of other securities. In general, this lead is reciprocal, so that between closely related securities there will be both leads and lags. If the information revealed in prices is correlated across securities, the cross-security informativeness of realised prices is reduced, and consequently, lead-lag effects are weakened. If the correlation in revealed information is strong, returns may even become negatively cross-autocorrelated.

The lead-lag relation is normally expected to be bidirectional, but empirically there are cases where the lead is virtually unidirectional. One example of such a relation is the case of stocks and stock options. Returns on the underlying stock lead option returns but evidence of the reverse influence is weak. Two reasons for this are discussed in section 4.5. Firstly, an option price is less informative for a stock price than *vice versa*. Secondly, the large number of traded option series results in a one–to–many effect. Each individual option price has low informativeness for the stock price, while the stock price is highly informative for all traded options.

Empirically, long-term returns are usually more strongly correlated across securities than short-term returns. This is also the predicted effect of microstructure effects such as nonsynchronous trading and bid-ask bounce effects. However, as shown in section 5, it is not uncommon that short-term returns are more strongly correlated than long-term returns. This correlation pattern is incompatible with existing models of cross-security price formation,[1] but, according to the model presented in this paper, it is the result of strong cross-security correlation in revealed information.

Most empirical work on lead-lag effects concentrates on the *speed* of price adjustment. A security is said to lead other securities if its price adjustment

[1] Including Admati (1985), Amihud and Mendelson (1987), Lo and MacKinlay (1990a), Chan (1993) and Mech (1993).

to a common factor is earlier than that of other securities. This definition is often used in the literature on lead-lag effects between index futures and their corresponding cash indices.[2] In this paper, the mechanism is different. Trading reveals information that *causes* price revisions of securities with correlated underlying values or information.

Five sections follow this introduction. The next section, section 2, provides a theoretical background based on the body of rational expectations equilibrium models. Section 3 presents a formal model of cross-security information aggregation and derives implications for cross-autocorrelation of securities returns. Section 4 discusses the interpretation and estimation of the model and the empirical results are presented in section 5. The conclusion and suggestions for further development of the model are offered in section 6.

2 Rational expectations equilibrium models

2.1 Introduction

The model developed in this paper uses the large literature on asset pricing in noisy rational expectations equilibria (REE) as a starting point. These models share a large number of properties that make them useful for analysing information transmission in financial markets.[3] Furthermore, the REE models are adaptable to various trading environments. This paper focuses on the auction (order driven) market, but given the similarity of REE models, the model can be used to analyse a price formation in, for example, a specialist dealer or multiple dealer market.

In an REE market, profit maximising agents trade risky assets among themselves in a usually centralised marketplace. Prices result from equilibrium demand strategies, where agents use private information and take any exogenous noise, such as liquidity trading or imperfect information, into account.

The rational expectations equilibrium implies that agents' demand strategies are optimal with regard to the demand strategies of all other agents. All demand strategies are thus optimal with regard to the resulting price. Therefore, the REE prices aggregate all publicly available information about future values. Since the REE prices are optimal with regard to rational agents' demand strategies, the information revealed in a security price can-

[2]Examples include Lo and MacKinlay (1990b), Badrinath et al. (1995), Chan (1992), Brennan et al. (1993) and McQueen et al. (1996).

[3]Seminal papers include Grossman (1976), Grossman and Stiglitz (1980), Hellwig (1980), Glosten and Milgrom (1985) and Kyle (1985, 1989). The basic similarities between the various REE models have been demonstrated by several authors, e.g., Krishnan (1992), Paul (1994), Rochet and Vila (1994), Sarkar (1994), and Vives (1995).

not affect the valuation of the security proper. However, the realisation of a price is still an information event, since it can be used to update estimates of the value of *other* securities.

In addition to information that is revealed through trading, other sources of information also influence asset prices. Examples include scheduled announcements or overnight trading in other markets. Such information will affect asset prices by changing all agents' valuation of securities, and prices change accordingly without trading.[4]

The noise in REE securities prices has two separate sources. Firstly, the information collected by informed speculators may not perfectly reveal the underlying value of securities. In an economy with many speculators, this requires that agents' measurement (signal) errors are correlated across individuals. Secondly, liquidity trading (or any trading not based on the expected returns), introduces additional noise into the price system.

2.2 The competitive REE

The model presented in this paper is based on a competitive REE model. In such models, prices are martingales and the expected profits of a rational, but uninformed, speculator is zero. Hellwig (1980) and Kyle (1985) are examples of competitive REE models.

If the economy is not competitive, individual uninformed speculators have market power over residual supply. They will use their market power to share some of the profits that informed speculators make from trading with liquidity traders. In this kind of equilibrium, returns are negatively autocorrelated (Kyle, 1989).

The market power, and the expected profits, of speculators decrease rapidly with the number of speculators active in the market. With as few as 3–4 informed speculators, pricing will be close to the competitive prices.[5] The non-competitive case is consistent with the model of cross-security information aggregation, but is not discussed in this paper.

2.3 REE in a multi-security market

A multi-security REE model is an analytically complex, but intuitively simple extension of the single-security REE model. This is evident in Admati's (1985) multi-security extension of the Hellwig (1980) model. The main difference is that demand strategies must be optimal with regard to the *whole* price vector, not only the price of a single security.

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[4]In practice, an announcement may also trigger information aggregation through prices, in particular when each agent makes an independent analysis of the news event, or when the announcement affects individual agents' demand functions.

[5]See Holden and Subrahmanyam (1992) for a multi-period setting, and Caballé and Krishnan (1994) for a multi-security setting.

In the Admati model, agents submit multidimensional demand schedules, conditioned on the full price vector. Such demand schedules require the calculation of N^2 parameters, where N is the number of securities in the market. Theoretically, this may be achieved in markets with only a few securities, but it is obviously an unrealistic assumption for markets where hundreds of securities are traded. Furthermore, stock exchanges only offer rudimentary types of cross-security limit orders, such as conditional trades or basket trades.

If traders cannot condition their orders on the full set of prices, even REE prices will be inefficient across securities. It is this inefficiency that is exploited in the model presented in this paper. The cross-security information aggregation is equivalent to the difference between single-security REE prices, derived by Hellwig (1980), and the multi-security REE prices, derived by Admati (1985).[6]

It must be pointed out that the resulting lead-lag effects do not present arbitrage opportunities. Although returns are cross-autocorrelated, and thus predictable, the price inefficiency cannot be used to make trading profits. Prices will adjust without trading, since the predictability of price changes is known by all agents.

2.4 Earlier cross-autocorrelation models

This paper is close in spirit to the paper of Chan (1993), who studies the pricing problem of a Kyle (1985) style market maker who acts in a market where underlying value innovations are correlated across securities. The market maker is a specialist who only observes order flow in "his own" security. As order flows in other securities are unobservable, the market maker must deduce the information content of these flows by observing the *prices* of other market makers. As a result, returns will be positively cross-autocorrelated.

This paper makes two important theoretical extensions to the Chan model. Firstly, it implements the model for a general REE setup. This is conceptually important as it is obvious that a specialist market maker has a physical information monopoly over the incoming order flow. That similar effects persist in an auction market, where order flow is visible to all traders, is far from obvious. Secondly, the extended model allows signals to be correlated across securities. This addition is of both theoretical and empirical importance. Theoretically, it adds the possibility of modelling index arbitrage trading and other multi-security trading strategies. Empirically, it is necessary in order to model observed return patterns on the Paris

[6]With some minor caveats regarding optimal information revelation and optimal information acquisition.

Bourse. The observed high cross-security correlation in short-term returns is simply not compatible with the basic Chan model.

In another extension of the Chan (1993) model, Shin and Singh (1996) model what the authors call "spurious predictability." Their results are nested by the results of this paper.[7]

3 Model

3.1 General model

Assume a Walrasian stock market of the Hellwig (1980) type. There are two types of traders, namely speculators and liquidity traders. Speculators are rational and profit maximising agents, some of whom have received or acquired information, "a signal," relative to the underlying value of a security. Liquidity traders trade for some exogenous reason (e.g. hedging, liquidity constraints) and their demand is independent of the expected value of securities. Liquidity trading can be correlated across securities, but is assumed to be independent of past liquidity trading, value innovations and any private signals.

There are N securities that are claims to separate underlying values, arranged in the vector $\mathbf{V}$. The underlying values are not observable, but before trading, agents share a prior valuation of securities, denoted $\mathbf{P}^*_{-1}$. The prior reflects all public information available before demand schedules are submitted. The valuation error of the prior is normally distributed, with a publicly known covariance matrix, $\mathbf{\Pi}$.

$$\mathbf{P}^*_{-1} = \mathrm{E}\left[\mathbf{V} \mid \mathcal{F}_{-1}\right] \sim \mathrm{N}\left(\mathbf{V},\ \mathbf{\Pi}\right), \tag{1}$$

where $\mathcal{F}_{-1}$ denotes the public information set before trading.

Before trading takes place, some of the speculators receive or acquire a (private) noisy measurement of the underlying values of one or several securities. Agents calculate optimal demand schedules using the private signal and the equilibrium covariance structure of signals and returns.[8]

Each security is traded in a separate, frictionless, competitive call auction. Before trading, a Walrasian auctioneer collects demand schedules for individual securities. At a predetermined point in time, the auctioneer sets a price vector, $\mathbf{P}$, clearing supply and demand for all stocks.

[7]The term "spurious predictability" is somewhat misleading. While equilibrium returns are predictable, the predictability cannot be traded away by arbitrageurs, because of the imposed informational constraints. The results of Shin and Singh (1996) correspond to establishing when $\omega_{ij} \neq 0$ (equation 23 of this paper).

[8]Under standard assumptions (exponential utility over next period's wealth and normality) demand schedules will be linear in the price.

Table 1: Sequence of events and information in the model of cross-security information aggregation

Event	Description
A	All agents share a common prior, $\mathbf{P}^*_{-1}$, which is a normally distributed measurement of underlying values $\mathbf{V}$ with covariance matrix $\mathbf{\Pi}$
B	Each agent submits N, optimally calculated, linear demand schedules to a Walrasian auctioneer. Submitted demand schedules are not revealed to other traders.
Trading	The Walrasian auctioneer simultaneously sets market clearing prices, P_i, in all N markets. Orders are executed immediately.
C	Agents observe the realised price vector, $\mathbf{P}$.
D	Agents use the equilibrium noisiness of prices to deduce a signal, $\mathbf{F}$, from realised prices, $\mathbf{P}$. The signal has covariance matrix $\mathbf{\Phi}$.
E	Agents calculate posterior beliefs $\mathbf{P}^*$ of $\mathbf{V}$ using Bayesian updating and the revealed signal $\mathbf{F}$.

Sequence of events: A → B → Trading → C → D → E. All agents know the information structure of underlying returns, that is, the true value of $\mathbf{\Phi}$ and $\mathbf{\Pi}$. They also know the precision of their own, and other agents' signals. Transaction costs are zero.

Relying on standard REE results, we know that each price realised in trading will reveal a signal, F_i, relative to the underlying value of security i.[9] In this paper, the signal is modelled as a noisy measurement of the error in the prior valuation. For all stocks, we use vectors and matrices to write

$$\mathbf{F} \sim \mathrm{N}\left(\mathbf{V} - \mathbf{P}^*_{-1},\ \mathbf{\Phi}\right). \tag{2}$$

For an individual stock we write

$$F_i \sim \mathrm{N}\left(V_i - P^*_{i,-1},\ \Phi_{ii}\right), \tag{3}$$

where Φ_{ii} is the ith diagonal element of the covariance matrix $\mathbf{\Phi}$. Basically, the signal is a weighted sum of investors' private information distorted by the extent of liquidity trading and other price noise.[10]

Relying on the competitiveness assumption, the price in each of the N separate markets can be represented by the following equation of Bayesian updating:

$$P_i = \frac{\Phi_{ii}}{\Pi_{ii} + \Phi_{ii}} P^*_{i,-1} + \frac{\Pi_{ii}}{\Pi_{ii} + \Phi_{ii}} \left(F_i + P^*_{i,-1}\right), \tag{4}$$

where Π_{ii} is the ith diagonal element of the covariance matrix $\mathbf{\Pi}$. Under the normality assumption, equation 4 holds for all competitive single-security

[9] See, e.g., Hellwig (1980), proposition 5.2. It also follows directly from the martingale property of prices.

[10] The properties of its covariance matrix, $\mathbf{\Phi}$, are discussed in some more detail in section 4.2.

REE models, i.e., whenever realised prices are unbiased predictors of the underlying value or future price sequence.

Define κ_i as the immediate response of an individual price to new information, F_i. We have,

$$P_i = P^*_{i,-1} + \kappa_i F_i, \qquad \kappa_i = \frac{\Pi_{ii}}{\Pi_{ii} + \Phi_{ii}}. \tag{5}$$

In vector and matrix notation, the κ_i:s are arranged in a diagonal matrix, $\hat{\mathbf{\Omega}}$.

$$\hat{\mathbf{\Omega}} = \begin{bmatrix} \kappa_1 & 0 & \cdots & 0 \\ 0 & \kappa_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \kappa_N \end{bmatrix}, \tag{6}$$

to obtain

$$\mathbf{P} = \mathbf{P}^*_{-1} + \hat{\mathbf{\Omega}}\mathbf{F}. \tag{7}$$

When prices are observed, they will be used to extract the information revealed in trading using equation 4. Next, a posterior estimate of $\mathbf{V}$, denoted $\mathbf{P}^*$, is formed using Bayesian updating and the extracted signal $\mathbf{F}$:

$$\mathbf{P}^* = \mathrm{E}\left[\mathbf{V} \mid \mathcal{F}_{-1}, \mathbf{F}\right] = \mathbf{P}^*_{-1} + \mathbf{\Omega}\mathbf{F}, \tag{8}$$

where $\mathbf{\Omega}$ is an updating matrix that efficiently updates all N prices using the N individual signals. In the case of normally distributed variables, Bayesian theory provides an explicit solution for $\mathbf{\Omega}$:

$$\mathbf{\Omega} = \mathbf{\Pi}\left(\mathbf{\Pi} + \mathbf{\Phi}\right)^{-1}. \tag{9}$$

Two sets of returns are defined. The first stage returns, $\mathbf{r}$, are calculated as the difference between recorded prices and the prior,

$$\mathbf{r} = \mathbf{P} - \mathbf{P}^*_{-1} = \hat{\mathbf{\Omega}}\mathbf{F}. \tag{10}$$

Secondly, define posterior returns, $\mathbf{r}^*$, which take all information in $\mathbf{F}$ into account. Posterior returns are thus simply the difference between posterior and prior,

$$\mathbf{r}^* = \mathbf{P}^* - \mathbf{P}^*_{-1} = \mathbf{\Omega}\mathbf{F}. \tag{11}$$

It is easy to see that returns will be cross-autocorrelated whenever $\mathbf{P}^* \neq \mathbf{P}$ or, equivalently, when $\mathbf{r}^* \neq \mathbf{r}$. The cross-autocorrelation results because the price adjustment from the observed price, $\mathbf{P}$, to the posterior valuation, $\mathbf{P}^*$, use observed returns to extract information about $\mathbf{F}$. We have,

$$\mathbf{P}^* - \mathbf{P} = \mathbf{r}^* - \mathbf{r} = \left(\mathbf{\Omega} - \hat{\mathbf{\Omega}}\right)\mathbf{F} = \left(\mathbf{\Omega}\hat{\mathbf{\Omega}}^{-1} - \mathbf{I}\right)\mathbf{r}, \tag{12}$$

where $\mathbf{I}$ is an $N \times N$ identity matrix.

Equation 12 summarises the model. Before interpreting equation 12, define the elements of $\mathbf{\Omega}$ as:

$$\mathbf{\Omega} = \begin{bmatrix} \omega_{11} & \omega_{12} & \cdots & \omega_{1N} \\ \omega_{21} & \omega_{22} & \cdots & \omega_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ \omega_{N1} & \omega_{N2} & \cdots & \omega_{NN} \end{bmatrix}. \tag{13}$$

As $\hat{\mathbf{\Omega}}$ is a diagonal matrix, $\mathbf{\Omega}\hat{\mathbf{\Omega}}^{-1}$ can be seen as a normalisation of the updating matrix $\mathbf{\Omega}$:

$$\mathbf{\Omega}\hat{\mathbf{\Omega}}^{-1} = \begin{bmatrix} \omega_{11}/\kappa_1 & \omega_{12}/\kappa_1 & \cdots & \omega_{1N}/\kappa_1 \\ \omega_{21}/\kappa_2 & \omega_{22}/\kappa_2 & \cdots & \omega_{2N}/\kappa_2 \\ \vdots & \vdots & \ddots & \vdots \\ \omega_{N1}/\kappa_N & \omega_{N2}/\kappa_N & \cdots & \omega_{NN}/\kappa_N \end{bmatrix}. \tag{14}$$

Returns will thus be cross-autocorrelated whenever there are non-zero off-diagonal elements in the matrix $\mathbf{\Omega}$. From the structure of $\mathbf{\Omega}\hat{\mathbf{\Omega}}^{-1}$ we deduce that only the relative informativeness of signals matters for cross-autocorrelations. First stage returns are already adjusted for the informativeness of signals via the $\hat{\mathbf{\Omega}}$ matrix. Therefore, the matrix $\mathbf{\Omega}\hat{\mathbf{\Omega}}^{-1}$ is not affected by the absolute informativeness of revealed information.

It is straightforward, but complicated due to the matrix algebra, to show that the expected value of $P_i^* - P_i$, can be written as a weighted sum of "unexpected" returns or signals of all other securities.[11] Equation 15 formulates this intuitive result.

$$\begin{aligned} P_i^* - P_i &= \sum_{j=1}^{N} \omega_{ij} \left(F_j - \mathrm{E}\left[F_j | \mathcal{F}_{-1}, F_i\right]\right) \\ &= \sum_{j=1}^{N} \frac{\omega_{ij}}{\kappa_j} \left(r_j - \mathrm{E}\left[r_j | \mathcal{F}_{-1}, r_i\right]\right) \end{aligned} \tag{15}$$

In the first part of equation 15, the adjustment is formulated in terms of the revealed information. The weights ω_{ij} measure the relative informativeness of security j for the pricing of security i. The second part of the same equation provides the results expressed in returns instead. When using returns, the informativeness is normalised by κ_j, security j's initial response to the revealed information.

[11] This also follows directly from the optimal signal extraction implied by Bayesian updating.

3.2 A one-factor model

Equation 12 provides an explicit solution for cross-autocorrelation. However, in order to demonstrate the model's implications, a less general setting is needed. Therefore, this section develops a "one-factor model," where priors and signals have both a market component and an individual stock component.

Assume that the covariance matrix of the prior has the structure

$$\Pi_{ij} = \begin{cases} \pi^m + \pi^s & \text{if } i = j \\ \pi^m & \text{if } i \neq j \end{cases} \quad \forall\, i, j, \tag{16}$$

where π^m is the variance of the market level prior and π^s is the additional variance for individual securities. The covariance matrix of the prior can thus be visualised as

$$\underset{N\times N}{\mathbf{\Pi}} = \begin{bmatrix} \pi^m + \pi^s & \pi^m & \cdots & \pi^m \\ \pi^m & \pi^m + \pi^s & \cdots & \pi^m \\ \vdots & \vdots & \ddots & \vdots \\ \pi^m & \pi^m & \cdots & \pi^m + \pi^s \end{bmatrix}. \tag{17}$$

Similarly, we let the revealed information have a one-factor structure with the variance of the market signal ϕ^m and the additional variance of individual stock signals, ϕ^s:

$$\Phi_{ij} = \begin{cases} \phi^m + \phi^s & \text{if } i = j \\ \phi^m & \text{if } i \neq j \end{cases} \quad \forall\, i, j. \tag{18}$$

Using this simplified structure it is easy to calculate explicit returns and cross-autocorrelations. The returns in excess of the prior, $\mathbf{r}$, are simply κ^s, equal for all stocks, multiplied by the revealed signal, $\mathbf{F}$:

$$\mathbf{r} = \kappa^s \mathbf{F}, \tag{19}$$

$$\kappa^s = \frac{\pi^m + \pi^s}{\pi^m + \pi^s + \phi^m + \phi^s}. \tag{20}$$

The posterior returns, $\mathbf{r}^*$, can be interpreted as the sum of a market return and a security-specific return:

$$\mathbf{r}^* = \mathbf{\Omega}\mathbf{F} = \mathbf{\Omega}\frac{1}{\kappa^s}\mathbf{r}, \tag{21}$$

$$\mathbf{\Omega} = \left(\frac{\pi^s}{\pi^s + \phi^s}\mathbf{I} + \frac{\pi^s \phi^s \left(\pi^m/\pi^s - \phi^m/\phi^s\right)}{\left(\pi^s + \phi^s + N\left(\pi^m + \phi^m\right)\right)\left(\pi^s + \phi^s\right)}\mathbf{1}\mathbf{1}' \right), \tag{22}$$

where $\mathbf{I}$ is an $N \times N$ identity matrix, $\mathbf{1}$ is an $N \times 1$ column vector of ones and, consequently, $\mathbf{1}\mathbf{1}'$ is an $N \times N$ matrix of ones. The first term in the definition of $\mathbf{\Omega}$ (equation 22) can be interpreted as the Bayesian response

to security-specific information. The second term is the optimal response of individual stocks to revealed market-wide information. All off-diagonal elements, ω_{ij}, in $\mathbf{\Omega}$ are equal, which implies that all securities react similarly to information revealed in all stocks,

$$\omega_{ij} = \frac{\pi^s \phi^s \left(\pi^m/\pi^s - \phi^m/\phi^s\right)}{\left(\pi^s + \phi^s + N\left(\pi^m + \phi^m\right)\right)\left(\pi^s + \phi^s\right)} \quad \forall i,j \quad i \neq j. \tag{23}$$

We can derive most of the direct implications of the model from equation 22. First note that cross-autocorrelation between individual stocks will converge to zero as N, the number of securities, increases. When a large number of securities contribute to the price discovery, individual lead-lag effects are weakened. However, it is easily shown that the cross-autocorrelation with the market return is strengthened as the number of securities grows. The reason is intuitively simple; if many securities share a market factor, the market factor will be better known, but individual securities' contribution to information revelation is reduced. Therefore, individual cross–autocorrelations are reduced, while the cross-autocorrelation with the market return is strengthened.

The sign of cross-autocorrelation is determined by $\pi^m/\pi^s - \phi^m/\phi^s$:

$$\operatorname{sign}\left(\omega_{ij}\right) = \operatorname{sign}\left(\frac{\pi^m}{\pi^s} - \frac{\phi^m}{\phi^s}\right) \quad \forall i,j \quad i \neq j. \tag{24}$$

This implies that if priors are more strongly correlated across securities than signals, cross-autocorrelation will be positive. If signals are more strongly correlated than underlying returns, the observed returns will be negatively cross-autocorrelated. The reason is straightforward; if the prior has strong cross-security correlation, the market factor is not well known before trading, and prices will therefore be used to identify the current market factor. If, however, there is high cross-security correlation in revealed signals, returns provide a bad measurement of the index level, and the index innovation is more likely to be caused by signal errors. Therefore, stocks react negatively to innovations in other stock prices.

3.3 The two securities case

A second intuitive example of the model's direct effects is the two securities case. Here, cross-effects can be calculated explicitly. As before, $\mathbf{\Pi}$ measures the covariance of the prior estimate of the underlying values:

$$\mathbf{\Pi} = \begin{bmatrix} \pi^m + \pi_1 & \pi^m \\ \pi^m & \pi^m + \pi_2 \end{bmatrix}. \tag{25}$$

If $\pi_1 > \pi_2$, the prior of security 1 is relatively more noisy than the prior of security 2. If π^m is big, the errors in prior valuation are strongly correlated.

Similarly, $\mathbf{\Phi}$ measures the precision of the information revealed in trading:

$$\mathbf{\Phi} = \begin{bmatrix} \phi^m + \phi_1 & \phi^m \\ \phi^m & \phi^m + \phi_2 \end{bmatrix}. \tag{26}$$

If $\phi_1 > \phi_2$, information revealed from trading security 1 is more noisy than information revealed from trading security 2. If ϕ^m is big, signal errors are strongly correlated. $\mathbf{\Omega}$ can be calculated explicitly from equation 9. The off-diagonal elements, ω_{12} and ω_{21} determine the cross-autocorrelation:

$$\omega_{12} = \frac{\pi_1\phi_1}{|\mathbf{\Pi} + \mathbf{\Phi}|}\left(\frac{\pi^m}{\pi_1} - \frac{\phi^m}{\phi_1}\right), \tag{27}$$

$$\omega_{21} = \frac{\pi_2\phi_2}{|\mathbf{\Pi} + \mathbf{\Phi}|}\left(\frac{\pi^m}{\pi_2} - \frac{\phi^m}{\phi_2}\right), \tag{28}$$

where $|\mathbf{\Pi} + \mathbf{\Phi}|$ is the determinant of $(\mathbf{\Pi} + \mathbf{\Phi})$. The term ω_{12} measures how security 1 reacts to unexpected returns in security 2. Similarly ω_{21} measures effect *from* security 1 *to* security 2.

From the symmetric nature of the lead-lag relation, simple comparative static analysis allows the following conclusions to be drawn from equation 27–28.

1. If the prior of the underlying values is highly correlated across securities, both leads and lags will increase ($\pi^m \uparrow \Rightarrow \omega_{12} \uparrow$ and $\omega_{21} \uparrow$).

2. If revealed signals are strongly correlated across stocks, leads and lags will decrease, and may become negative ($\phi^m \downarrow \Rightarrow \omega_{12} \downarrow$ and $\omega_{21} \downarrow$).

3. A security with higher prior variance will exhibit weaker (or more negative) leads to other securities ($\pi_1 \uparrow \Rightarrow \omega_{12} \downarrow$).

4. A security with higher prior variance will be less affected by events in other securities. The absolute value of the positive or negative lag is reduced. ($\pi_1 \uparrow \Rightarrow |\omega_{21}| \downarrow$).

5. A security with noisy revealed signals tends to lag the other securities ($\phi_1 \uparrow \Rightarrow \omega_{12} \uparrow$).

6. A security with noisy revealed signals tends not to lead other securities. Both positive and negative leads are reduced ($\phi_1 \uparrow \Rightarrow |\omega_{21}| \downarrow$).

4 Discussion

The model, as presented in the previous section, is highly stylised, and the adaptation to real world settings may not be altogether intuitive. Therefore, this section discusses some aspects of the model and its applicability.

For simplicity, the discussion focuses on the one-factor model and the two securities case. Implications are equally valid for more general factor specifications.

4.1 The cross-security correlation of the prior

The properties of the common prior are critical for predicted lead-lag effects. If the cross-security correlation of the prior is high, the first stage response to common factors is lower than the optimal response after having observed information revealed in other securities prices. The model thus predicts positive cross-autocorrelation between individual securities.

Therefore, whenever the noisiness of the common factor is high relative to the additional noisiness of individual securities, positive lead-lag relations are expected. This is one of the reasons why most empirical studies document positive lead-lag relation, say between the cash index and index futures or between options and underlying stocks. In both cases the common factor carries most noise, and positive lead-lag effects should be expected.

In a multi-period setting, the covariance of the prior has two separate components, the covariance of the last posterior and the covariance of value innovations since the last transaction.[12] In a market with many individual securities, Bayesian updating ensures that the covariance matrix of the posterior is close to diagonal since the common factors are known with much higher precision than individual stock factors. Therefore, the cross-security correlation of the prior valuation will be determined mostly by the covariance of value innovations.

An examination of securities returns reveals that the correlation structure of value innovations is relatively constant. It is clear, for instance, that stocks exhibit consistent and strong cross-security correlation in daily returns. For practical purposes it can be assumed that the covariance structure of value innovations is also similar for other choices of return periods, such as close-to-open or intraday. Therefore, the cross-security correlation in long-term returns (e.g. monthly returns) can be used as a simple proxy for the correlation in the prior.

During continuous trading, the common factor prior will be known with relatively high precision, at least in markets with many traded securities, such as stock markets. Therefore, lead-lag effects tend to be relatively weak during continuous trading.[13] However, during periods of high return volatility, normally in early morning trading and before the close, the index level prior can be assumed to be more noisy, relative to the level of uncer-

[12]In addition, it is possible that new public information reduces the uncertainty concerning the underlying value of securities.

[13]In addition, they may be impossible to verify using econometric techniques, due to the effects of nonsynchronous trading.

tainty in individual stocks. Therefore, lead-lag effects can be expected to be relatively strong around open and close.

4.2 Cross-security correlation of signals

Modelling information revelation as a signal $\mathbf{F}$ gives the model both generality and simplicity. The formulation is valid for all REE models. However, depending on the market setting, the interpretation is different. In a market maker framework, the signal will be equal to the realised net order flow facing the market maker. In an auction market setting, however, the signal is the net demand facing *any* agent.

The cross-security correlation of signals plays an important role in the theoretical analysis. If signal correlation is high, cross-autocorrelation will be reduced. If signal correlation is higher than the cross-security correlation in the prior, negative cross-autocorrelation will result. Although the cross-security correlation of revealed information cannot be observed, REE models clearly indicate what to expect.[14]

In a rational expectations equilibrium, the equilibrium pricing rule is known by all agents, and prices thus reveal net demand at all price levels. $\mathbf{\Phi}$, the variance of $\mathbf{F}$, is thus also a direct measure of the covariance of net demand. Net demand is the sum of informed demand and liquidity demand, and the same is true for the $\mathbf{\Phi}$ matrix.[15] We can thus write,

$$\mathbf{\Phi} = \mathbf{\Phi}_I + \mathbf{\Phi}_L, \tag{29}$$

where $\mathbf{\Phi}_I$ is the covariance of the price effect from informed demand and $\mathbf{\Phi}_L$ is the covariance from liquidity demand. If the number of informed agents is relatively large, the covariance of informed trading, $\mathbf{\Phi}_L$, is primarily caused by a correlation of errors in private information across individuals and securities. The covariance of signals across individuals determines the level of aggregate price noisiness while the level of covariance across securities determines the noisiness of the index level. Such covariances can be seen as a "market mood," a signal shared by all informed investors.

The weight of an individual agent's private signal is determined by how aggressively the agent trades based on private information. The weight increases with the precision of the private signal and decreases with the agent's risk aversion.[16]

In a real-world trading situation, most traders only trade in a few securities (relative to the total number traded on the stock exchange). Therefore, $\mathbf{\Phi}$ is most easily seen as the correlation of net demand across securities.

[14]Explicit results concerning the correlation structure of revealed information are found in Admati (1985) and Caballé and Krishnan (1994).

[15]Liquidity trading is, by assumption, uncorrelated with informed trading.

[16]See, e.g., Hellwig (1980) and Admati (1985).

The correlation in net demand can originate both from informed trading or liquidity trading. Index arbitrage or basket trading are good examples of trading strategies that induce positive cross-security correlation in net demand, regardless of whether trading is informed or not. Another case is when prices reveal a universal "market mood" or investor sentiment related to a common factor of securities prices.

4.3 Cross-security correlation in short-term returns

The cross-security correlation in short-term returns will be approximately equal to the average of cross-security correlation in the prior and the revealed information. This easily seen by examining the covariance matrix of first stage returns. Standard algebra gives us,

$$\mathrm{Var}\,(\mathbf{r}) = \mathrm{Var}\left(\hat{\mathbf{\Omega}}\mathbf{F}\right) = \hat{\mathbf{\Omega}}\,(\mathbf{\Pi}+\mathbf{\Phi})\,\hat{\mathbf{\Omega}}. \tag{30}$$

As $\hat{\mathbf{\Omega}}$ is diagonal, it is clear that the cross-security correlation of one-period returns is approximately equal to the average of $\mathbf{\Pi}$ and $\mathbf{\Phi}$.

As discussed above, the covariance matrix of the prior can be assumed to be "close" to the covariance matrix of long-term returns. When observed one-period returns are more strongly correlated than corresponding long-term returns, the revealed signals must be more strongly correlated across securities than the value innovations. Equivalently, the correlation in $\mathbf{\Phi}$ must be larger than the correlation in $\mathbf{\Pi}$.

4.4 Empirical implications

The empirical implications of the model are mostly straightforward. Prices that are informative for other prices will tend to lead other prices. Empirical testing thus primarily requires a theoretical analysis of which prices are most informative for other prices.

As argued above, securities with highly correlated return processes will have relatively stronger correlation of their prior valuations. Therefore, lead-lag effects will be stronger between strongly correlated securities. This is easily applicable to lead-lag effects between stocks. There are several ways of identifying closely related stocks, some of which are trivial. Stocks of companies that share characteristics such as geographic location, industry, size range, volatility or market factor loading, will tend to be more strongly cross-autocorrelated than other stocks.

In particular, this approach can be used when testing lead-lag effects within various financial markets, including option markets, bond markets and commodity markets. For example, lead-lag effects can be expected to be strong between bonds in the same maturity range and between options on the same stock. The argument can be extended to lead-lag effects

between different markets, such as the lead-lag effect between stocks and stock options. Using the Black-Scholes formula, it is evident that the value of out-of-the-money options is less correlated with the value of the underlying stocks than in-the-money options. Therefore, the strongest lead-lag effects can be expected between stocks and in-the-money options.

Cross-autocorrelation decreases in the correlation of revealed signals. The revealed signals are, however, not observable. Therefore, signal correlation must be identified theoretically or econometrically. Testable hypotheses are mainly generated by models of investor behaviour. When traders are more prone to cross-security trading strategies, cross-autocorrelation would tend to be weaker. For example, index arbitrage trading will tend to reduce cross-autocorrelation while pure liquidity trading will tend to increase cross-autocorrelation. Theoretical models of the trading strategies can thus be tested using cross-autocorrelation data.

Using econometric methods it is possible to identify when the return dispersion is high. One way is to estimate the cross-sectional return dispersion across all traded securities. However, this method must be used with care, especially if the estimation of return dispersion is performed in-sample. The risk of spurious effects is high, since low return dispersion automatically implies weak lead-lag effects if the cross-security correlation in long-term returns is kept constant.

Another implication of the model is that stocks that reveal highly informative signals tend to lead other securities. An obvious problem of this proposition is that the informativeness of stock prices and signals is not observable. However, since trading reveals information, we expect the most heavily traded securities to be less noisy estimates of the corresponding true value. Returns on liquid securities should thus tend to lead returns on less liquid securities.

4.5 Application: The lead-lag relation between stocks and stock options[17]

As the leverage effect of options (especially of deep out-of-the-money options) should make these attractive to informed investors, Chan et al. (1993) conjecture that option returns should lead stock returns. However, several empirical studies, including Stephan and Whaley (1990), Easley et al. (1993) and Chan et al. (1993), report that returns in the stock market lead returns in the options market. Although there is a feedback from options to stocks, it is generally much weaker.

The predictions of cross-security information aggregation are broadly in line with the empirical evidence of this lead-lag relation. In the model, two separate effects make it more likely that options lead stocks than *vice versa*.

[17] I thank Robert E. Whaley for suggesting this extension.

Firstly, the value of the option is "more stochastic" than the value of the underlying stock. Its value depends not only on the price of the underlying stock, but also on interest rates and future return volatility, both of which are stochastic. In an option that is deep out-of-the-money, the stock return volatility provides a larger, albeit still small, proportion of option return volatility.

Secondly, the large number of traded option series will reduce the measured lead-lag effects. As an example, it can be mentioned that in Stockholm, more than 20 options, calls and puts combined, with different strike prices and maturities are traded on Volvo B shares alone. Any lead from options to stocks will be diluted by this one-to-many effect.

Documenting lead-lag relation would therefore be easier if an "option index" was used. This is exactly the approach used by Easley et al. (1993). By adding trading volume in different option series, the authors create an index that measures stock information innovation in option trading more precisely than any individual option price series could.[18] This option index leads stock returns by at least 5 minutes, but the reverse lead extends to at least 20 minutes. Clearly, as noted by Chan et al. (1993), even when using an option index, nonsynchronous trading in options, reduces the probability of observing a lead from options to stocks.

When using the model presented in this paper to analyse the lead-lag relation between stocks and options, we must be cautious since options are rarely traded in the kind of pure auction market modelled in this paper. However, as the pricing of the model is equivalent to the zero-profit market makers' pricing decision, we can feel relatively comfortable that the results will also carry over to other market settings.

The key to the lead-lag effects is the relative information revelation in the respective markets. If less information is revealed in the option market, it will tend to lag the stock market. A simple example shows that this can indeed be the case, even under very strong assumptions of trading efficiency.

The underlying value of the stock 1 is V_1. Create an option portfolio with option δ equal to unity. This implies that the option portfolio has the same marginal price response to the change in the stock value (that is – unity). This also implies that the variance of the option prior will be equal to the variance of stock prior, π_1, plus the variance of the prior of implied volatility (π_σ):

$$\Pi = \begin{bmatrix} \pi_1 & \pi_1 \\ \pi_1 & \pi_1 + \pi_\sigma \end{bmatrix}. \tag{31}$$

Assume that agents investigate the underlying value and volatility separately. Individuals' private signals will then be more noisy for the option

[18]The fact that Easley et al. (1993) use volume data instead of price data does not matter for the conclusions, assuming, as in standard REE models, that there is a known mapping from excess demand to option price changes.

than for the stock. Even if agents trade optimally in stock and options markets, this added noise will persist in the realised market price (Admati, 1985). The covariance of revealed information can therefore be written as:

$$\mathbf{\Phi} = \begin{bmatrix} \phi_1 & \phi_1 \\ \phi_1 & \phi_1 + \phi_\sigma \end{bmatrix}. \tag{32}$$

The off-diagonal elements of $\mathbf{\Omega}$ can now be calculated explicitly as in equation 27–28:

$$\omega_{12} = 0, \tag{33}$$

$$\omega_{21} = \frac{\pi_\sigma \phi_\sigma}{|\mathbf{\Pi} + \mathbf{\Phi}|} \left(\frac{\pi_1}{\pi_\sigma} - \frac{\phi_1}{\phi_\sigma} \right). \tag{34}$$

As seen in equation 33–34, this very simple setup implies that stock returns will lead option returns while option returns will not lead stock returns. Although the same information is available among the *agents* in both markets, the realised *prices* contain different information. The strength of the lead depends on the stock price's informativeness for option valuation. It thus increases in π_1/π_σ and decreases in ϕ_1/ϕ_σ.[19]

The assumption that all traders trade optimally in both markets is obviously fairly strong. However, it shows that an information-based lead from options to stocks must be based on transaction costs or other market imperfections. Given that the informed investor *can* trade in both markets, it will always be optimal to reveal exactly as much private information in both markets (profits in both markets increase with the amount of private information revealed in trading and are unaffected by the amount of information revealed elsewhere).

5 Empirical tests

5.1 Testing under continuous trading

Most stock markets operate on a continuous basis. Although this is perfectly consistent with the model, continuous trading poses some problems for empirical testing of the model. The simultaneity of price discovery is a key element of the theoretical model. Without this simultaneity, the model becomes very difficult to test for two separate reasons. Firstly, if two stocks trade in random order at different points in time, the cross-autocorrelation effects are very similar to those predicted by cross-security information

[19]Intuitively, the ratio π_1/π_σ should be quite high. Using the Black-Scholes formula with a given stock price leaves little additional noise in option prices. The ratio ϕ_1/ϕ_σ depends on the price precision in each market, which is hard to judge in the general case.

aggregation.[20] Secondly, a large share of observed lead-lag effects can be attributed to improved knowledge of a market factor. If stocks trade nonsynchronously, realised market returns can be observed between trades in a single security. This will bias estimates of cross-autocorrelation.[21]

Therefore, any test of the model must try to reduce the nonsynchronicity of prices. In addition, it is preferable to test the model just after the occurrence of an "information event" where the high return volatility makes the identification of lead-lag effects less sensitive to measurement errors and other noise. For intraday returns, it is probable that cross-stock adjustments will be too small to be identifiable using econometric techniques.

This demand for exact simultaneity strongly restricts the choice of dataset. Clearly, it is possible to assume that prices realised within, say 10 seconds, are *de facto* simultaneous. This may be a correct interpretation of the actual information processing capacity of the market place, but testing should preferably be carried out using data which is not subject to any nonsynchronicity in trading.

The best real world candidate for testing the model is an opening call auction of the kind used at the Toronto Stock Exchange and the Paris Bourse. This market setting closely resembles the model setup of this paper. All limit orders are submitted to the electronic trading system *before* the opening call auction. Prices are then set *simultaneously* for all stocks, i.e., without any nonsynchronicity.

5.2 Data

The data chosen for the empirical testing comprises opening and closing prices for all stocks traded in the automated CAC system of the Paris Bourse.[22] In order to minimise possible problems of nontrading and low liquidity, the sample is restricted to the 70 most traded stocks on the monthly settlement list (*Reglement Mensuel*). All stocks used have at least 1000 days of price data during the sample period. For the chosen stocks, there are virtually no nontrading days. The sample covers five trading years, 1991–1995.

Opening prices are set in a simultaneous call auction procedure. During the preopening period, starting 08:30 (09:00 until 1992), orders can be freely added and cancelled. Traders observe an indicative opening price based on limit orders entered into the system. However, most executed orders are entered into the system during the last 5-10 minutes of the preopening period. At 10:00, an opening price is calculated and all crossing orders are executed (approximately 5% of total daily trading volume is traded at the

[20]See, e.g., Fischer (1966), Scholes and Willams (1977) and, in particular, Lo and MacKinlay (1990a,b).

[21]The sign of the bias depends on the chosen specification of price formation.

[22]The data has been provided by SBF–Paris Bourse.

opening prices). After the opening, trading is continuous until the close (17:00). [23]

In the Paris market, closing prices are also suitable for testing the model. As in most continuous stock markets, trading is very active in the last minutes of trading. This almost eliminates the problems of nonsynchronous trading. Average non-trading for the stocks in the sample is only a few seconds, as a number of traders in fact compete to trade at the day's last prices. For practical purposes, closing prices can therefore be treated as simultaneously determined.

The main advantage of the dataset is the absence of nontrading. However, the long time period between open and close makes the observation of lead-lag effects less probable. It is possible that cross-security price effects drown in the noise induced by overday trading and overnight information. Except for stocks listed on US exchanges, it is impossible to observe prices after the close, but it is possible to use prices from, say, 15 minutes into the trading day to test the properties of lead-lag effects at open. However, the available intraday time series are too short for a meaningful analysis.

5.3 Methodology

5.3.1 Returns

In order to use both opening and closing prices, two types of returns are calculated. Overday returns are calculated as the log difference between opening and closing prices:

$$r_{i,t}^{\text{day}} = \log\left(P_{i,t}^{\text{close}}\right) - \log\left(P_{i,t}^{\text{open}}\right). \tag{35}$$

Overnight returns are similarly measured from close to open:

$$r_{i,t}^{\text{night}} = \log\left(P_{i,t}^{\text{open}}\right) - \log\left(P_{i,t-1}^{\text{close}}\right). \tag{36}$$

Overnight returns are dated with the day when the return period ends. For example, Monday overnight return measures the return from Friday close to Monday open.

5.3.2 Cross-autocorrelation estimates

Cross-autocorrelations at open are estimated using the regression model

$$r_{i,t}^{\text{day}} = \beta_0 + \beta_1 r_{j,t}^{\text{night}} + \varepsilon_{i,t}, \tag{37}$$

[23] Detailed accounts of the trading procedures are provided by Biais et al. (1995, 1996) and de Jong et al. (1995).

while cross-autocorrelation at close is calculated using the regression model

$$r_{i,t}^{\text{night}} = \beta_0 + \beta_1 r_{j,t-1}^{\text{day}} + \varepsilon_{i,t}. \tag{38}$$

Regressions use Least squares estimation with heteroskedasticity consistent GMM standard errors (Hansen, 1982). Regressions do not exclude or control for outliers.

5.3.3 Cross-sectional testing

As expected from the model and the large number of traded securities on the Paris Bourse, lead-lag effects between individual securities returns are relatively weak. Therefore, testing requires the aggregation of data. Relative to Chan (1993), this paper provides a methodological innovation in investigating the cross-sectional properties of cross-autocorrelation estimates between individual securities pairs.[24]

The cross-sectional approach provides a total of 4830 estimates of pairwise cross-autocorrelation. As these estimates are produced from a mere 70 return series, there is strong dependence between individual estimates. To alleviate this problem, the cross-sectional estimation (table 3) is performed in two steps. In the first step, 70 separate regressions are estimated, holding either leading or lagging security constant. This provides 70 sets of parameter estimates, the mean of which is reported along with the cross-sectional standard error (across the 70 regressions). Reported significance levels test whether the mean is different from zero.

5.4 Results

5.4.1 Cross-autocorrelation with market return

One of the model's predictions is that stock returns should be more strongly cross-autocorrelated with the market return than with other individual stock returns. Results in table 2 strongly support this hypothesis. Average cross-autocorrelation between individual stock returns is much lower than cross-autocorrelation with the market return (*0.019*, *0.037* versus *0.098*, *0.114*).

The model also predicts that "noisy" securities should be most strongly cross-autocorrelated with the market return. As trading volume can be used as a proxy for price informativeness, the least traded securities should thus lag the market return more strongly than more liquid securities. Since the sample provides a relatively narrow range of liquidity, the effect should be relatively weak within the sample. Empirical results (not reported) show

[24] Chan (1993) aggregates returns to index series and uses time series methods on the less noisy index series. This approach is also used in a companion paper, Säfvenblad (1997).

Table 2: Return correlations and cross-autocorrelations

	Mean	Median	Min	Max	N
Pairwise correlations					
Overday returns	0.188	0.162	-0.043	0.505	2415
	(0.101)				
Overnight returns	0.131	0.089	-0.500	0.603	2415
	(0.132)				
20-day returns	0.269	0.258	-0.172	0.863	2415
	(0.169)				
Pairwise cross-autocorrelations					
At open	0.019	0.017	-0.335	0.148	4830
	(0.039)				
At close	0.037	0.033	-0.092	0.185	4830
	(0.043)				
Cross-autocorrelation with market return					
At open	0.098	0.105	-0.124	0.279	70
	(0.071)				
At close	0.114	0.111	-0.056	0.267	70
	(0.057)				

Reported cross-autocorrelations are the estimates of β_1 from the regression model: $r_{i,t} = \beta_0 + \beta_1 r_{j,t}$, $i \neq j$. N is the number of distinct security pairs in the sample. 20-day returns are calculated using closing prices. Cross-sectional standard errors in parentheses.

that cross-autocorrelation at open decreases in trading volume. However, at close the effect of trading volume is weakly positive. The most traded securities lag the market return more strongly than less traded securities. This is partly the expected result of less idiosyncratic noise in the most liquid stocks, but other trading-based explanations must be used to explain these effects. This question is not pursued any further in this paper.

5.4.2 Cross-autocorrelation and the cross-security correlation of the prior

As discussed above, the correlation in long-term returns can be used as a measurement of cross-security correlation in the common prior valuation of securities (π^m, in the single-factor model). Table 3, panel *a*, reports the results obtained using the correlation in 20-day returns as a proxy for π^m, in a linear specification of the relation between cross-autocorrelation and cross-security correlation of the prior.[25]

Results show that lead-lag effects are significantly stronger between highly correlated securities, as predicted by the model. Parameter estimates of

[25]Other return lengths yield similar results. Choosing long return lengths minimises the influence between daily cross-autocorrelation and measured return correlation.

Table 3: Cross-autocorrelation as a linear function of return correlation and trading volume

	Average across 70 regressions		
	$\hat{\beta}_0$	$\hat{\beta}_1$	R^2
Panel *a*: Correlation in 20-day returns			
At open	0.003*	0.049**	0.081
	(0.011)	(0.062)	
At close	0.019**	0.053**	0.059
	(0.018)	(0.044)	
Panel *b*: Trading volume of leading stock			
At open	−0.116**	0.078**	0.081
	(0.102)	(0.069)	
At close	−0.257**	0.171**	0.252
	(0.189)	(0.123)	
Panel *c*: Trading volume of lagging stock			
At open	0.190**	−0.102**	0.134
	(0.149)	(0.086)	
At close	−0.160**	0.114**	0.127
	(0.151)	(0.100)	

This table reports the average of 70 separate regressions of the following type. Panel *a*: $[\textit{Estimated cross-autocorrelation}]_{i,j} = \beta_0 + \beta_1[\textit{Estimated correlation in 20-day returns}]_{i,j} + \varepsilon_j$. Panel *b*: $[\textit{Estimated cross-autocorrelation}]_{i,j} = \beta_0 + \beta_1[\log \textit{trading volume for leading stock } /10]_{i,j} + \varepsilon_j$. Panel *c*: $[\textit{Estimated cross-autocorrelation}]_{i,j} = \beta_0 + \beta_1[\log \textit{trading volume for lagging stock } /10]_{i,j} + \varepsilon_j$. Trading volume is measured in millions of FRF per day. There are 69 observations in each regression. Standard errors in parentheses report the standard error of the parameter estimate across the 70 regressions. Significance levels test whether the mean of estimates is different from zero. **/*/° Significantly different from zero at the 0.01/0.05/0.10 level.

the correlation effect are similar at open and close (*0.049*, *0.053*). Lead-lag effects are, however, still fairly weak even between strongly correlated securities.

5.4.3 Cross-autocorrelation and the precision of the prior

In panels *b* and *c* of table 3, similar methodology is used to estimate the effects of price precision on lead-lag effects. Assuming that high trading volume implies better price precision, both in prior and revealed information, the theoretical results of section 3.3 predict that high volume stocks will exhibit stronger leads to other securities.

This prediction is confirmed by data both at open and close. The lead of a stock increases significantly in the stock's trading volume. Judging from parameter estimates and R^2, the volume effect is particularly important at close.

Table 4: Same-industry effects on cross-autocorrelation

	Correlation in			
	Returns	20-day returns	Cross-auto-correlation†	Stock pairs
Paris overday (at open)				
Same industry	0.212	0.311	0.020	80
	(0.101)	(0.183)	(0.036)	
Different industry	0.188	0.270	0.018	2335
	(0.102)	(0.168)	(0.039)	
Paris overnight (at close)				
Same industry	0.124	0.311	0.028	80
	(0.138)	(0.183)	(0.042)	
Different industry	0.134	0.270	0.037	2335
	(0.132)	(0.168)	(0.043)	

Cross-sectional standard errors in parentheses. †Average cross-autocorrelation (both ways) across stock pairs.

It was also predicted that the most liquid securities would exhibit weaker lags to other securities. However, the empirical evidence is mixed. At open, the lag is significantly decreasing in the lagging stock's trading volume. At close, the relation is reversed. The most liquid securities also exhibit the strongest lags to other securities. This is analogous to the increased cross-autocorrelation with the market return mentioned in section 5.4.1. The result is partly due to the most liquid stocks' higher market factor loading, but it is most probable that other effects contribute to this relation. It should also be pointed out that since all stocks in the sample are very liquid, the range of liquidity may not be large enough to detect the basic effect.

5.4.4 Same industry shares

It is also possible to test whether the cross-autocorrelation is stronger between companies with highly correlated return processes, without using correlation data as explanatory variable. One way is to identify closely related shares using another method of identification such as industry classifications. Returns on stocks within the same industry can be expected to be more strongly correlated than other shares, are therefore also expected to exhibit stronger lead-lag effects than other stocks.

The industry effect seems to be quite small for the stocks in this sample. The 20-day correlation between stock returns for stocks within the same industry is *0.311*, compared to *0.270* between other stocks (table 4). Not surprisingly, the difference in cross-autocorrelation is small, and not stat-

istically significant. At close, it is even slightly higher between firms in different industries.

5.4.5 Cross-security correlation in short-term returns

One important feature of the model is that it is sufficiently rich to model both positive and negative cross-autocorrelations in stock returns. This property is not present in alternative models such as the Chan (1993) model or the nonsynchronous trading specification of Lo and MacKinlay (1990a). Both models predict that the cross-security correlation of short-term returns is lower than the correlation in long-term returns for all security pairs.[26]

In the Chan, model this result is obtained because signals (revealed net demand) are uncorrelated across securities. In the Lo-MacKinlay framework, price measurements are delayed. Therefore, for shorter return intervals, measured returns reflect partly different value innovations.

This difference in predictions makes it possible to test whether the model of cross-security information aggregation developed here is a useful extension of the Chan (1993) model or a good complement to the nonsynchronous trading model.

The effect on measured returns is most easily described using simulations. Figure 1 presents a simulation of the relation between correlations in short-term and long-term returns for four separate specifications of multi-security stock markets. Each dot represents the short- and long-term correlation between a pair of securities. For dots below the dashed 45° line, short-term correlation is lower than long-term correlation.[27] The solid line is a least squares regression line, included to help compare different panels.

Panel *a* presents a simulation of the model of cross-security information aggregation, developed in section 3. The average correlation between signals varies between *0.3* and *0.6*. For many stocks with lower cross-security correlation than *0.4* in long-term returns, the short-term correlation is *higher* than long-term correlation.

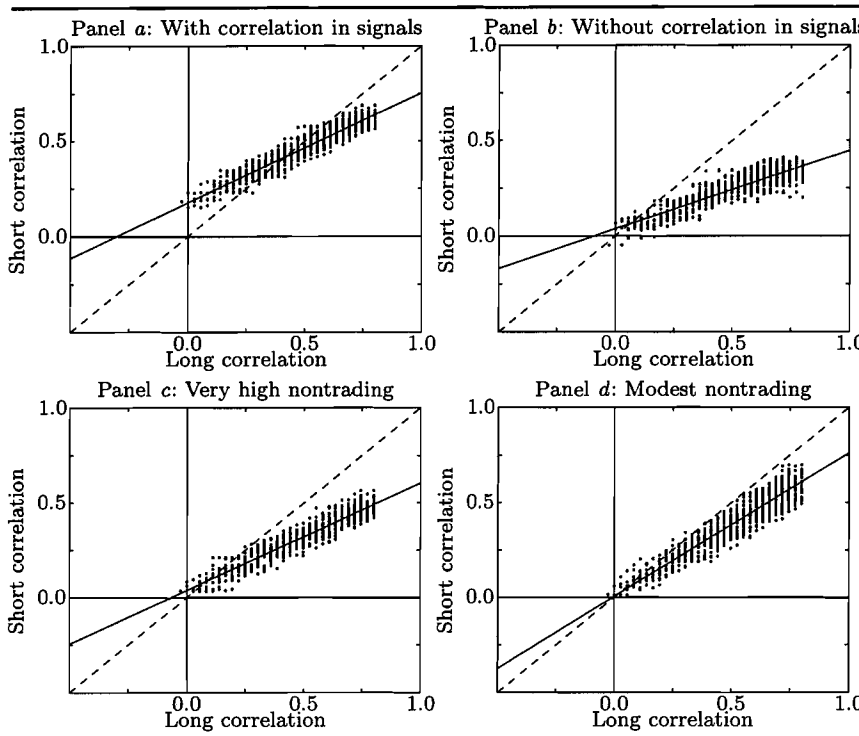
Panel *b* presents the results of a similar simulation where the correlation in signals has been set to zero, as in the Chan (1993) model. The regression line does not pass exactly through the origin, but it is clear that short-term returns are less strongly correlated than long-term returns for virtually all security pairs.

Panels *c* and *d* present simulations of a pure Lo and MacKinlay (1990a) model, where stock prices are nonsynchronous measurements of an under-

[26] Closer to zero is the exact formulation, but negatively correlated stock returns are very rare. This can, e.g., be seen in figure 2. The prediction can also be formulated in terms of the least squares regression lines in figures 1 and 2. Both models predict a positive slope and an intercept of zero.

[27] An addition of a temporary component, such as bid-ask bounce, does not alter the basic relation between short and long-term correlation for any of the models.

Figure 1: Simulation of the cross-security correlation in short- and long-term returns using four separate specifications of price return behaviour in a multi-security market

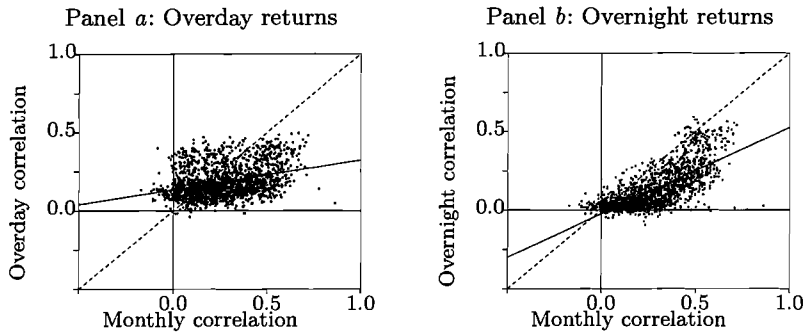


Correlation in 1-period returns plotted against the correlation in 20-period returns for four separate specifications of cross-security return behaviour. Each dot represents the long-term and short-term correlation of a security pair. Dots below (above) the dashed 45° line indicate that securities have higher (lower) long-term than short-term correlation.

Panels *a* and *b* show a simulation of the model of cross security information aggregation. In panel *a*, the cross-security correlation of revealed information varies between *0.3* and *0.6* ($\phi^m/(\phi^m + \phi^s) \in [0.3, 0.6]$). In panel *b*, the correlation of signals is set to zero, similar to the Chan (1993) model. Panel *c* and *d* present the return behaviour under nonsynchronous trading modelled according to Lo and MacKinlay (1990a). In panel *c*, the trading frequency is set to *0.50* per stock per day, spread evenly throughout 25 daily subperiods. In panel *d*, the trading frequency is a more "normal" *0.95* per day.

The solid line is a least squares regression line using all observations. The cross-security correlation of value processes varies between *0.10* and *0.80* for all four panels ($\pi^m/(\pi^m + \pi^s) \in [0.0, 0.8]$).

Figure 2: Cross-security correlation in overday and overnight returns compared to correlation in monthly returns



Cross-security correlation in overday and overnight returns plotted against the correlation in monthly (20-day) returns. Each dot represents a pair of securities (in total 2415). Dots below (above) the dashed 45° line indicate that for this security pair, short-term returns are less (more) strongly correlated than long-term returns. The solid line is a least squares regression line using all observations.

lying value process. In panel *c*, prices are subject to very high nontrading (50% per day); in panel *d*, the nontrading frequency is close to what can be observed empirically for less liquid markets (5%).

The cross-security correlation of overday and overnight returns in the Paris Bourse sample is presented in figure 2. For the overnight returns in panel *b*, both the Chan model and the nonsynchronous trading model seem to fit the observed relation between short- and long-term returns. However, given the absence of nonsynchronicity in the sample, nonsynchronous trading is obviously not a possible explanation. This conclusion is further strengthened by the large difference between correlation in short- and long-term returns. Nontrading of at least 50% per day is needed to generate a similar pattern.

In the case of overday returns (panel *a*), approximately one third of security pairs exhibit *higher* short-term than long-term correlation. As mentioned above, this cannot be reconciled with the nonsynchronous trading model or the Chan (1993) model.[28]

In order to generate this return structure, revealed information must be strongly correlated across stocks. This implies an initial overreaction to common information for about a third of the stock pairs. These empirical results suggest that order submission in the Paris market is strongly correlated across stocks at close.

[28]The same conclusion can be drawn from the fact that the intercept of the least squares regression line is significantly different from zero for overday returns, but not for overnight returns (not reported).

To the best of the author's knowledge, this kind of analysis of short-term versus long-term correlation is new. It is therefore impossible to say whether the cross-security return correlations documented in this paper are representative for other stock exchanges.

6 Conclusion

The model of cross-security information developed in this paper provides results that are intuitive and easily adaptable to stock price data. For individual stock returns, the model predicts a well-defined and testable structure of cross-autocorrelations. Securities with informative prices will tend to lead other securities, especially if revealed information is uncorrelated across securities. If the number of stocks sharing a factor is large, the cross-autocorrelation of individual stock returns will be low. However, it can still be significant if stocks share a factor not shared by other securities. Implications can be drawn to lead-lag structures of, for example, stocks, debt, warrants, and options related to a single company. As the model uses information extraction from realised prices, empirical testing is straightforward.

In the empirical section, several of the model's predictions were supported by data from the Paris Bourse. Cross-autocorrelation is higher between securities with highly correlated long-term returns at open and close. More liquid securities, should have less noisy prices, and therefore tend to lead other securities. This conjecture was supported by data both at open and close. However, the most liquid securities were also strongly lagging other securities at close, hinting at very strong reciprocal leads and lags between the most liquid securities. Cross-autocorrelation with the market return is, as predicted, much stronger than cross-autocorrelation between individual securities.

It was also shown that the model presented in this paper can explain observed return patterns better than the alternative models. The Lo and MacKinlay (1990a) model requires unrealistically high nontrading frequencies to explain the big difference between the short-term and long-term correlation of stock returns. The Chan (1993) model, which is nested by the model of this paper, is not sufficiently rich to generate higher short-term than long-term correlation of returns. As this property was observed for roughly one third of Paris overday return pairs, the addition of cross-security correlation in revealed information clearly adds empirical usefulness to the model.

The model of cross-security information aggregation has a large potential for modelling stock price behaviour. The model is set in a general REE framework, which makes it easy to adapt to different trading environments. Moreover, its generality makes it a useful tool for analysing a large number

of price discovery issues. In this paper, the lead-lag relation between stock options and corresponding stock returns was discussed. A companion paper, Säfvenblad (1997), studies the implications for stock index returns.

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2

Learning the True Index Level

Abstract:
This paper develops and tests implications of cross-security information aggregation on index return autocorrelation. In the model, prices are realised individually and simultaneously in REE auction markets, then realigned to take information revealed in other prices into account. This adjustment is symmetric across stocks, leading to index return autocorrelation of MA(1) type.

Autocorrelation will be high if the index level prior is noisy, for example, at Monday open and after high volatility in overnight trading. Autocorrelation will also be higher in portfolios of highly correlated securities. Overnight information revelation and high trading volume reduces the noisiness of the index level prior and, consequently, return autocorrelation.

Index return autocorrelation will be low, or even negative, if there is high cross-security correlation in revealed information, due to, for example, index arbitrage trading or profit taking.

All major predictions are supported by tests using data from the Paris Bourse. In contrast to earlier models of index return autocorrelation, the model can generate both positive and negative index return autocorrelation. This paper also documents instances of negative index return autocorrelation.

1 Introduction

Short-term stock index returns are, in most observed cases, positively autocorrelated. This apparent breach of the efficient market hypothesis has attracted much attention, both theoretically and empirically. Three explanations dominate the theoretical literature: nonsynchronous trading, transaction costs and time-varying expected returns.[1]

The oldest and most widely accepted of these hypotheses is the nonsynchronous trading hypothesis, originated by Fischer (1966) and Scholes and Willams (1977). Prices are assumed to be informationally efficient, but only measurable when stocks actually trade. If the component stocks of a stock index trade at separate points in time (nonsynchronously), last recorded prices reflect partly old market-wide information and a delay will occur in the index's reaction to new information even if the "true" index level is known by all market participants.

It is possible to fine-tune the nonsynchronous trading model to generate high levels of index return autocorrelation by assuming extreme nontrading in certain stocks or assuming that thinly traded stocks have high betas. However, even with these enhancements, nonsynchronous trading only accounts for parts of the observed index return autocorrelation.[2]

The transaction cost hypothesis, as formulated in Cohen et al. (1980) and Mech (1993), conjectures that stocks periodically trade at prices that do not reflect all available information, the reason being that transaction or information costs make additional cross-security price analysis non-profitable. This may be a reasonable assumption in a specialist or market maker environment where most traders only trade in a single security. However, if speculators trade in several securities, the effects from imperfect information should be small. Also, order submission and withdrawal are in fact close to costless on automated exchanges.

The advocates of time-varying expected returns argue that risk premia can be time-varying, following predictable patterns, typically mean reversion, and that, as a result, observed returns will be positively autocorrelated (See, for example, Campbell et al., 1993). However, under time-varying risk premia the same autocorrelation is expected to be visible in related asset returns such as individual stock returns or index futures returns. However,

[1] See Boudoukh et al. (1994).

[2] See, e.g., Atchison et al. (1987), Berglund and Liljeblom (1988), Lo and MacKinlay (1990a), Mech (1993).

both these asset classes have consistently proved *not* to have serially correlated short-term returns.[3]

In addition, the shorter the return frequency considered, the less likely it is that time variation in expected returns is caused by time variation in risk premia. In fact, the observed autocorrelation in intraday index returns is usually strong enough to generate *negative* expected returns. Since plausible expected returns must be higher than the risk-free rate, time-varying expected returns could possibly explain autocorrelation in long-term returns (weekly, monthly, etc.). However, time-varying risk premia do not provide a sensible explanation for the behaviour of intraday returns.

In contrast to these earlier models of index return autocorrelation, this paper uses a model of cross-security information aggregation first developed in Säfvenblad (1997). Trade is modelled as taking place in separate, simultaneous call auctions of the Hellwig (1980) type. There are no transaction costs, all stocks trade at efficient prices, and speculators may trade in all securities. The only restriction used to generate the theoretical results is the time and information constraint imposed by a simultaneous call auction procedure.

Each equilibrium transaction price will reveal information, i.e. a signal, to the rest of the market. As stocks trade separately, resulting prices may be inefficient with regard to the other realised prices, simply because other prices were not observable when demand schedules were formulated. A large part of the lead-lag relation can be captured using the index level. When aggregate stock prices are known, the index level is known with greater precision and prices will be revised to take this into account. The autocorrelation in index returns results from this price revision.

Any cross-stock price inefficiencies will, of course, be corrected in subsequent trading. Therefore, the model's scope is limited to the analysis of short-term lead-lag effects and information inefficiencies. The return horizons considered ranges from minutes to hours. Questions related to long-term returns, such as autocorrelation in weekly and monthly stock index returns, require other modelling approaches.

The paper is organised as follows. In the next section (section 2) the model of cross-security information aggregation is presented and testable hypotheses with regard to index return autocorrelation are provided. Section 3 starts by discussing some earlier empirical evidence on index return autocorrelation, and continues by testing the model using data from the Paris Bourse. Section 4 summarises and concludes.

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[3]This observation was probably first made by Boudoukh et al. (1994). If individual stock returns are autocorrelated, they are normally *negatively* autocorrelated, probably as a result of bid-ask bounce. That index futures returns have very low, if any, serial correlation is reported by, amongst others, Stoll and Whaley (1990), Chan et al. (1991) and Chan (1992).

2 A model of cross-security information aggregation

2.1 Background

The model of cross-security information aggregation used in this paper was originally developed in Säfvenblad (1997) to adapt the market maker model of Chan (1993) to a noisy rational expectations equilibrium (REE) auction market.[4] This implies that the model can serve as multi-security extension to several REE models, including Grossman (1976), Grossman and Stiglitz (1980), Hellwig (1980) , Glosten and Milgrom (1985) and Kyle (1985, 1989).[5]

The stochastic environment of the Chan model is extended by introducing cross-security correlation in revealed information. Säfvenblad (1997) shows that this richer information structure is needed to model open-to-close returns on the Paris Bourse. It is also a necessary condition for negative index return autocorrelation, and allows for common cross-security trading strategies such as index arbitrage trading.

The model is a two-stage mechanism for cross-security information aggregation within a market with many securities. In the first stage, an equilibrium price is reached for each security in an auction market of the Hellwig (1980) type. In the second stage, prices are realigned across securities using information revealed in first stage prices. As a result, observed returns are autocorrelated, following an MA(1)-process with, depending on parameters, positive or negative autocorrelation.

The model clearly shows why index returns are mostly positively autocorrelated. As all stock prices are noisy, their response to new information is proportional to the precision of the information. For an individual stock, the signal precision is low. However, if a large number of prices are observed, these can be used to construct a less noisy estimate of the market factor. The improved precision of the market level estimate justifies a stronger response. As stocks react symmetrically to the new information, index return autocorrelation results.

Normally, the index return autocorrelation is positive, but an important feature of the model is that it can also generate negatively autocorrelated index returns. This will be the case when the error in revealed information has higher cross-security correlation than the error in the prior valuation of securities. Under such circumstances, index returns rather than cross-

[4]The Chan (1993) model is based on Kyle (1985). Information is modelled as the net order flow observed by a stock specialist.

[5]These, and other REE models, share a large number of basic properties. The similarities are demonstrated in several papers, including Krishnan (1992), Paul (1994), Rochet and Vila (1994), Sarkar (1994) and Vives (1995).

security information will be used to identify price errors. The result is negatively autocorrelated index returns.

The model's implications are not limited to index return autocorrelation. In fact, the model may also be used whenever there is *simultaneous* information revelation in several securities or in several markets. Some examples are the lead-lag effects between stocks and stock options, between index futures and cash index returns, between prices for the same asset on two exchanges. Säfvenblad (1997) specifically analyses the model's implications for cross-autocorrelation among individual stock returns, and the lead-lag relation between stock returns and stock option returns.

In this model, security prices reflect all historical information, but not information made available simultaneously (or later) in other securities. Individual securities will therefore exhibit a delayed response *only* to information revealed simultaneously in *prices* of other securities. Public information releases, or other information not revealed in prices, will be reflected in all prices simultaneously, and therefore do not result in index return autocorrelation.[6]

In contrast to both the nonsynchronous trading and the transaction cost hypotheses, there is no lagged response to public information. All prices are efficient and react instantly to public information. The index return autocorrelation is not a result of lagging returns, but of causality. Realised prices *cause* a revaluation of all other securities. When securities trade simultaneously the causality will be symmetric and reciprocal, resulting in index return autocorrelation.

Although returns are cross-autocorrelated, and thus predictable, the price inefficiency cannot be used to make trading or arbitrage profits, since price revisions are predicted by all agents. Prices will therefore adjust *without* trading.

Several authors have discussed the questions of price informativeness and information acquisition in the context of REE models.[7] Those questions however, are not addressed in this paper. Price informativeness is taken to be exogenously determined, but the results of the model have clear implications for information acquisition. As market-wide information is imperfectly reflected in stock prices, it is relatively more profitable to trade on market-wide information in this setting than in the Admati (1985) framework.[8]

The model is best adapted to a simultaneous opening call auction in an electronic limit order book market, such as the Paris Bourse or the Toronto

[6]Public information may, however, generate increased uncertainty about the current value of stocks. If this uncertainty is resolved in trading, autocorrelated index returns may result. Compare with the empirical tests in section 3.5.3.

[7]See, e.g., Grossman and Stiglitz (1980) and Holden and Subrahmanyam (1992).

[8]For a formal development in a market maker environment of the Kyle (1985) type, see Shin and Singh (1996).

Table 1: Sequence of events and information in the model of cross-security information aggregation

Event	Description
A	All agents share a common prior, $\mathbf{P}^*_{-1}$, which is a normally distributed measurement of underlying values $\mathbf{V}$ with covariance matrix $\mathbf{\Pi}$
B	Each agent submits N, optimally calculated, linear demand schedules to a Walrasian auctioneer. Submitted demand schedules are not revealed to other traders.
Trading	The Walrasian auctioneer simultaneously sets market clearing prices, P_i, in all N markets. Orders are executed immediately.
C	Agents observe the realised price vector, $\mathbf{P}$.
D	Agents use the equilibrium noisiness of prices to deduce a signal, $\mathbf{F}$, from realised prices, $\mathbf{P}$. The signal has covariance matrix $\mathbf{\Phi}$.
E	Agents calculate posterior beliefs $\mathbf{P}^*$ of $\mathbf{V}$ using Bayesian updating and the revealed signal $\mathbf{F}$.

Sequence of events: A $\rightarrow$ B $\rightarrow$ Trading $\rightarrow$ C $\rightarrow$ D $\rightarrow$ E. All agents know the information structure of underlying returns, that is, the true value of $\mathbf{\Phi}$ and $\mathbf{\Pi}$. They also know the precision of their own, and other agents' signals. Transaction costs are zero.

Stock Exchange. Under this trading arrangement, no (or very little) cross-stock information is available until *after* the morning call, and only then can prices adjust to the information revealed in opening prices. Clearly, prices can adjust to any information available *before* the opening procedure.

2.2 Basic model

In the economy, N securities trade separately in simultaneous call auction markets of the Hellwig (1980) type. Each security is a claim to an unobservable underlying value. The fundamental value can, for example, be interpreted as the value of all securities in the absence of private information. The N values are arranged in the $N \times 1$ vector $\mathbf{V}$.

There are two types of traders in the market, namely speculators and liquidity traders. Speculators are rational and profit maximising agents, some of whom have received or acquired information, "a signal," relative to the underlying value of securities. Liquidity traders trade for some other exogenous reason (e.g. hedging or liquidity constraints) and their demand is independent of the expected value of securities. Liquidity trading can be correlated across securities, but is assumed to be independent of past liquidity trading, value innovations and any private signals.

Before trading, agents share a normally distributed, noisy prior belief, $\mathbf{P}^*_{-1}$, about the underlying value of all securities:

$$\mathbf{P}^*_{-1} = \mathrm{E}\left[\mathbf{V} \mid \mathcal{F}_{-1}\right] \sim \mathrm{N}\left(\mathbf{V}, \mathbf{\Pi}\right), \tag{1}$$

where $\mathcal{F}_{-1}$ is the public information set available before trading. The covariance matrix of the common prior, $\mathbf{\Pi}$, is known by all agents.

Agents calculate optimal demand schedules using any private information and the equilibrium covariance structure of signals and returns. Standard assumptions (normal distribution and exponential utility over next period's wealth) provide optimal demand schedules that are linear in price.

Demand schedules for individual securities are collected by a Walrasian auctioneer who sets a price vector $\mathbf{P}$ that clears supply and demand for all stocks simultaneously.

Relying on standard REE results, it is known that each price realised in trading reveals a signal, F_i for each stock.[9] Here, the signal is modelled as a noisy measurement of the error in the prior valuation. For all stocks, vectors and matrices are used to write

$$\mathbf{F} \sim \mathrm{N}\left(\mathbf{V} - \mathbf{P}^*_{-1}\,,\ \mathbf{\Phi}\right). \tag{2}$$

For an individual stock we write

$$F_i \sim \mathrm{N}\left(V_i - P^*_{i,-1}\,,\ \Phi_{ii}\right), \tag{3}$$

where Φ_{ii} is the ith diagonal element of the covariance matrix $\mathbf{\Phi}$. Intuitively, the aggregate signal can be seen as a weighted sum of all investors' private information distorted by the extent of liquidity trading.[10]

The price in each of the N separate markets can be represented by the following equation of Bayesian updating:

$$P_i = \frac{\Phi_{ii}}{\Pi_{ii} + \Phi_{ii}} P^*_{i,-1} + \frac{\Pi_{ii}}{\Pi_{ii} + \Phi_{ii}} \left(F_i + P^*_{i,-1}\right). \tag{4}$$

Equation 4 holds for all *competitive* single-security REE models, i.e., in all cases where realised prices are unbiased predictors of the underlying value or future price sequence. Otherwise the realised prices must be adjusted for the predictable part of future returns.

Although P_i reflects information available in F_i, it does not reflect all information available in the full signal vector, $\mathbf{F}$. Therefore, stock prices, and the index level, will be adjusted to take this information into account. First, define κ_i as the price's responsiveness to new information in F_i:

$$P_i = P^*_{i,-1} + \kappa_i F_i \qquad \kappa_i = \frac{\Pi_i}{\Pi_i + \Phi_i}. \tag{5}$$

[9] See, e.g., Hellwig (1980), proposition 5.2. It also follows directly from the martingale property of prices.

[10] See Admati (1985) for a formal derivation and Säfvenblad (1997) for a short discussion.

Rewrite equation 5 to vector and matrix notation by arranging the κ_i:s in the diagonal matrix, $\hat{\mathbf{\Omega}}$:

$$\hat{\mathbf{\Omega}} = \begin{bmatrix} \kappa_1 & 0 & \cdots & 0 \\ 0 & \kappa_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \kappa_N \end{bmatrix}. \tag{6}$$

The realised price can then be written as the prior plus the signal vector, $\mathbf{F}$, premultiplied by $\hat{\mathbf{\Omega}}$:

$$\mathbf{P} = \mathbf{P}^*_{-1} + \hat{\mathbf{\Omega}}\mathbf{F}. \tag{7}$$

As price and signals are normally distributed, standard Bayesian theory can be used to calculate a closed form solution for the posterior, $\mathbf{P}^*$, given the extracted signal vector $\mathbf{F}$:[11]

$$\mathbf{P}^* = \mathrm{E}\left[\mathbf{V} \mid \mathcal{F}_{-1},\ \mathbf{F}\ (\text{or } \mathbf{P})\right] = \mathbf{P}^*_{-1} + \mathbf{\Omega}\mathbf{F}, \tag{8}$$

$$\mathbf{\Omega} = \mathbf{\Pi}\left(\mathbf{\Pi} + \mathbf{\Phi}\right)^{-1}. \tag{9}$$

The posterior is linear in $\mathbf{F}$ with $\mathbf{\Omega}$ as an updating matrix which maps N signals into N efficient prices.

Two sets of returns are defined. The first stage returns, $\mathbf{r}$, are calculated as the difference between recorded prices and the prior:

$$\mathbf{r} = \mathbf{P} - \mathbf{P}^*_{-1} = \hat{\mathbf{\Omega}}\mathbf{F}. \tag{10}$$

Secondly, posterior returns, $\mathbf{r}^*$, which take all information in $\mathbf{F}$ into account are defined. Posterior returns are thus simply the difference between posterior and prior valuation:

$$\mathbf{r}^* = \mathbf{P}^* - \mathbf{P}^*_{-1} = \mathbf{\Omega}\mathbf{F}. \tag{11}$$

It is easy to see that returns will be cross-autocorrelated whenever $\mathbf{P}^* \neq \mathbf{P}$ or, equivalently, when $\mathbf{r}^* \neq \mathbf{r}$. The cross-autocorrelation results because the price adjustment from the observed price, $\mathbf{P}$, to the posterior valuation, $\mathbf{P}^*$, depends on earlier returns, which are used to extract information about $\mathbf{F}$:

$$\mathbf{P}^* - \mathbf{P} = \mathbf{r}^* - \mathbf{r} = \left(\mathbf{\Omega} - \hat{\mathbf{\Omega}}\right)\mathbf{F} = \left(\mathbf{\Omega}\hat{\mathbf{\Omega}}^{-1} - \mathbf{I}\right)\mathbf{r}, \tag{12}$$

where $\mathbf{I}$ is an $N \times N$ identity matrix. This price adjustment is the core of the cross-security information aggregation model. The adjustment return of security i is a weighted sum of "unexpected" returns on all other

[11] In the more general case, such an explicit solution may not be available; in addition, the optimal updating rule need not always be linear.

securities.[12] The weights are determined by the off-diagonal elements in the updating matrix $\mathbf{\Omega}$, normalised by the strength of securities' initial response to information κ_i. We can therefore write:

$$r_i^* - r_i = \sum_{j=1}^{N} \frac{\omega_{ij}}{\kappa_j} \left(r_j - \mathrm{E}\left[r_j | \mathcal{F}_{-1}, r_i\right]\right), \tag{13}$$

where ω_{ij} is the jth element on row i in the matrix $\mathbf{\Omega}$, and κ_j is the jth diagonal element in $\hat{\mathbf{\Omega}}$.

2.3 Index returns

Let r_m denote the first stage return of an equally weighted stock index. The index return can be written as the weighted average of the information revealed in each stock:

$$r_m = \frac{1}{N}\mathbf{1}'\mathbf{r} = \frac{1}{N}\mathbf{1}'\hat{\mathbf{\Omega}}\mathbf{F} = \frac{1}{N}\sum_{i=1}^{N} \kappa_i F_i, \tag{14}$$

where $\mathbf{1}$ is an $1 \times N$ column vector of ones. The weights of individual signals are determined by the κ_i:s, the stocks' first stage response to the revealed information in the stock proper. The information revealed in stocks with precise signals (high κ_i) will therefore be more strongly reflected in stock prices and the index level.

Also define the posterior index returns, r_m^* as the difference between the prior and posterior index level:

$$r_m^* = \frac{1}{N}\mathbf{1}'\mathbf{r}^* = \frac{1}{N}\sum_{i=1}^{N} r_i^* = \frac{1}{N}\mathbf{\Omega}\mathbf{F}. \tag{15}$$

The posterior returns, unlike the first stage returns, cannot be rewritten as a sum of signals, since all posterior returns depend on all signals with varying weights, determined by $\mathbf{\Omega}$.

However, from Bayesian theory it is known that for an average of individual values, the average of individual signals is the most efficient aggregate signal. Therefore, an index level signal can be defined as the average of individual stock signals:

$$F_m = \frac{1}{N}\mathbf{1}'\mathbf{F}. \tag{16}$$

Similarly, the index level prior can be defined as:

$$P_{m,-1}^* = \frac{1}{N}\mathbf{1}'\mathbf{P}_{-1}^*. \tag{17}$$

[12] From the equilibrium condition, it follows that the expected value of $P_i^* - P_i$, conditional on the realised r_i, is zero. It can be shown that equation 13 satisfies this condition.

Since the stochastic properties of signals and priors are well-known, it is easy to calculate the variance of the index level prior and signal. Denote the variances by π_m and ϕ_m, respectively:

$$P^*_{m,-1} \sim \mathrm{N}\left(V_m, \pi_m\right), \tag{18}$$

$$\pi_m = \frac{1}{N^2}\mathbf{1}'\mathbf{\Pi}\mathbf{1}, \tag{19}$$

$$F_m \sim \mathrm{N}\left(V_m - P^*_{m,-1}, \phi_m\right), \tag{20}$$

$$\phi_m = \frac{1}{N^2}\mathbf{1}'\mathbf{\Phi}\mathbf{1}, \tag{21}$$

where V_m is an equally weighted index of underlying values. From the definitions above, it follows that π_m is the average of all N^2 elements in $\mathbf{\Pi}$. It will thus be close to the average cross-security correlation in the prior valuation of component stocks.

Likewise, the variance of the market signal, ϕ_m, is approximately equal to the average cross-security correlation in revealed information. Intuitively, it can be seen as the variance of the "market mood," unfounded optimism or pessimism, or just the covariance of liquidity trading across securities.

Using the above development, the optimal market response to information, r^*_m, can be expressed as a constant, κ^*_m, multiplied by the market signal,

$$r^*_m = \kappa^*_m F_m, \tag{22}$$

$$\kappa^*_m = \frac{\pi_m}{\pi_m + \phi_m}. \tag{23}$$

The parameter κ^*_m measures how agents' beliefs react to new market-wide information F_m. If signals are only weakly correlated across securities (ϕ_m small), it is possible to know the index level with high precision when the number of securities is large. In this case, κ^*_m will be close to unity.

Now, define a parameter κ_m as a parallel to κ^*_m, measuring the first stage response to index level information, in order to compare first stage and posterior returns:

$$\kappa_m = \frac{\frac{1}{N}\sum_{i=1}^{N}\kappa_i F_i}{F_m} \approx \frac{1}{N}\sum_{i=1}^{N}\kappa_i. \tag{24}$$

In general, κ_m will be approximately equal to the average of κ_i:s. When $\kappa_m \neq \kappa^*_m$ index returns will be autocorrelated, following an MA(1)-process. If $\kappa_m < \kappa^*_m$ the market return underreacts to new information, resulting in positive autocorrelation. On the other hand, if $\kappa_m > \kappa^*_m$ the market overreacts to new information resulting in negative autocorrelation.

Whether index return is positive or negative is determined by the off-diagonal elements in $\mathbf{\Omega}$. If they are "mostly" positive, index returns will be positively autocorrelated; if they are mostly negative, index returns will

be negatively autocorrelated. The intuition behind this result will be made clearer in the next section.

2.4 A one-factor model

A direct and simple way to analyse the model's implications is to set up a "one-factor" model, where priors and signals have both a market component and an individual stock component. For an individual security, assume that the prior has the structure

$$\Pi_{ij} = \begin{cases} \pi^m + \pi^s & \text{if } i = j \\ \pi^m & \text{if } i \neq j \end{cases} \quad \forall i, j, \tag{25}$$

where π^m is the variance of the market level prior and π^s is the additional variance for individual securities. π^s is equal for all securities. The covariance matrix of the prior priors can be visualised as:

$$\underset{N \times N}{\mathbf{\Pi}} = \begin{bmatrix} \pi^m + \pi^s & \pi^m & \cdots & \pi^m \\ \pi^m & \pi^m + \pi^s & \cdots & \pi^m \\ \vdots & \vdots & \ddots & \vdots \\ \pi^m & \pi^m & \cdots & \pi^m + \pi^s \end{bmatrix}. \tag{26}$$

Let the revealed information have a similar structure with the variance of the market signal ϕ^m, and the additional variance of individual stock signals, ϕ^s:

$$\Phi_{ij} = \begin{cases} \phi^m + \phi^s & \text{if } i = j \\ \phi^m & \text{if } i \neq j \end{cases} \quad \forall i, j. \tag{27}$$

Using this simplified structure, it is possible to calculate explicit returns. The returns in excess of the prior, $\mathbf{r}$, are simply κ^s, equal for all stocks, multiplied by the revealed signal, $\mathbf{F}$:

$$\mathbf{r} = \kappa^s \mathbf{F}, \tag{28}$$

with

$$\kappa^s = \frac{\pi^m + \pi^s}{\pi^m + \pi^s + \phi^m + \phi^s}. \tag{29}$$

In the first stage of trading, the index level reacts to market-wide information *exactly as* individual stocks react to stock specific information. The realised index return r_m, is therefore the same constant, κ^s, multiplied by the aggregate signal:

$$r_m = \kappa_m F_m, \tag{30}$$

$$\kappa_m = \kappa^s = \frac{\pi^m + \pi^s}{\pi^m + \pi^s + \phi^m + \phi^s}. \tag{31}$$

However, the optimal response of the market level to the same information is different:

$$r_m^* = \kappa_m^* F_m, \tag{32}$$

$$\kappa_m^* = \frac{N\pi^m + \pi^s}{N\pi^m + \pi^s + N\phi^m + \phi^s}. \tag{33}$$

Index returns will be autocorrelated whenever $\kappa_m \neq \kappa_m^*$. Some necessary conditions for index return autocorrelation are immediately visible from equation 31 and 33. There must be several securities ($N > 1$) and prior or signals must be correlated across securities ($\pi^m \neq 0$, or $\phi^m \neq 0$). Index return autocorrelation will be positive if $\pi^m/\pi^s > \phi^m/\phi^s$, that is, when the prior has higher cross-security correlation than the revealed signals. Consequently, provided that $\kappa_m/\kappa_m^* > 0.5$, autocorrelation increases in π^m and ϕ^s and decreases in ϕ^m and π^m.

If signals are more strongly cross-correlated than underlying returns ($\pi^m/\pi^s < \phi^m/\phi^s$) the observed index returns will be negatively autocorrelated. If signal noise is strongly correlated across securities, any common return movements are more likely to be the result of noise than of underlying returns. Therefore, prices will react negatively to any common price movement.

2.5 *Implications for a market with continuous trading*

The formal model rules out continuous trading, but it is possible to adapt the model to the continuous trading case. In the case of frictionless trading, prices can and will react instantly to new information. Any cross-security price error is eliminated immediately and index return autocorrelation would be observed only over infinitely short time intervals. The model therefore approximates the Admati (1985) model.

The model will still have some effect under continuous, but *nonsynchronous* trading. As stocks trade at irregular intervals, there will be a delay in information about the market factor that adds to the delayed reaction imposed by the nonsynchronicity itself. However, in such a model, the effect of delayed information will be relatively small compared with the effect of nontrading. Also, the index level innovation will be relatively well known after only a small number of securities have traded (say 10–20); the additional information from the remaining (normally 100+) securities is small.

Therefore, measured index return autocorrelation would mostly be attributed to nonsynchronous trading effects. However, the model can generate significantly higher estimates of index return autocorrelation if there is a time restriction on information transmission. Under an explicit information restriction, autocorrelation will be highest when intraday volatility is high, that is, when cross-security price errors can be expected to be large.

2.6 Autocorrelation in intraday returns

Financial markets normally exhibit strong "U-shapes" during the trading day, with both volatility and trading volume at their highest at the opening and closing.[13] Therefore, nonsynchronous trading should add less to index return autocorrelation in early morning and late afternoon trading. However, this is clearly not the case. As shown by McInish and Wood (1991), autocorrelation can even be *higher* during periods of active trading. As transaction costs can be expected to be small when trading volume is high, this is also contrary to the transaction cost hypothesis of Mech (1993).

From the perspective of cross-security information aggregation, this result is not at all surprising. The high volatility and trading volume immediately before closing make transitory cross-security price inaccuracies more probable. As the high volatility is coupled with high trading volume, there is also a real possibility that traders suffer from information overload.

The model not only explains the results of McInish and Wood (1991), but also provides a good explanation for the high observed index return autocorrelation in daily data. Most studies use closing prices to calculate returns. Closing prices are less subjected to nonsynchronous trading but realised in a period of very high volatility. Therefore, cross-security information aggregation could account for the large difference between the autocorrelation expected from nonsynchronous trading and observed levels of autocorrelation.

2.7 Testable hypotheses

The model of cross-security information aggregation provides two main testable predictions of index return autocorrelation. Firstly, autocorrelation increases in the ratio π^m/π^s, that is, the variance of the index level prior divided by the average additional variance of the prior of individual stock prices, or, equivalently, the level of cross-security correlation in the prior.

Secondly, autocorrelation decreases in the ratio ϕ^m/ϕ^s, the level of index level signal noise divided by the additional noise in individual stock signals. This ratio can also be interpreted as the level of cross-security correlation in revealed information.

Index return autocorrelation will thus be strong if there is high uncertainty about the true index level and much security-specific noise in revealed information. On the other hand, index return autocorrelation will be low if uncertainty about individual stock values is high and revealed information is strongly correlated across securities. In the case of strong

[13]See Chan et al. (1991) and Chan (1992), for some empirical evidence and Admati and Pfleiderer (1988) and Foster and Viswanathan (1993) for a theoretical discussion.

cross-security correlation in revealed information, index return autocorrelation may be negative.

An econometrician cannot observe the covariance structure of the prior valuation. However, the covariance of the prior can be estimated relatively easily, since the error in the prior largely consists of value innovations since the last trade. If the correlation structure of value innovations can be believed to be constant, it can be estimated using the correlation in realised long-term returns. Therefore, index return autocorrelation will tend to be higher for portfolios of highly correlated stocks.

When trading is closed, no information is revealed in trading, but both value innovations and new information will be revealed outside trading. Depending on the proportions between new information and value innovations, the prior may become both more and less noisy when trading is closed. Although information events, such as scheduled macroeconomic announcements, may reduce the noise in the index level, nontrading will generally increase noisiness of the index level prior. This effect will be strong at Monday open, when index level noise has accumulated over two nontrading days.

However, overnight developments can also enhance (at least relatively) the precision of the index level prior and thus reduce autocorrelation. This will be the case when there is new information revealed to the market during the night. Overall prior precision will improve, leading to less autocorrelation when the market opens. The empirical test of section 3.5.3 uses changes in US interest rates that are assumed to relatively improve the precision of the index level prior. Similar results would be expected from, for example, earnings announcements and exchange rate changes.

Any index level innovation revealed outside trading will not result in index return autocorrelation. In the model, such information will enter directly into agents' prior valuation before the next round of trading. This implies that changes in the index level that are the result of macro announcements, interest rate changes and so on, should be reflected in stock prices faster than market-wide information that is revealed through trading, primarily reflecting changes in investor valuations or preferences.

The index level prior will be particularly noisy when the index level volatility is high. Using various volatility estimates, it is relatively straightforward to identify when the index prior is more noisy than otherwise. As an example, we know that volatility exhibits a U-shape over the trading day, and we therefore expect that autocorrelation will also be U-shaped. This prediction is thus consistent with the empirical evidence reported by McInish and Wood (1991).

It is much harder to measure the correlation in revealed signals. As these are derived from realised prices, they cannot be used to explain return patterns. In order to capture the cross-security correlation in signals, it is necessary to use other data besides prices. For intraday returns, an example is the index arbitrage trading, which will induce cross-security correlation

in revealed information. It may also be possible to analyse the order book movements at opening and closing to identify index arbitrage trading. For the daily data used in this paper, the possibilities are limited to theoretical arguments. Section 3.6 tests an argument based on short-selling restrictions.

3 Empirical evidence

3.1 Some earlier empirical evidence

Table 2 presents a selection of published evidence on index return autocorrelation, and clearly shows that, index returns are positively autocorrelated, for most return frequencies and markets. As discussed in section 2.5, the results of McInish and Wood (1991) provide support for the model, documenting high index return autocorrelation under high trading activity.

Similar results are also reported by Chan (1992), who finds that cash index returns lag index futures returns more strongly when the trading intensity is high (the marginal impact is small, but statistically significant). Similar to the results of McInish and Wood (1991), this implies higher index return autocorrelation when trading is active, contrary to the predictions of nonsynchronous trading. Chan also shows that the futures lead is stronger when there are large changes in the index level. This result is also consistent with cross-security information aggregation. High index return volatility implies a combination of a noisy index prior (π^m/π^s high) and a precise index signal (ϕ^m/Φ^s low), both leading to high index return autocorrelation.

3.2 Choice of data

In continuous trading, cross-security information aggregation and nonsynchronous trading have similar implications for observed cross-autocorrelation. It is therefore important to test for cross-security information aggregation in a setting with minimal nontrading. In addition, the physical trading arrangements should be as close to the theoretical model as possible.

Trading at the opening call auction at the Paris Bourse fulfils both these criteria. There is no nonsynchronicity in recorded prices and the trading arrangements are very close to the theoretical model. Data was kindly made available by SBF–Paris Bourse. The dataset provides opening prices, closing prices and trading volume for all stocks and other instruments traded through the CAC electronic trading system. The sample period is five years (1991–1995), comprising 1302 daily observations.[14]

[14]Only stocks with more than 1000 trading days during the sample period were considered.

Table 2: Selected empirical evidence on index return autocorrelation

Source	Series	Sample period	Return frequency	First autocorrelation
Campbell et al. (1993)	CRSP^{vw}	1950-62	daily	0.13**
		1962-74	daily	0.28**
		1975-87	daily	0.17**
Atchison et al. (1987)	CRSP^{ew}	1978-81	daily	0.17**
	CRSP^{vw}	1978-81	daily	0.31**
Lo and MacKinlay (1990b)	CRSP^{ew}*small stocks*	1962-87	daily	0.35**
	CRSP^{ew}*large stocks*	1962-87	daily	0.17**
Berglund and Liljeblom (1988)	Helsinki^{vw}	1977-82	daily	0.49**
McInish and Wood (1991)	NYSE^{ew} open	1984-85	daily	0.15*
	NYSE^{ew} midday	1984-85	daily	0.06
	NYSE^{ew} close	1984-85	daily	0.27**
Abhyankar (1995)	FT-SE 100	1986-90	60 min.	0.14**
Stoll and Whaley (1990)	S&P 500	1982-87	5 min.	0.51**
	MMI	1984-86	5 min.	0.24**
Chan et al. (1991)	S&P 500	1984-85	5 min.	0.45**
	S&P 500	1988-89	5 min.	0.27**
Chan (1992)	MMI	1984-85	5 min.	0.31**
Abhyankar (1996)	FT-SE 100	1992	5 min.	0.48**

Significance levels as reported or calculated from reported standard errors. ^{ew}Equally weighted index. ^{vw}Value-weighted index. **/*/° Significantly different from zero at the 0.01/0.05/0.10 level.

During the sample period, the electronic order book is opened for order submission at 08:30 (09:00 until 1992). The orders are accumulated until the opening call at 10:00, when matching orders are executed at the price that maximises the number of shares traded.[15] This price is recorded as the opening price in the dataset. Approximately 5% of the daily trading volume is executed at opening prices.

To minimise problems of low liquidity, the sample is restricted to the 70 most traded stocks on the monthly settlement list (*Reglement Mensuel*). All selected stocks have an average daily trading volume of at least 5 million FRF per day during the sample period. Summary statistics on all the individual stock series used are reported in table 8 (p. 61–62).[16]

The closing price is realised in continuous trading and is the last price at which a transaction is executed (trading closes at 17:00). As trading is very active during the last minutes of the day, the average nontrading is only a few seconds for sample stocks. Any return spill-over from nonsynchronous trading should thus be negligible.

With the exception of the exact simultaneity in the SBF dataset, the data is thus similar in character to the NYSE data used by Amihud and Mendelson (1987).

3.3 Portfolio construction

As a measure to further reduce effects of low liquidity or other measurement errors, three portfolios of 23-24 stocks are created on the basis of trading volume (*High Volume*, *Medium Volume* and *Low Volume*). The portfolio containing the most liquid stocks, *High Volume*, contains only very liquid stocks. The time series results for this portfolio should thus be considered most robust.

To test hypotheses relative to the cross-security correlation of the prior cross-sectionally, three correlation sorted portfolios of 23-24 stocks are created (*High Correlation*, *Medium Correlation* and *Low Correlation*, see section 3.5.1 for the test). Stocks were ranked according to the average correlation in monthly returns between the stock and all other stocks. The *High Correlation* portfolio has very high cross-security correlation in monthly returns (*0.499*), and is thus created from securities with low idiosyncratic risk. A seventh portfolio, *All Stocks*, contains all 70 stocks in the sample. Opening prices, closing prices and daily transaction volume are calculated

[15]There is, however, one important difference from the model setup. During the preopening stage, an indicative price is available to the market. Biais et al. (1996) study the information content at the preopening stage using mainly a single-security perspective. They show that preopening prices are not very informative. Most limit orders are submitted in the final minutes before opening. Detailed accounts of the trading structure are also found in Biais et al. (1995).

[16]The same data is used in Säfvenblad (1997).

Table 3: Summary statistics for stock portfolios

Portfolio	Autocorrelation at open	Autocorrelation at close	Cross-security correlation in monthly returns§	Trading volume‡
High Volume	0.066	0.157**	0.336	87.4
	(0.042)	(0.022)	(0.187)	(1.3)
Medium Volume	0.023	0.052*	0.212	21.4
	(0.043)	(0.026)	(0.133)	(0.3)
Low Volume	0.185**	0.045	0.227	8.6
	(0.054)	(0.033)	(0.142)	(0.1)
High Correlation	0.070	0.123**	0.499	57.4
	(0.043)	(0.025)	(0.077)	(0.9)
Medium Correlation	0.151**	0.097**	0.283	24.6
	(0.048)	(0.032)	(0.089)	(0.3)
Low Correlation	0.080°	0.066**	0.079	35.8
	(0.042)	(0.024)	(0.096)	(0.5)
All Stocks	0.150**	0.122**	0.248	39.1
	(0.043)	(0.027)	(0.156)	(0.5)

Regressions use least squares estimation with asymptotic GMM standard errors (in parentheses) that are robust to heteroskedasticity (Hansen, 1982). §Cross-sectional standard errors in parentheses. ‡Average per day, per stock, trading volume in million FRF. Standard deviation across trading days in parentheses. **/*/° Significantly different from zero at the 0.01/0.05/0.10 level.

for each portfolio. Summary statistics for the portfolios are reported in table 3.

3.4 Methodology

In order to use both opening and closing prices, two types of returns are calculated. Overday returns are calculated as the log difference between opening and closing prices:

$$r_{i,t}^{\text{day}} = \log\left(P_{i,t}^{\text{close}}\right) - \log\left(P_{i,t}^{\text{open}}\right). \tag{34}$$

Overnight returns are similarly measured from close to open:

$$r_{i,t}^{\text{night}} = \log\left(P_{i,t}^{\text{open}}\right) - \log\left(P_{i,t-1}^{\text{close}}\right). \tag{35}$$

Overnight returns are dated with the day when the return period ends. For example, Monday overnight return measures the return from Friday close to Monday open. Using these two types of return observations, autocorrelation at open is estimated using the regression model

$$r_{i,t}^{\text{day}} = \beta_0 + \beta_1 r_{i,t}^{\text{night}} + \varepsilon_{i,t}, \tag{36}$$

while autocorrelation at close is calculated using the regression model

$$r_{i,t}^{\text{night}} = \beta_0 + \beta_1 r_{i,t-1}^{\text{day}} + \varepsilon_{i,t}. \tag{37}$$

Regressions use least squares estimation with heteroskedasticity consistent GMM standard errors (Hansen, 1982). Regressions do not exclude or control for outliers.

3.5 Testing effects from the variance of the index level prior

This section presents five separate tests of the prediction that index autocorrelation increases in the variance of the index level prior (π^m in the theoretical model).

3.5.1 Highly correlated return series

We start by testing whether portfolios of highly correlated securities exhibit higher return autocorrelation. Parts of the error in the prior result from value innovations. If innovations are strongly correlated across securities, so will the errors of prior estimates. Industry portfolios are thus expected to exhibit stronger autocorrelation than "mixed" portfolios.[17]

At open the hypothesis is supported for *Medium Correlation* and *Low Correlation* but rejected for *High Correlation* (results in table 3). *High Correlation* has lower autocorrelation than both the other portfolios (*0.070* versus *0.151*, *0.080*). The most probable reason for this rejection is the significantly higher liquidity of stocks in *High Correlation*. Trading volume of stocks in *High Correlation* is about twice that of stocks in *Medium Correlation* and *Low Correlation*.

Given the results at open, results at close are surprisingly well in line with predictions. The autocorrelation increases in the level of cross-security correlation (*0.066*, *0.097*, *0.123*) and the difference between *High Correlation* and *Low Correlation* is statistically significant. This result must be considered particularly strong as the high liquidity of stocks in *High Correlation* should tend to reduce autocorrelation.

3.5.2 A Monday effect

As a second test, we analyse day-of-the-week effects on autocorrelation. The index prior can be expected to be particularly noisy when markets open after the weekend, that is, at Monday open. Private information and other uncertainty have then accumulated during two nontrading days. The

[17]Using industry portfolios however, is not a good way to test this proposition for two reasons. Firstly, to obtain a reasonable number of securities, industry portfolios must include less liquid stocks. Secondly, the average correlation between same-industry shares is not much higher than the average correlation among all stocks.

Table 4: Index return autocorrelation conditional on day-of-the-week

Portfolio	$\hat{\beta}_1$ *Mon.*	$\hat{\beta}_2$ *Tue.*	$\hat{\beta}_3$ *Wed.*	$\hat{\beta}_4$ *Thu.*	$\hat{\beta}_5$ *Fri.*	Wald
At Open						
High Volume	0.218**	0.076	−0.066	−0.019	−0.001	8.1°
	(0.066)	(0.110)	(0.116)	(0.077)	(0.117)	
Medium Volume	0.173*	0.090	−0.158	−0.090	0.049	10.1*
	(0.080)	(0.109)	(0.103)	(0.063)	(0.092)	
Low Volume	0.328**	0.156°	0.147	0.048	0.186*	4.3
	(0.114)	(0.088)	(0.112)	(0.079)	(0.076)	
All Stocks	0.302**	0.193°	−0.001	0.014	0.158	12.4*
	(0.068)	(0.106)	(0.111)	(0.058)	(0.108)	
At Close						
High Volume	0.160**	0.100*	0.183**	0.162**	0.169**	1.7
	(0.050)	(0.047)	(0.061)	(0.039)	(0.048)	
Medium Volume	0.041	0.032	0.105	0.061°	0.014	1.2
	(0.063)	(0.048)	(0.077)	(0.037)	(0.055)	
Low Volume	−0.074	0.040	0.079	0.108*	0.066	4.4
	(0.078)	(0.049)	(0.099)	(0.043)	(0.051)	
All Stocks	0.094	0.084°	0.163°	0.145**	0.114*	1.4
	(0.060)	(0.051)	(0.085)	(0.037)	(0.054)	

Results are similar for the correlation-sorted portfolios (not reported). Trading volume is approximately equal across days of the week, with the exception of Mondays, when trading volume is approximately 25% lower than on other days (not reported). Regression model: $r_t = \beta_0 + (\beta_1 D_{1,t-1} + \ldots + \beta_5 D_{5,t-1}) r_{t-1} + \varepsilon_t$. $D_{1,t}, \ldots, D_{5,t}$ are dummy variables for the day of the week (1=Monday). The time indices refer to return periods (overnight or overday). The Wald statistic tests the restriction $\beta_1 = \ldots = \beta_5$. $\chi^2(4)$ critical values: 13.2/9.4/7.7 at the 0.01/0.05/0.10 level. Regressions use least squares estimation with asymptotic GMM standard errors (in parentheses) that are robust to heteroskedasticity (Hansen, 1982). **/*/° Significantly different from zero at the 0.01/0.05/0.10 level.

highest autocorrelation should thus be observed at the Monday open. For closing returns, day-of-the-week effects should be less pronounced as the closing is always preceded by a full trading day during which index level uncertainty can be reduced to "normal" levels.

Both these conjectures are supported by the results presented in table 4. At close, the null of all days having the same autocorrelation cannot be rejected for any of the portfolios. However, at open there is a strong, significantly positive, Monday effect in all stock portfolios.[18]

[18]The strong Monday effect motivates the use of a dummy for Monday open in the remaining regressions.

3.5.3 High overnight volatility

Large overnight changes in foreign stock market values result in a noisier than usual index prior at opening. Although investors observe information about overnight events, they cannot judge the full impact on French stock values. As discussed earlier, this should result in higher autocorrelation at open.

The results presented in panel *a* of table 5 support this prediction. Autocorrelation at open is higher following large absolute index returns in overnight US trading for all portfolios, although the statistical significance for individual portfolios is weak.

Another important observation from table 5 is that index return autocorrelation is *negative* conditional on low overnight volatility (-0.078, -0.161, -0.077, -0.047). Although this result is not statistically significant, it shows that a comprehensive model of index return autocorrelation must be capable of modelling both positive and negative autocorrelation.

3.5.4 Improved index level precision

The argument above can also be extended to include new information about the value of French equities released during the night. As an overnight change in the US index level implies a probable change in the unobservable French "fundamentals", US index returns always increase the level of noise in the index level prior. However, a change in the US interest rates should have less influence on the fundamental values of French stocks, although it certainly affects the discounted value of these fundamentals.

There will consequently be relatively low uncertainty about the valuation of French stock after the realisation of large overnight interest rate changes. The change in interest rates provides an additional signal that can be used to update the common index level prior. Large large changes in interest rates should *lower* the uncertainty of the index prior and thus reduce autocorrelation at open.

The results presented in panel *b* of table 5 support this prediction. Autocorrelation at open is significantly lower, and in some cases even negative, following large absolute changes in US interest rates. The statistical significance for individual portfolios is not strong, but the point estimates indicate the same pattern for all portfolios.

3.5.5 High trading volume

As argued in the theoretical section, trading increases the precision of prices by releasing private information to the market.[19] If trading is intense, the index level will be a better estimate of the "true" index level than oth-

[19] This has also been demonstrated empirically by, e.g., Amihud and Mendelson (1987).

Table 5: Index return autocorrelation at open conditional on overnight stock returns and interest rate changes

Portfolio	$\hat{\beta}_1$ *small*	$\hat{\beta}_2$ *large*	$\hat{\beta}_3$ *Monday*	Wald
Panel *a*: Conditional on index returns				
High Volume	−0.078	0.033	0.241**	1.5
	(0.084)	(0.056)	(0.085)	
Medium Volume	−0.161*	0.002	0.229*	3.6°
	(0.077)	(0.048)	(0.093)	
Low Volume	−0.077	0.205**	0.222*	13.0**
	(0.068)	(0.048)	(0.097)	
All Stocks	−0.047	0.118*	0.244**	4.2*
	(0.076)	(0.049)	(0.080)	
Panel *b*: Conditional on interest rate changes				
High Volume	0.011	−0.059	0.234**	0.7
	(0.067)	(0.068)	(0.084)	
Medium Volume	−0.027	−0.130*	0.247**	1.8
	(0.052)	(0.064)	(0.090)	
Low Volume	0.255**	0.028	0.175°	7.8**
	(0.063)	(0.057)	(0.096)	
All Stocks	0.122*	−0.015	0.240**	3.4°
	(0.059)	(0.062)	(0.077)	

Both panels: Regression model, $r_t = \beta_0 + (\beta_1 D_{1,t-1} + \beta_2 D_{2,t-1} + \beta_3 D_{Monday,t-1}) r_{t-1}$. $D_{Monday,t}$ is a dummy variable for Monday open. Panel *a*: $D_{1,t}$ is a dummy variable for the central 50% of return observations, while $D_{2,t}$ is a dummy variable for the remaining observations. Uses daily S&P 500 returns collected by Findata. Panel *b*: $D_{1,t}$ is a dummy variable for the central 60% of interest rate changes, while $D_{2,t}$ is a dummy variable for the remaining observations. Uses changes in 10 year US Treasury bond rates collected by Sveriges Riksbank. The regressions use raw returns (not filtered for the expected effect of overnight US index returns and interest rate changes). Regressions using filtered data give similar parameter estimates and test statistics. The Wald statistic tests the restriction $\beta_1 = \beta_2$. $\chi^2(1)$ critical values: 6.6/3.8/2.7 at the 0.01/0.05/0.10 level. Regressions use least squares estimation with asymptotic GMM standard errors (in parentheses) that are robust to heteroskedasticity (Hansen, 1982).

Table 6: Index return autocorrelation at close conditional on trading volume

Portfolio	$\hat{\beta}_1$ *Low*	$\hat{\beta}_2$ *High*	Wald
High Volume	0.232**	0.097**	9.0**
	(0.037)	(0.026)	
Medium Volume	0.118**	0.009	4.2*
	(0.045)	(0.030)	
Low Volume	0.090	0.005	1.6
	(0.056)	(0.038)	
All Stocks	0.199**	0.065*	5.4*
	(0.050)	(0.029)	

Regression model: $r_t = \beta_0 + (\beta_1 D_{1,t-1} + \beta_2 D_{2,t-1}) r_{t-1}$. $D_{1,t}$ ($D_{2,t}$) is a dummy variable for low (high) trading volume in the portfolio *All Stocks*. The Wald statistic tests the restriction $\beta_1 = \beta_2$. $\chi^2(1)$ critical values: 6.6/3.8/2.7 at the 0.01/0.05/0.10 level. Regressions use least squares estimation with asymptotic GMM standard errors (in parentheses) that are robust to heteroskedasticity (Hansen, 1982). **/*/° Significantly different from zero at the 0.01/0.05/0.10 level.

erwise. Consequently, high trading volume should be associated with low autocorrelation, in particular at close.

The results reported in table 6 support the model's prediction. Autocorrelation at close is lower after days of high trading volume for all reported portfolios. For three out of four portfolios, the difference is statistically significant. There is also a weak spill-over of reduced autocorrelation at the following day's opening (not statistically significant, not reported).

3.6 Testing effects from cross-security correlation in revealed information

The results of section 3.5.3 (table 5), show that the autocorrelation at open is negative conditional on a "quiet night," that is, small US index returns. In the model, this implies that there is non-zero cross-security correlation of the information revealed in the opening call auction (high ϕ^m/ϕ^s), contrary to the assumption of Chan (1993).

Unfortunately, the signals are not observable and the cross-security correlation in revealed information is not measurable. For empirical testing, theoretical arguments must be used to identify situations where the cross-security correlation of revealed information is particularly high or low.[20]

[20] It is also possible to measure cross-security correlation of revealed information using the cross-security correlation in short-term returns. However, for empirical testing of the model, in-sample measures cannot be used (in the presence of measurement errors, the null would tend to be rejected). However, it is possible to identify cross-security correlation using matching samples or out-of-sample techniques.

As the correlation depends on events in the trading process itself, and not on the events prior to the auction, it is hard to find good testable cases of high and low correlation in revealed information. The two possible tests discussed here are based on index arbitrage trading and short-selling restrictions.

3.6.1 Index arbitrage

If some agents buy or sell several securities simultaneously, as in the case of index arbitrage trading, realised returns and revealed information will be more strongly correlated across securities. Therefore, index return autocorrelation will be reduced or even negative after index arbitrage transactions.

This hypothesis is supported by the empirical results of Harris et al. (1994). The authors use NYSE intraday data to study return behaviour close to large index arbitrage transactions. Index returns are strongly positively autocorrelated, but following on index arbitrage transactions, returns reversals are documented (returns are thus negatively autocorrelated). Conditional on non-arbitrage program trades, index return autocorrelation is close to zero, i.e. significantly lower than normal levels of autocorrelation.

3.6.2 Short-selling restrictions

In a market with explicit or self-imposed short-selling restrictions, downward price pressure originates (mostly) from the owners of the security in question. In contrast, upward price pressure may originate from any market participant, owners and non-owners alike. Investors can thus be "stock-picking" in a rising market, but must sell whatever stocks they already hold in a falling market.

As investors in aggregate hold the market portfolio, cross-security correlation in revealed information is higher conditional on an index level decrease. Consequently, there will be lower index return autocorrelation conditional on an index level decrease.

This conjecture is supported by the results in table 7 where return autocorrelation is conditioned on the preceding index return. At open, autocorrelation results are mixed. For the least liquid portfolio, autocorrelation is somewhat higher following on negative index returns, but all other portfolios exhibit higher autocorrelation conditional on index level increases. At close, the pattern is in line with predictions, and index return autocorrelation is consistently higher after days of above average stock market performance. In three out of four reported cases, the difference is statistically significant.

To test whether this asymmetry is, in fact, a result of an asymmetry in investor behaviour, is outside the scope of this paper. It is, however, an interesting topic for future research.

Table 7: Index return autocorrelation conditional on high and low returns

Portfolio	$\hat{\beta}_1$ *Low*	$\hat{\beta}_2$ *High*	$\hat{\beta}_3$ *Monday*	Wald
At open				
High Volume	−0.085	0.055	0.253**	1.4
	(0.087)	(0.069)	(0.092)	
Medium Volume	−0.098	0.003	0.239**	1.1
	(0.069)	(0.059)	(0.091)	
Low Volume	0.147°	0.104	0.197°	0.1
	(0.079)	(0.066)	(0.112)	
All Stocks	0.010	0.126*	0.255**	1.3
	(0.076)	(0.060)	(0.089)	
At close				
High Volume	0.071°	0.242**	...	6.0*
	(0.040)	(0.042)		
Medium Volume	−0.046	0.137**	...	5.4*
	(0.048)	(0.046)		
Low Volume	−0.027	0.094°	...	1.3
	(0.069)	(0.056)		
All Stocks	0.026	0.205**	...	4.4*
	(0.048)	(0.052)		

Regression model: $r_t = \beta_0 + (\beta_1 D_{1,t-1} + \beta_2 D_{2,t-1} + \beta_3 D_{Monday,t-1}) r_{t-1}$. $D_{1,t}$ ($D_{2,t}$) is a dummy variable for low (high) realised index returns in the preceding trading period. $D_{Monday,t}$ is a dummy variable for Monday open. The Wald statistic tests the restriction $\beta_1 = \beta_2$. $\chi^2(1)$ critical values: 6.6/3.8/2.7 at the 0.01/0.05/0.10 level. Regressions use least squares estimation with asymptotic GMM standard errors (in parentheses) that are robust to heteroskedasticity (Hansen, 1982). **/*/° Significantly different from zero at the 0.01/0.05/0.10 level.

3.7 Interpreting empirical results within the model

The following example is not a formal test of the model. Instead it is intended to show how the model can be used as an analytical tool to interpret observed return phenomena and generate testable hypotheses.

In table 3, we can compare index return autocorrelation at open and close. It is clear that the point estimate of autocorrelation is higher at close than at open for *High Volume*, the portfolio of most liquid stocks (*0.066* at open , *0.157* at close). For the *Medium Volume* portfolio there is no large difference between autocorrelation at open and close (*0.023*, *0.052*), but for *Low Volume* the relationship is the reverse with high autocorrelation at open but low at close (*0.185*, *0.045*).

It seems reasonable to believe that the index level uncertainty is lower at close than at open as overday trading reduces the uncertainty about the true index level.[21] Still, autocorrelation is stronger at close for *High Volume*. In terms of the model of cross-security information aggregation, this effect must be a result of reduced cross-security correlation in revealed information at close.

What may be the cause of this reduction in cross-security correlation of the revealed information? The obvious suspect is the trading behaviour of individual investors. It is well known (albeit from anecdotal evidence) that many investors on the Paris Bourse prefer to trade at the close or as near as possible to the close. This is probably because most performance evaluation is carried out against closing prices as these are most readily available. Some speculators may also want to close open positions before the trading day ends.

In an REE, market such trades are considered to be liquidity trading since they are not based on expected future returns. If the closing transactions are uncorrelated across securities, this can explain the empirical results. This proposition is clearly testable using intraday data.

Why, then, is the same result not observed for the *Low Volume* portfolio? Although component stocks are less liquid than the *High Volume*stocks, they are still quite liquid. If these less liquid stocks are not subject to position closing liquidity trading at close it could be that positions are closed in earlier trading, or that traders do not let positions grow too big during the day. Both hypotheses are testable using dealer inventory data.

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[21]This conjecture is supported by results reported in table 8. While individual stock returns are strongly negatively autocorrelated at open (average: -0.125) they are only weakly autocorrelated at close (-0.044). This result is consistent with higher price precision at close.

4 Conclusion

This paper derives a model of autocorrelation in stock index returns based on information aggregation across stocks that trade individually.

The first main implication of the model is that increased cross-security correlation in the market prior of security prices increases index return autocorrelation. This proposition was tested using several different approaches. High cross-security correlation of the prior is expected, for example, at Monday open, after overnight US market volatility and in portfolios of highly correlated stocks. All tests support the model at varying levels of statistical significance.

The other main implication of the model is that autocorrelation decreases in the cross-security correlation of the information revealed in trading. This aspect of the model is significantly more difficult to test as signals and signal correlations are unobservable.

One empirical test supported the prediction that index return autocorrelation should be lower after days with negative index returns. Empirical evidence of Harris et al. (1994) supports the prediction of lower index return autocorrelation conditional on index arbitrage trading. They even report return reversals, i.e. negative return autocorrelation.

An important advantage of the model is that information is extracted from prices using standard REE theory. The model is therefore formulated from the point of view of an econometrician who only observes realised prices.

Relative to earlier work on index return autocorrelation, the paper provides a methodological innovation by using a narrow, carefully selected, dataset instead of market-wide stock portfolios. This makes it possible to eliminate other possible sources of index return autocorrelation such as nonsynchronous trading or transaction costs.

Although testing is carried out in a controlled environment, it is highly probable that the same price adjustments are present in intraday trading. There, the resulting autocorrelation will be lower, but cross-security information aggregation can help to account for the index return autocorrelation not explained by nonsynchronous trading, especially during active trading. The model thus explains the findings of McInish and Wood (1991), that is, the U-shape in index return autocorrelation. High autocorrelation at open and close is consistent with the high uncertainty of the index level prior present at open and close.

An important application of the model is as a tool to analyse empirical evidence of cross-security information aggregation. For example, the model can be used to analyse lead-lag effects between index futures returns and cash index returns. The example in section 3.7 shows how testable hypotheses can be generated from "stylised results." Hypotheses are left as suggestions for future research as they require intraday data for the empirical testing.

Two major conclusions can be drawn from the model. Firstly, index return autocorrelation is consistent with efficient markets and prices. Transaction costs, measurement errors and other inefficiencies may increase autocorrelation, but autocorrelation need not be zero in the absence of such imperfections. Secondly, the model can generate both positive and negative autocorrelation in index returns. Almost all earlier theoretical and empirical work has focused on positive return autocorrelation, but as the empirical results show, negative index return autocorrelation is observed in several cases. This is an interesting field for further empirical study.

Table 8: Summary statistics of stocks used for portfolio construction

Corr No.†	Name	Autocorrelation At open	Autocorrelation At close	Trading volume‡	Volatility × 100 close-to-open	Volatility × 100 open-to-close
2	Alcatel Alsthom	0.163*	0.082**	217.2	0.900	0.536
1	Elf Aquitaine	−0.050	0.065**	174.1	1.039	0.627
3	Total	0.002	0.006	116.8	1.035	0.739
3	LVMH Moët Vuitton	0.008	0.019	116.0	0.926	0.717
3	Générale des Eaux	0.015**	0.309	114.1	1.046	0.671
1	Groupe Danone	−0.169**	0.000	107.4	0.847	0.483
1	Société Générale A	−0.012	0.043*	96.3	1.036	0.607
1	Suez (Compagnie de)	−0.081	0.102**	93.3	1.127	0.676
1	Saint-Gobain	−0.074	0.058**	90.8	1.101	0.638
1	Peugeot	−0.041	0.088**	90.2	1.066	0.585
3	Carrefour	−0.053*	0.093	80.9	0.964	0.605
1	l'Oreal	−0.046	−0.003	80.2	1.085	0.630
1	Paribas (fin.)	−0.050	0.069**	74.0	1.228	0.726
1	Lafarge	−0.099*	0.040°	66.3	1.135	0.640
1	Air Liquide	−0.116*	−0.008	65.0	0.931	0.525
3	UAP	−0.006	−0.051	63.2	1.425	0.905
1	Michelin B	0.001	0.047*	62.7	1.248	0.689
2	Axa	0.018**	0.062**	60.6	1.241	0.807
1	Lyonnaise des Eaux	−0.116*	0.029	60.3	1.034	0.604
2	Eurotunnel	−0.004	0.112**	56.5	1.589	1.022
1	Accor	0.018	0.056**	46.3	1.017	0.590
1	Havas	−0.192**	0.037°	39.5	1.188	0.672
3	Canal+	−0.024	0.004	37.0	1.097	0.627
3	Sanofi	−0.014	−0.013	34.9	1.082	0.737
2	CLF	−0.082°	0.014	33.9	1.145	0.713
3	EuroDisney sca	−0.140**	0.139**	31.4	1.579	1.095
3	Pernod-Ricard	0.005	0.087	28.9	1.105	0.800
1	Bouygues	−0.195**	−0.006	28.2	1.112	0.683
1	CCF	−0.183**	−0.070**	25.9	1.190	0.733
1	Bancaire (Cie)	−0.275**	−0.016	25.0	1.524	0.856
3	Pinault-Printemps	−0.286**	−0.121**	25.6	1.104	0.722
2	Carnaud Metalbox	−0.302**	−0.020	24.1	0.996	0.599
1	Schneider	−0.279*	−0.124**	24.4	1.440	0.980
1	Thomson-CSF	−0.223**	−0.019	24.6	1.508	0.858
3	Valeo	−0.012	−0.044	21.4	1.229	0.823

The table continues on the next page.

Table 8 continued

Corr No.†	Name	Autocorrelation At open	Autocorrelation At close	Trading volume‡	Volatility × 100 close-to-open	Volatility × 100 open-to-close
3	AGF	−0.044	−0.084**	21.3	1.086	0.753
2	Eridania Beghin	−0.241**	−0.062*	20.2	1.002	0.598
3	Promodes	−0.026	−0.177	19.3	1.080	0.767
2	CFF	−0.061*	−0.059*	17.9	1.395	0.874
3	Legrand	−0.014**	−0.215**	16.7	1.107	0.846
2	Chargeurs	−0.180**	−0.059*	15.0	1.157	0.694
3	Castorama Dubois	−0.037**	−0.133**	14.3	1.093	0.663
1	Saint Louis	−0.364**	−0.085**	14.8	1.044	0.649
2	Pechiney Intl	−0.155**	−0.102**	13.9	1.276	0.764
3	Rhone-Poulenc cip	−0.158*	−0.356**	12.7	1.836	1.795
3	Roussel-Uclaf ord.	−0.019	−0.344*	12.6	1.182	0.944
2	Credit Lyonnais ci	−0.386**	−0.095**	11.0	1.431	1.022
2	Pechiney cip	−0.292**	−0.081**	11.3	1.337	0.790
2	Credit National	−0.044	−0.183°	11.5	1.055	0.716
2	Casino Guichard	−0.392**	−0.125**	11.6	1.424	0.855
2	Club Mediterranée	−0.204**	−0.040	11.7	1.155	0.747
3	Synthelabo	−0.013	−0.147**	10.3	1.140	0.811
3	Docks de France	0.012**	−0.066	10.7	0.970	0.703
2	Cap Gemini Sogeti	−0.216**	0.008	10.1	1.315	0.824
2	Matra Hachette	−0.152*	−0.138**	10.2	1.759	1.194
2	Cetelem	−0.071	−0.076°	9.5	1.245	0.774
2	Lagardere groupe	−0.197**	−0.075**	9.8	1.434	0.883
3	Groupe Ass. Nat.	−0.026	−0.082*	9.5	1.291	0.887
3	Bic	−0.055°	−0.004	9.1	1.071	0.791
1	CGIP	−0.219**	−0.120**	9.4	1.179	0.779
1	Schneider	−0.361**	−0.071**	7.9	1.510	0.902
1	Imetal	−0.347**	−0.128**	7.7	1.330	0.820
2	Sodexho	−0.355**	−0.118**	6.1	0.975	0.579
3	Rhone-Poulenc Rorer	0.045**	−0.268**	6.8	0.847	0.892
2	Cerus-Europ. Reun.	−0.311**	−0.045°	6.0	1.312	0.879
2	Comptoirs Modernes	−0.341**	−0.153**	6.4	0.982	0.630
2	Sovac	−0.010	−0.121**	5.9	1.164	0.840
2	Essilor Intl	−0.327**	−0.116**	5.9	1.152	0.727
2	Ecco	−0.254**	−0.103**	5.5	1.207	0.763
3	Seb	−0.008	−0.131*	5.9	1.155	0.861
Average		−0.125	−0.044	39.0	1.186	0.771
Sample standard error		(0.131)	(0.108)		(0.203)	(0.184)

Regressions use least squares estimation with asymptotic GMM standard errors (not reported) that are robust to heteroskedasticity (Hansen, 1982). †Included in correlation portfolio, 1=*High Correlation*, 2=*Medium Correlation*, 3=*Low Correlation*. ‡Average per day, per stock, trading volume in million FRF. **/*/° Significantly different from zero at the 0.01/0.05/0.10 level.

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3

An Empirical Study of Index Return Autocorrelation

Abstract:
This paper provides an extensive empirical investigation into the sources of index return autocorrelation, focusing on the relation between autocorrelation in individual stock returns and autocorrelation in index returns. The study uses daily data from the Stockholm Stock Exchange over the period 1980–1995 and reports three main empirical findings.

Daily Swedish stock index returns exhibit strong, and consistently positive, first order autocorrelation throughout the sample period. Positive autocorrelation is observed for return frequencies between 1 day and 3 months.

The most liquid stocks exhibit strong positive return autocorrelation. Less liquid stocks exhibit weak or negative return autocorrelation. Autocorrelation is asymmetric, high after days of above average performance of the stock market, low after days of below average performance. When compared to the other days of the week, both index returns and individual stock returns exhibit the strongest autocorrelation following on Friday returns.

The transaction cost hypothesis was tested using the Swedish stock market transaction tax. Results indicate lower precision of stock prices during the transaction tax period, but no direct effect on return autocorrelation.

The paper concludes that at least three sources contribute to observed return autocorrelation. For daily and short-term returns, profit taking and nonsynchronous trading are the probable causes of observed autocorrelation. For monthly and longer term returns, time-varying expected returns best describe the empirical results.

1 Introduction

It is well documented that daily stock index returns are positively autocorrelated. Positively autocorrelated returns are observed in most stock markets and for a wide range of return frequencies, from intraday to monthly data. This is contrary to most theoretical models of market efficiency, which generally require returns to be serially uncorrelated.

In an influential article, Boudoukh et al. (1994) discuss three explanations for the persistent index return autocorrelation. The causes mentioned are nonsynchronous trading, time-varying risk premia and (irrational) investor underreaction or overreaction. The authors conclude that nonsynchronous trading effects can explain most of the observed return patterns in US data.

Although nonsynchronous trading is clearly an important factor for index return autocorrelation, it is widely accepted that nonsynchronous trading must be complemented with other sources of autocorrelation to explain observed levels of autocorrelation (often in the *0.10–0.25* range).

In addition to the causes discussed by Boudoukh et al. (1994) there are several others, including transaction costs, cross-security information aggregation and bounded rationality. As no single theoretical model can account for the remaining autocorrelation, it is interesting to analyse the properties of autocorrelation on the Stockholm Stock Exchange.

Short-term returns on other similar assets, such as index futures and individual stocks, rarely exhibit positive return autocorrelation. The only difference between the calculated cash index and the price of an index future is that the latter is a traded asset. Thus the source of the short-term index autocorrelation must be searched in the microstructure of stock trading and index composition.

In this paper, the properties of individual stock returns are explicitly compared to those of index returns. The comparison provides a better understanding of the sources of autocorrelation for both types of returns.

This paper is structured as follows. The next section (section 2) briefly reviews some theoretical models that have implications for return autocorrelation. Section 3 discusses some earlier empirical evidence and presents new empirical results from the Stockholm Stock Exchange and section 4 summarises the findings of the paper.

2 Background — causes of autocorrelated returns

2.1 Nonsynchronous trading and sampling errors

Nonsynchronous trading adds autocorrelation to observed stock index returns. This has been modelled by, for example, Fischer (1966), Scholes and Willams (1977) and Lo and MacKinlay (1990a). In a pure nonsyn-

chronous trading model, it is assumed that stock returns are continuous processes sampled whenever the stocks are traded. As all stocks do not trade simultaneously (synchronously), there will be some outdated stock prices in a compiled stock index. These old prices will lead to a delay in the observation of market factors. If nontrading probabilities are constant, the measured index return will follow an AR(1)-process with positive first order autocorrelation (Lo and MacKinlay, 1990a).

Several papers test the empirical relation between nonsynchronous trading and index return autocorrelation. Lo and MacKinlay (1990a) conclude that the level of nontrading in their sample cannot explain more than part of the observed index return autocorrelation.[1]

Atchison et al. (1987) calculate the autocorrelation induced by nonsynchronous trading for portfolios of NYSE stocks. The authors report an autocorrelation coefficient due to nonsynchronous trading of *0.02–0.04*, which is far from, and significantly less than, the observed autocorrelation of *0.13–0.30*. Berglund and Liljeblom (1988) investigate whether nonsynchronous trading is the cause of the very high autocorrelation in a value-weighted Finnish stock index (*0.49*). They too conclude that nonsynchronous trading only explains a part of the observed index return autocorrelation.

A further problem with the nonsynchronous trading hypothesis is that the time series behaviour of index return autocorrelation differs from the model's predictions. McInish and Wood (1991) study the autocorrelation in daily returns, measured at different points in time during the day. During the active trading at open and close, nonsynchronous trading will have less impact on measured returns. Therefore, open-to-open and close-to-close returns should be less autocorrelated than midday-to-midday returns. However, McInish and Wood show that, contrary to the nonsynchronous trading hypothesis, index return autocorrelation is significantly higher when trading is active, that is, at open and close.

Although nonsynchronous trading cannot account for more than part of the observed index return autocorrelation, it is still an important factor, especially when considering less liquid markets, such as the Stockholm Stock Exchange. Fortunately, nonsynchronous trading effects are independent of other sources of autocorrelation, including time-varying expected returns, transaction costs and information revelation. Therefore, it is possible to model observed levels of index return autocorrelation as a sum of effects from nontrading and other contributing factors.

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[1] Boudoukh et al. (1994) discuss the possibility of generating high index return autocorrelation by assuming extreme nontrading patterns. However, there is no empirical support for the existence of such nontrading patterns.

2.2 *Return autocorrelation in a rational expectations equilibrium*

In the nonsynchronous trading model, prices are explicitly modelled as efficient, and returns on individual stocks are therefore not serially correlated. The most common type of model leading to such prices is the rational expectations equilibrium (REE). In such an environment, trading and prices are modelled as the result of a Nash equilibrium in demand strategies.

Resulting prices efficiently aggregate all public information and all information revealed by net demand at equilibrium prices. If the market is competitive, prices will follow a random walk. This is the case, for example, in the auction market model of Hellwig (1980) and the market maker model of Kyle (1985).

In the case of a non-competitive market, explored theoretically by Kyle (1989), rational traders *without* private information can expect to earn positive profits by providing liquidity to the market. This will result in observed prices being negatively autocorrelated, imposing transaction costs on non-informational trades.[2]

In the market maker setting, this negative autocorrelation is often called bid-ask bounce. In periodic auction markets there are no formal bid and ask prices, but it is well known that realised returns exhibit return properties similar to bid-ask bounce. Although bid-ask bounce often causes strong negative autocorrelation in individual stock returns, it is only of limited importance for stock index returns. Most effects disappear in portfolios of as few as 10–20 stocks.

REE models, including Hellwig (1980) and Kyle (1985), rely heavily on the use of linear optimal demand schedules and pricing rules. Non-linearity will have important and hard-to-predict effects on optimal trading strategies, but the linearity assumption is of no importance for the resulting price dynamics. If markets are competitive, returns will be serially uncorrelated; if markets are non-competitive, returns will be negatively autocorrelated.

2.3 *Feedback trading*

Short-term returns in a non-competitive REE environment are strictly negatively autocorrelated. However, for longer return horizons, both positively and negatively autocorrelated returns can result, if the non-competitive market is combined with feedback trading.[3] Feedback trading is the part of non-informational demand that can be predicted using observable variables, such as past returns.

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[2]The negative autocorrelation is often used as a measure of transaction costs in a financial market. See Roll (1984).

[3]In a competitive REE environment, competition for order flow will lead to serially uncorrelated returns even in the face of feedback trading.

Feedback trading includes several well-known trading strategies, such as profit taking, herding, contrarian investment and dynamic portfolio reallocation. A distinction is usually made between positive and negative feedback trading. In the case of positive feedback trading, traders buy after price increases (similar to herding), while in the case of negative feedback trading, traders sell after price increases (similar to profit taking).

A simplified model of feedback trading and return autocorrelation is developed by Sentana and Wadhwani (1992). The authors show that positive feedback trading results in *negative* return autocorrelation while negative feedback trading results in *positive* return autocorrelation.[4]

If traders react differently to price increases than to price decreases, the effect may be asymmetric. According to the prospect theory, agents are eager to realise profits, but unwilling to realise losses (Kahneman and Tversky, 1979). Since actual and implicit short selling restrictions leave the market with more "winners" after a day of good stock market performance, most profit taking should be expected after such days. As a result, autocorrelation in measured returns would tend to be more positive after price increases. If present, this effect should be visible both in individual stock returns and stock index returns.

2.4 *Cross-security information aggregation*

Chan (1993) and Säfvenblad (1997a), show that cross-autocorrelation in stock returns can result from the information realised in competitive REE prices. Both models analyse the difference between the efficient pricing of an individual security and the pricing of a large number of securities. If securities trade simultaneously, information revealed in one security will improve the precision of stock prices in general and the index level in particular. Säfvenblad (1997b) shows that the resulting price adjustment is symmetric in all stocks leading to index return autocorrelation. Autocorrelation will depend on the covariance structure of revealed information and price priors. Mostly, the model predicts positively autocorrelated index returns, but negative autocorrelation is also possible.

Index return autocorrelation will be low when price precision is high, for example, after a day of high trading volume. Measured autocorrelation will be high in periods of high trading volume and volatility. For the Swedish sample studied in this paper, cross-security information aggregation is less relevant due to the high nonsynchronicity of data. As effects predicted from

[4]The following example may clear the intuition. After a day of strong market performance, a number of traders are left with positive positions and profits that they wish to close before the trading day ends. This selling, negative feedback trading, will lead to a price pressure that will lead closing prices to be biased downward relative to public information. This bias will be recovered the following day, resulting in positive expected returns conditional on positive returns, i.e., positive return autocorrelation.

nonsynchronous trading are similar, but usually weaker, it is impossible to separate the two effects empirically in a market where securities trade nonsynchronously.

2.5 The role of trading volume

In REE models, such as Admati and Pfleiderer (1988), trading volume is a measure of the amount of information revealed in trading.[5] Therefore, prices realised in high trading volume are expected to be better estimates of the underlying, or "true," value of securities. In the same vein, Foster and Viswanathan (1993) show that trading volume is positively correlated with the precision of the informed trader's signal, and the resulting price precision. Similarly, in the model of Campbell et al. (1993), high trading volume makes the aggregate risk aversion more easily observable.

In models where the autocorrelation is the result of an information extraction process, such as Campbell et al. (1993), Chan (1993) and Säfvenblad (1997b), high trading volume lowers the expected return autocorrelation.

2.6 The transaction cost hypothesis

Cohen et al. (1980) and Mech (1993), discuss the effect of transaction costs on cross-security price discovery. It is argued that transaction costs hold back transactions aimed at exploiting cross-security price errors, thus slowing prices' reaction to new cross-security information. Mech (1993) analyses a market maker market where returns are driven by private information. When spreads are positive, informed traders will only trade when the expected profit from private information exceeds transaction cost. Therefore, private information will only be exploited if its price effects exceed the prevailing spread. There will thus be a delayed reaction to "small" market-wide information events, while "large" events will be efficiently reflected in prices.

This argument presumes that the provider of liquidity (the market maker) is passive, only observing the incoming order flow. Therefore, some of the market makers' transactions are made at inefficient prices. However, in an auction market, this argument loses much of its cutting power, as traders are also the providers of liquidity, when trading using limit orders. Optimally, informed agents will use a combination of limit and market orders

[5]Other sources of trading volume, such as portfolio rebalancing or liquidity trading, will generally only contribute small portions of total trading volume. Particularly, as non-informational demand "attracts" informed trading, such as in the models of Grossman and Stiglitz (1980) and Admati and Pfleiderer (1988). It can also be mentioned that new public information will only generate relatively low trading volume. The price effect is realised without trading, and portfolio rebalancing will be relatively small given that portfolios are close to optimal before the information event.

to exploit their information.[6] In most limit order markets, direct trading costs are not an issue since limit orders can be submitted and cancelled at virtually no cost.

2.7 Time-varying risk premia

Another way to explain autocorrelation in stock returns is to assume that the equity risk premia are time-varying. Campbell et al. (1993) model an economy where the aggregate level of risk aversion is mean reverting, but unobservable. The risk aversion must therefore be inferred from asset prices. In periods of high trading volume, agents' estimates of the market risk aversion is more accurate and thus the autocorrelation in stock returns is reduced.

However, in order to credibly affect asset returns, the speed of mean reversion must be low. Explaining autocorrelation in daily returns simply requires too strong a time variation in expected returns. Economically, the equilibrium expected return on risky assets is bounded below by the riskfree interest rate. However, empirical predictions from autocorrelation-based models often yield expected returns that are lower than the riskfree rate, or even negative. [7] Time-varying expected returns can thus only be considered an explanation for longer term returns.

An important property of time-varying risk premia is that returns and return autocorrelations should be consistent and visible in all assets, including index futures and individual stocks.[8] If the autocorrelation in long-term returns is similar for index returns and individual stock returns, time-varying expected returns could provide the explanation for the observed effects.

2.8 Bounded rationality

In a rational expectations equilibrium, prices are efficient, reflecting the beliefs of market participants. However, if agent's beliefs are non-rational, that is, if market participants make consistently erroneous predictions, autocorrelated returns can result. One example of this approach to modelling is "bounded rationality" examined by Hussman (1992).

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[6]See, e.g., Handa and Schwartz (1996) and Harris and Hasbrouck (1996).

[7]As an example, it can be mentioned that the expected close-to-close return on holding the AFGX *after* a day of negative returns is negative, corresponding to an annualised yield of -34% (sample period 1980-1995, results not reported). This is clearly not an equilibrium risk premium.

[8]Both these asset classes exhibit low, or negative, autocorrelation in daily and intraday returns. A similar observation is made by Boudoukh et al. (1994). For empirical support, see, e.g., Atchison et al. (1987) and the literature on lead-lag effects between index futures and cash index returns, for example, Chan (1992), Miller et al. (1994) and Abhyankar (1995, 1996).

Agents are assumed to use simplified decision rules instead of the computationally difficult REE rules. In Hussman's model, agents use historical data to fit individual ARMA models of expected stock returns. When fundamentals change, agents will only be able to reestimate the parameter values of their ARMA specification gradually.

Hussman analyses the behaviour of asset prices close to a steady state where the fitted and actual ARMA processes are equal. As a result of the delayed learning of fundamentals, realised returns will be positively autocorrelated.

However, the short-term autocorrelation generated from this type of model is quite low. As time-varying risk premia, bounded rationality also requires that expected returns are relatively equal across asset classes. The model is clearly not compatible with observed levels of autocorrelation but may nevertheless contribute to aggregate levels of return autocorrelation. Bounded rationality is not considered in the empirical section as it is very difficult to test.[9]

3 Empirical evidence

3.1 Some earlier empirical evidence on autocorrelation

Table 1 provides a small selection of the rich earlier empirical evidence of index return autocorrelation. It is easily seen that index return autocorrelation is predominantly positive, regardless of data source or frequency. Positively autocorrelated index returns have prevailed for most of the twentieth century. There is some evidence of index return autocorrelation declining in recent years but there are no indications of autocorrelation disappearing altogether.

Of the stylised facts of autocorrelation, the small firm effect is the most prominent. Autocorrelation in portfolios of small stocks is significantly higher than for portfolios of large stocks.[10]

For the Swedish market, a few preceding studies exist. Nordén (1992) reports data on autocorrelation from the Stockholm Stock Exchange based on the OMX index. Similar to the findings in this paper, Nordén finds strong positive autocorrelation between Friday and Monday returns.

Nordén (1994) provides a study of Swedish intraday index returns, basically replicating the study of McInish and Wood (1991) using the Swedish OMX index. Although volatilities exhibit the standard U-shape, the results

[9]Model selection is critical for both results and predictions. However, there is no clear economic rationale for choice of lag-lengths, return frequencies, ARMA-model, investor preferences etc.

[10]See, e.g., Lo and MacKinlay (1990b), Boudoukh et al. (1994) and McQueen et al. (1996).

for autocorrelation are different. The highest autocorrelations are found in intraday-to-intraday returns.

In contrast to index return data, few examples of positive autocorrelation are to be found in empirical investigation of individual stock prices. Intraday returns are normally negatively autocorrelated due to bid-ask bounce.

Chan (1993) provides own-autocorrelation for size-sorted securities on the NYSE and AMEX. The reported average own stock autocorrelation ranges between -0.09 and 0.05, and is clearly increasing in firm size. Berglund and Liljeblom (1988) report evidence of strong positive autocorrelation (≈ 0.30) in daily stock returns of individual stocks on the Helsinki Stock Exchange. They also report that autocorrelation in individual stock returns is increasing (although not significantly) in the trading frequency. Berglund and Liljeblom (1990) also show that average autocorrelation in individual stock returns was lower (0.05–0.11) in the high-volume years 1986–88 than in the low-volume years 1978–80 (0.30).

3.2 Data

The empirical tests use the following, comprehensive sample of return data from the Stockholm Stock Exchange. All data series are collected by Findata.

- Daily closing returns and trading volume on Affärsvärldens Generalindex (AFGX). The AFGX is a value-weighted stock market index covering all stocks traded on the Stockholm Stock Exchange. The index is calculated daily from the last recorded ask price of each stock. The index is not corrected for dividends. The sample period is 1980–1995, sixteen years with a total of 3998 observations.

- Daily closing returns of the OMX index, a narrow base index covering the 30 most traded stocks on the Stockholm Stock Exchange. This index is less affected by nontrading than the AFGX. Calculation of the OMX started in 1984.

- Closing returns and daily trading volume for 62 major stocks traded on the Stockholm Stock Exchange. The stocks were selected from all traded stocks based on sample length (more than ten years) and trading volume (highest), including all listed share classes of each company.

- Two indices created from the closing prices of the 62 stock series, one equally weighted (SSE^{ew}) and one value-weighted (SSE^{vw}).

Table 1: Selected empirical evidence on index return autocorrelation

Source	Series	Sample period	Return frequency	First autocorrelation
Campbell et al. (1993)	CRSP^{vw}	1950-62	daily	0.13**
		1962-74	daily	0.28**
		1975-87	daily	0.17**
Atchison et al. (1987)	CRSP^{ew}	1978-81	daily	0.17**
	CRSP^{vw}	1978-81	daily	0.31**
	Individual stocks	1978-81	daily	0.02
Lo and MacKinlay (1990b)	CRSP^{ew}*small stocks*	1962-87	daily	0.35**
	CRSP^{ew}*large stocks*	1962-87	daily	0.17**
Berglund and Liljeblom (1988)	Helsinki^{vw}	1977-82	daily	0.49**
	Individual stocks	1977-82	daily	≈ 0.30**
McInish and Wood (1991)	NYSE^{ew} open	1984-85	daily	0.15*
	NYSE^{ew} midday	1984-85	daily	0.06
	NYSE^{ew} close	1984-85	daily	0.27**
Sentana and Wadhwani (1992)	US index data	1885-1988	daily	0.11**
Chan (1993)	small NYSE stocks	1980-89	daily	−0.09**
	large NYSE stocks	1980-89	daily	0.05**
Abhyankar (1995)	FT-SE 100	1986-90	60 min.	0.14**
Chan et al. (1991)	S&P 500	1984-85	5 min.	0.45**
	S&P 500	1988-89	5 min.	0.27**
Stoll and Whaley (1990)	S&P 500	1982-87	5 min.	0.51**
	MMI	1984-86	5 min.	0.24**
Abhyankar (1996)	FT-SE 100	1992	5 min.	0.48**
Chan (1992)	MMI	1984-85	5 min.	0.31**
Nordén (1994)	OMX	1991-93	5 min.	0.10**

Estimates and significance levels as reported in cited articles. Where significance levels were not reported, they were calculated using asymptotic standard errors. ^{ew}Equally weighted index. ^{vw}Value-weighted index. **/*/° Significantly different from zero at the 0.01/0.05/0.10 level.

3.3 Methodology

The returns are calculated using logarithmic differences of price (index) series. For individual stock series, returns are corrected for dividends:

$$r_{i,t} = \log\left(\frac{P_{i,t} + D_{i,t}}{P_{i,t-1}}\right), \tag{1}$$

where $D_{i,t}$ is positive only on ex-dividend days.

All regressions use least squares estimation. Standard errors are calculated using the GMM estimator of Hansen (1982), which is robust to both heteroskedasticity and, for the estimation of longer period returns, overlapping observations.

The reviewed theoretical models of return autocorrelation are limited to explaining return behaviour under "normal" circumstances. Therefore, it is natural to exclude observations from highly volatile periods. The only practical way to eliminate outliers in the large number of series studied here is to apply a mechanical rule. In all estimations, observations outside the central 95% of the return distribution are defined as outliers and excluded. The number of excluded observations for this reason is always close to 5%.[11]

The reported autocorrelations are all from regressions of the type

$$r_{i,t} = \beta_0 + \beta_1 r_{i,t-1} + \varepsilon_{i,t}. \tag{2}$$

The estimates of β_0 are always close to zero and are therefore not reported. Cross-autocorrelation with the market return is defined from regressions of the type

$$r_{i,t} = \beta_0 + \beta_1 r_{m,t-1} + \varepsilon_{i,t}. \tag{3}$$

Throughout this paper the AFGX index return is used as the market return.[12]

3.4 Results

3.4.1 First and second autocorrelation of stock returns

We start by examining the first and second autocorrelation of daily index returns. The results of table 2 show that stock index returns on the Stockholm Stock Exchange are strongly positively autocorrelated. The second autocorrelation is not statistically significant for any of the index series in the sample. Although not reported, there are no signs of any consistent higher order return autocorrelation.

[11] Inclusion of outliers increases the estimated standard error of estimates, but only marginally affects point estimates.

[12] Different choices of market return only marginally affect regression results .

As expected from the high liquidity of component stocks, the OMX index has the lowest autocorrelation of the studied index series. The autocorrelation of the calculated indices SSE^{ew} and SSE^{vw} is significantly higher than the autocorrelation of the AFGX index. The probable reason for this difference is that, for the AFGX, only the most liquid stock series of each company is used for the index calculation. In addition, the AFGX uses closing bid quotes, while the calculated indices are based on the last recorded transaction price. The autocorrelation in 11 industry indices included in the AFGX ranges between *0.132* and *0.271* (not reported). The AFGX index thus has higher autocorrelation than all component indices (*0.296*).

When the same test is repeated for individual stock returns, an interesting pattern is revealed with regard to trading volume (data in table 6, page 90–91). The average autocorrelation across all 62 securities is significantly positive (*0.114*). Individual estimates are significantly positive for more than half of the securities. As for indices, there are no signs of systematic higher order autocorrelation.

Figure 1*a* provides a scatter plot of the estimated autocorrelation against the stocks' average daily trading volume. It is evident that the autocorrelation is increasing in the stocks' trading volume. The natural interpretation of figure 1*a* is that stock returns are, in general, positively autocorrelated, but that bid-ask bounce reduces the measured autocorrelation for less liquid securities. Autocorrelation in individual stock returns is thus surprisingly close to the autocorrelation in index returns.

The similarity of autocorrelation in individual stock returns and index returns, indicates the likelihood of a common source to this autocorrelation. Among the sources of autocorrelation discussed in this paper, only profit taking, combined with imperfectly competitive markets, can generate this pattern of short-term autocorrelation in both individual stock returns and index returns.

3.4.2 Cross-autocorrelation with the market return

Having established that Swedish index returns are positively autocorrelated, it follows that individual stock returns will exhibit strong cross-autocorrelation with the market return (Lo and MacKinlay, 1990b). However, it is not clear whether all stocks are as strongly cross–autocorrelated.

Figure 1*b* plots autocorrelation and cross-autocorrelation with the AFGX against average trading volume (data in table 6, page 90–91). It is clear that, on average, the coefficient of cross-autocorrelation is higher (*0.385*) than the coefficient of autocorrelation (*0.114*). The most traded securities exhibit significantly lower cross-autocorrelation with the market return. This is consistent with several models of lagging adjustment to common factors, and most probably reflects the lower nonsynchronicity of the prices

Table 2: First and second autocorrelation of stock returns

	$\hat{\beta}_1$	$\hat{\beta}_2$	R^2	T
Stocks†	0.114**	−0.004	0.012	2088
	(0.074)	(0.033)		
AFGX	0.296**	−0.000	0.056	3483
	(0.023)	(0.025)		
OMX	0.194**	0.007	0.025	2623
	(0.028)	(0.029)		
SSE^{ew}	0.386**	−0.003	0.094	3473
	(0.025)	(0.028)		
SSE^{vw}	0.324**	−0.006	0.067	3473
	(0.024)	(0.023)		

Model used: $r_t = \beta_0 + \beta_1 r_{t-1} + \beta_2 r_{t-2} + \epsilon_t$. Regressions use least squares estimation with asymptotic GMM standard errors (in parentheses) that are robust to heteroskedasticity (Hansen, 1982). †Average of 62 individual estimates. Reported significance levels tests whether the *mean* is different from zero using the *sample* standard deviation (in parentheses). **/*/° Significantly different from zero at the 0.01/0.05/0.10 level.

of the most liquid stocks. As in figure 1*a*, autocorrelation in individual stock returns is increasing in average daily trading volume.[13]

3.4.3 Autocorrelation conditional on past returns

Table 3, panel *a*, presents autocorrelation conditional on the realised return on the preceding day (i.e., day $t-1$). This test is mainly exploratory and is aimed at investigating any asymmetry in return autocorrelation. Results show that autocorrelation is non-symmetric; positive following positive returns, but close to zero following negative returns. The results are similar for both individual stock returns and index returns. A similar asymmetry is documented by Sentana and Wadhwani (1992) for US data and by Säfvenblad (1997b) for French data.[14]

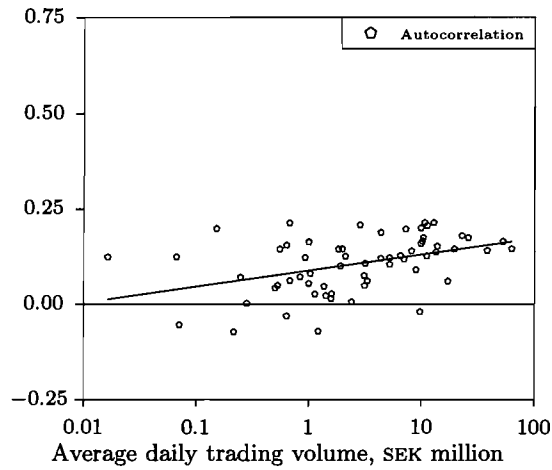
In relation to the surveyed autocorrelation models, this result is only consistent with profit taking under a short selling constraint in a non-competitive market, as modelled by Sentana and Wadhwani (1992), requiring, in addition, loss aversion of the kind hypothesised by Kahneman and Tversky (1979). This may be part of a more fundamental return property.

[13]The lower point estimates follow from the multicollinearity between index returns and individual stock returns, in combination with the relative noisiness of individual stock returns.

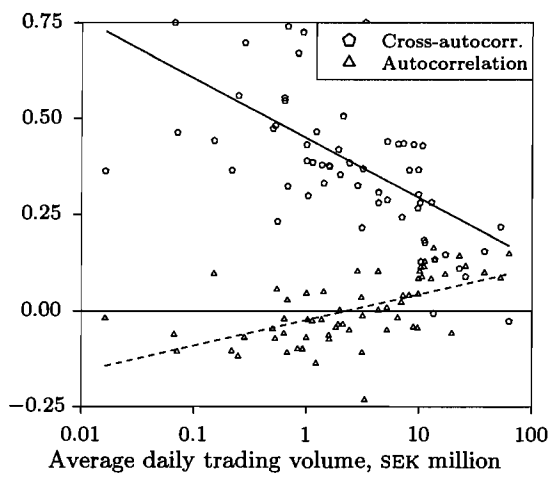
[14]A check of a number of foreign index series in the Findata database reveals similar patterns of asymmetric autocorrelation for index series from a number of countries, including Denmark, Norway, Finland, Germany, Japan and Italy, but excluding Great Britain and the US. Further work on the issue would be interesting, but is outside the scope of this paper.

Figure 1: Scatter plot of autocorrelation and cross-autocorrelation with the market return against average daily trading volume

Panel *a*: Autocorrelation



Panel *b*: Autocorrelation and cross-autocorrelation with the market return



Panel *a* regression model: $r_t = \beta_0 + \beta_1 r_{t-1} + \varepsilon_t$. Panel *b* regression model: $r_t = \beta_0 + \beta_1 r_{m,t-1} + \beta_2 r_{i,t-1} + \varepsilon_t$. The individual point estimates are reported in table 6. The lines are fitted least squares regression lines. The autocorrelation and volume data is taken from table 6. All slope coefficients are significantly different from zero (not reported).

3.4.4 Autocorrelation conditional on absolute returns

Chan (1993) predicts higher return autocorrelation after days of high absolute market returns. The intuition behind this claim is that high absolute returns give a higher signal-to-noise ratio in prices. Agents will therefore give higher weight to previous price changes when updating their private valuation. Chan also presents empirical evidence from the NYSE supporting this prediction.

However, Chan's prediction is only valid if the returns are realised at the closing. If the high market returns are realised during the trading day, all information will be efficiently included in closing prices. As index returns are predicted to follow an MA(1)-process, higher volatility during the trading day will increase the variance of returns while keeping the autocovariance constant, resulting in a reduced estimate of autocorrelation.

Campbell et al. (1993) make the opposite prediction. In periods of high volatility, autocorrelation should be lower as the aggregate level of risk aversion is known with higher precision.

Table 3, panel *b*, presents a test of the proposition, conditioning autocorrelation on absolute realised returns.[15] The results show that autocorrelation is *lower* conditional on high absolute returns. Results are similar both for index returns and individual stock returns. Most probably, this should be interpreted as support for the type of MA(1)-process discussed above.

3.4.5 Autocorrelation conditional on trading volume

Explanations of index return autocorrelation based on information extraction predict lower autocorrelation after days of high trading volume. The improved price precision at the closing close reduces the scope for information extraction from the closing prices. The same prediction is also made by the nonsynchronous trading hypothesis. High trading volume reduces the nonsynchronicity of prices and resulting index return autocorrelation. The prediction is strongly supported by the results in table 3, panel *c*. Autocorrelation after high volume days is significantly lower for all investigated index series.

For individual stocks, the improved price precision should have similar effects. However, this is not the case. On the contrary, autocorrelation is significantly stronger after days of high trading volume. During the sample period, high volume days are often high return days. Therefore, it seems intuitive to attribute this autocorrelation to profit taking. The results in table 3, panel *c*, can be seen as a time series test of the results presented in section 3.4.1 and figures 1*a*–1*b*. The results are the same: autocorrelation increases conditional on increased trading volume.

[15] Conditioning on absolute returns is similar to conditioning on volatility. However, when other measures (ARCH/GARCH, centred estimates) are used, this effect of volatility on autocorrelation is very weak or non-existent (not reported).

Table 3: Autocorrelation and cross-autocorrelation conditional on preceding day's return, trading volume and day-of-the-week

	$\hat{\beta}_1$ *low*	$\hat{\beta}_2$ *high*	Wald
Panel *a*: Fractiles of returns, $r_{i,t-1}$.			
Stocks†	−0.021°	0.125**	61.3**
Cross-autocorrelation†‡	0.258**	0.421**	11.3**
AFGX	0.063	0.308**	4.8*
OMX	0.030	0.254**	4.5*
SSE^{vw}	0.168*	0.349**	3.4°
SSE^{ew}	0.180*	0.342**	2.8°
Panel *b*: Fractiles of absolute returns, $\lvert r_{i,t-1}\rvert$.			
Stocks†	0.164**	0.047**	50.0**
Cross-autocorrelation†‡	0.504**	0.328**	17.2**
AFGX	0.368**	0.175**	7.0**
OMX	0.320**	0.132**	5.2*
SSE^{vw}	0.391**	0.259**	3.4°
SSE^{ew}	0.401**	0.261**	3.4°
Panel *c*: Fractiles of trading volume, $V_{i,t-1}$.			
Stocks†	0.084**	0.120**	4.8*
Cross-autocorrelation†‡	0.651**	0.373**	24.0**
AFGX	0.374**	0.199**	12.7**
OMX	0.312**	0.121**	11.5**
SSE^{vw}	0.458**	0.330**	8.0**
SSE^{ew}	0.461**	0.325**	9.2**
Panel *d*: Day-of-the-week	*Mon.–Thu.*	*Fri.*	
Stocks†	0.038**	0.123**	28.1**
Cross-autocorrelation†‡	0.291**	0.553**	36.0**
AFGX	0.143**	0.380**	9.0**
OMX	0.098**	0.339**	8.1**
SSE^{vw}	0.222**	0.463**	10.8**
SSE^{ew}	0.222**	0.480**	12.6**

Regression model: $r_t = \beta_0 + (\beta_1 D_{1,t-1} + \beta_2 D_{2,t-1}) r_{t-1} + \varepsilon_t$. Panel *a*, *b* and *c*: $D_{1,t}$ ($D_{2,t}$) is a dummy variable for low (high) returns/absolute returns/trading volume. Panels *a* and *b*: Outliers not excluded. Panel *c*: Trading volume uses logarithms of daily trading volume, detrended using a centred 100 trading day moving average. Panel *d*: $D_{1,t}$ ($D_{2,t}$) is a dummy variable for Monday–Thursday (Friday). Regressions use least squares estimation with asymptotic GMM standard errors (not reported) that are robust to heteroskedasticity (Hansen, 1982). The Wald statistic tests the restriction $\beta_1 = \beta_2$. $\chi^2(1)$ critical values: 6.6/3.8/2.7 at the 0.01/0.05/0.10 level. †Average of 62 individual estimates. Reported significance levels tests whether the *mean* is different from zero using the *sample* standard deviation (not reported). ‡Cross-autocorrelation with the AFGX. **/*/° Significantly different from zero at the 0.01/0.05/0.10 level.

3.4.6 Day-of-the-week effects

Table 3, panel *d*, presents autocorrelation conditional on day-of-the-week. Autocorrelation is significantly higher between Monday and Friday returns both for index returns and individual stock returns.[16] The results further strengthen the conclusion that the same factors drive autocorrelation in index returns and individual stock returns. In particular, the results strengthen the case for profit taking. It is reasonable to believe that profit takers are most eager to close their positions at Friday afternoon, when they risk a weekend of nontrading and possible losses.

3.4.7 Autocorrelation and the Swedish stock market transaction tax

During the period 1984-92, Sweden levied a transaction tax on all stock market transactions, which made short-term speculation in Swedish stocks very costly. This is thus a very direct testing ground for the transaction cost hypothesis that transaction costs increase observed index return autocorrelation.

The introduction, changes, and abolition of the turnover tax divide the sample period into five distinct subperiods: three separate tax regimes and two periods without transaction tax. The results given in table 4 provide some support for the predictions of the transaction cost hypothesis. Autocorrelation dropped significantly when the transaction tax was abolished. However, it also decreased when the transaction tax was first introduced. It is therefore impossible to draw any firm conclusions based on this evidence.

Cross-autocorrelation with the market return clearly increased during the transaction tax period. Using the cross-security information aggregation model of Säfvenblad (1997a), this is most likely due to reduced informativeness of individual stock prices relative to the informativeness of the index level. However, there is no direct way to test this hypothesis as it is impossible to measure the absolute level of stock price informativeness.

3.4.8 First order autocorrelation of N-day returns

Daily return series can be used to construct returns for longer holding periods.[17] Table 5 reports autocorrelation estimates for different holding period lengths, ranging from one trading day to almost three months. Longer holding periods are not considered due to the limited sample length.

In addition to the earlier observed autocorrelation in daily returns, positive autocorrelation extends to holding periods of up to at least one month. Effects seem to be smaller for the more liquid stocks contained in the OMX

[16] Boudoukh et al. (1994) also find the strongest index return autocorrelation between Friday and Monday returns (US data).

[17] The N-day returns are constructed by taking log differences of the price or index level N trading days apart.

Table 4: Return autocorrelation conditional on the level of transaction tax

Series	$\hat{\beta}_1$ 0.0%	$\hat{\beta}_2$ 0.5%	$\hat{\beta}_3$ 1.0%	$\hat{\beta}_4$ 0.5%	$\hat{\beta}_5$ 0.0%	Wald
Stocks†	0.117**	0.078**	0.124**	0.071**	0.069**	7.4
Cross-auto-correlation†‡	0.324**	0.564**	0.549**	0.619**	0.284**	44.8**
AFGX	0.382**	0.286**	0.263**	0.397**	0.169**	15.9**
OMX	...	0.234**	0.205**	0.270**	0.106*	57.7**
SSE^{vw}	0.543**	0.373**	0.364**	0.401**	0.204**	31.2**
SSE^{ew}	0.531**	0.374**	0.374**	0.413**	0.201**	29.2**

Regression model: $r_t = \beta_0 + (\beta_1 D_{1,t-1} + \ldots + \beta_5 D_{5,t-1})r_{t-1} + \varepsilon_t$. $D_{1,t}, \ldots, D_{5,t}$ are dummies for the five different tax periods; *1)* Jan. 1980 – Dec. 1983: no tax, *2)* Jan. 1984 – Dec. 1985: 0.5% (roundtrip), *3)* Jan. 1986 – Dec. 1990: 1.0%, *4)* Jan. 1991 – Nov. 1992: 0.5%, and, *5)* Dec. 1992 – Dec. 1995: no tax. Regressions use least squares estimation with asymptotic GMM standard errors (not reported) that are robust to heteroskedasticity (Hansen, 1982). The Wald statistic tests the restriction $\beta_1 = \ldots = \beta_5$. $\chi^2(4)$ critical values: 13.2/9.4/7.7 at the 0.01/0.05/0.10 level. †Average of 62 individual estimates. Reported significance levels tests whether the *mean* is different from zero using the *sample* standard deviation (not reported). ‡Cross-autocorrelation with the AFGX. **/*/° Significantly different from zero at the 0.01/0.05/0.10 level.

index. As in most earlier regressions, results are similar for stock index returns and individual stocks returns.

For the longer horizon returns, time-varying expected returns is the natural explanation, as results are similar for both individual stocks and stock indices. The expected (annualised) monthly return conditional on a down-month is approximately *12%*, compared with *23%* conditional on an up-month (not reported). However, time-varying expected returns cannot be used to explain the observed autocorrelation in daily and weekly returns. Furthermore, as discussed earlier, the short-term autocorrelation is too high to be explained by nonsynchronous trading. Judging from earlier regressions, profit taking seems to best explain the remaining autocorrelation in short-term returns.

Although it is important to interpret the significance levels of these results with care,[18] it is evident from table 5 that there is no negative autocorrelation or price reversals in returns, regardless of return frequency.

3.4.9 Stability of autocorrelation estimates

An interesting diagnostic test is whether the estimated coefficients of autocorrelations are stable over time. Exact estimates are not reported, but figure 2 shows the estimated time variation of autocorrelation (solid lines).

[18]The estimates of autocorrelation for different holding periods are highly correlated. See Richardson and Smith (1994).

Table 5: First order autocorrelation in N-day returns

N	Stocks†	Cross-auto-correlation†‡	AFGX	OMX	SSE^{vw}	SSE^{ew}
1	0.106**	0.456**	0.290**	0.193**	0.393**	0.391**
2	0.069**	0.279**	0.165**	0.127**	0.251**	0.270**
3	0.055**	0.224**	0.134**	0.102**	0.184**	0.183**
4	0.063**	0.244**	0.147**	0.106**	0.197**	0.203**
5	0.061**	0.229**	0.135**	0.085*	0.174**	0.180**
10	0.071**	0.300**	0.195**	0.136*	0.228**	0.238**
20	0.063**	0.226**	0.140°	0.124	0.219**	0.232**
30	0.051**	0.133**	0.121	0.079	0.209°	0.214°
40	0.067**	0.192**	0.162	0.047	0.250°	0.253°
60	0.070**	0.248**	0.224	−0.005	0.329*	0.334*

Regression model: $P_t - P_{t-N} = \beta_0 + \beta_1(P_{t-N} - P_{t-2N+1}) + \varepsilon_t$. Significance levels are calculated using GMM standard errors (not reported) that are robust to overlapping observations and heteroskedasticity (See Hansen (1982), Richardson and Smith (1994)) †Average of 62 individual estimates. Reported significance levels tests whether the *mean* is different from zero using the *sample* standard deviation (not reported). ‡Cross-autocorrelation with the AFGX. **/*/° Significantly different from zero at the 0.01/0.05/0.10 level.

It is evident from figures 2*a* and *b* that index return autocorrelation has been consistently positive throughout the sample period.

For autocorrelation in individual stock returns, striking patterns of changes can be seen over time (figures 2*c*–*d*). For the most liquid securities, autocorrelation increased in the last years of the sample period. The best explanation for this pattern is increased profit taking, in the sense that profit taking takes place nearer to the closing, and not earlier during the trading day. This may be a result of improved liquidity during the last trading hour.

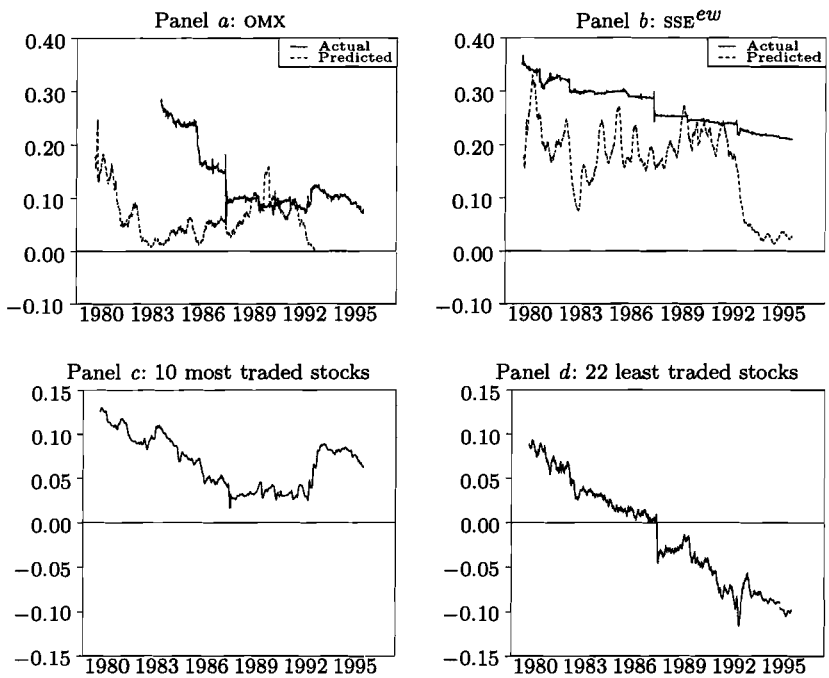
For the least liquid securities, autocorrelation has consistently decreased, and is strongly negative at the end of the sample period. This implies increased transaction costs for the less liquid securities or, simply, more noise trading at the closing.

3.4.10 Nonsynchronous trading

Nonsynchronous trading is a relatively important problem in the sample, in particular for the calculated return series, SSE^{ew} and SSE^{vw}. During the sample period, the daily nontrading frequency is approximately 15%. However, during the last 2–3 years of the sample period, daily nontrading is virtually non-existent.

Figures 2*a* and *b* compare the time-varying autocorrelation in the OMX and the SSE^{ew} (solid line) to the autocorrelation predicted by the Lo and MacKinlay (1990a) nonsynchronous trading model (dotted line). It is evid-

Figure 2: Time-varying autocorrelation in stock returns



Panels *a* and *b*: Time-varying autocorrelation estimated using a standard Kalman filter with time-varying coefficients (solid line). Predicted autocorrelation using estimates of nontrading and the model of Lo and MacKinlay (1990a) (dotted line). Panel *a*: Nontrading estimated from the 20 most traded stocks in the sample. Panel *b*: Actual nontrading. Panel *c* and *d*: Average autocorrelation in individual stock returns across the 10 most/22 least traded stocks in the sample.

ent that, especially for the early and late part of the sample period, nonsynchronous trading can only account for part of the observed autocorrelation.

3.4.11 Non-linear dynamics

Obviously, the relation between autocorrelation, return, and volume, can be non-linear. However, judging from a quadratic specification of returns, trading volume and autocorrelation, non-linearity is weak. The point estimates mostly confirm earlier findings and are therefore omitted. However, the point estimates can be used to illustrate how autocorrelation and expected returns depend on realised returns and trading volume.

Figure 3*a* shows the autocorrelation pattern of the AFGX using parameter estimates from the quadratic model. It is clear that autocorrelation is highest conditional on low trading volume and high returns (the back right corner). The inverted U-shape along the r_{t-1} axis shows the relatively weak volatility effect. Although trading volume reduces index return autocorrelation, the effect is not strong enough to eliminate the positive autocorrelation.

In figure 3*b* the corresponding expected returns are plotted. Here the asymmetry between high (right edge) and low returns (left edge) is highly visible. There is a strong volume effect conditional on high returns (right edge), while after low returns, trading volume does not seem to matter. If returns are strongly negative, lower returns do not seem to decrease expected returns any further. There is thus minimum possible expected return.

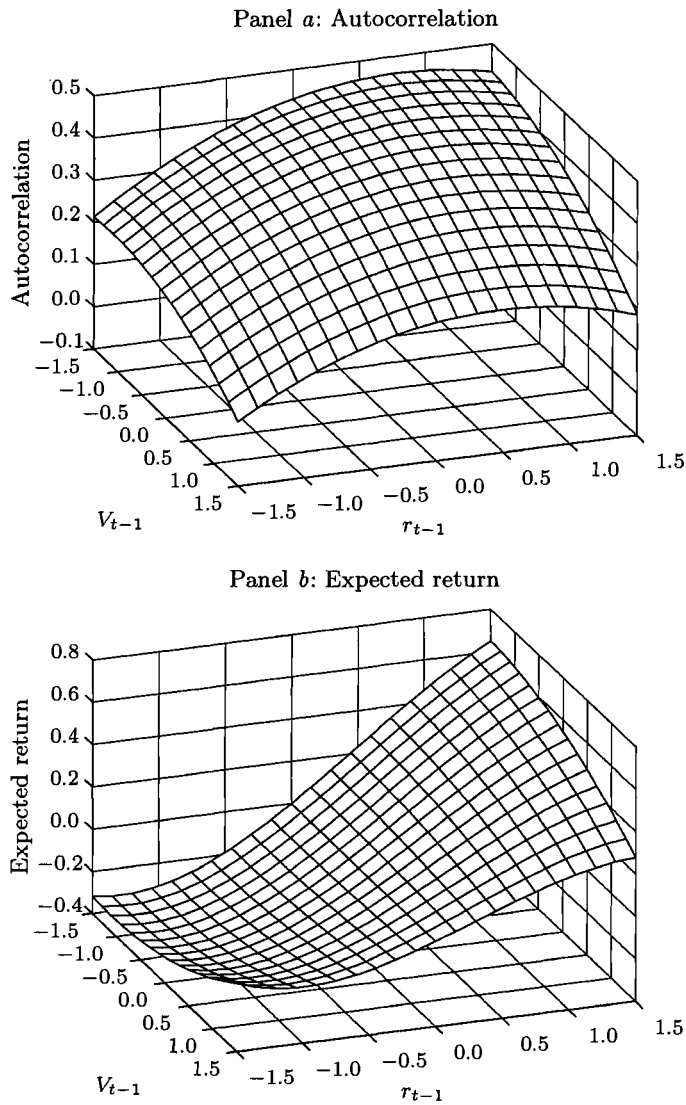
4 Conclusion

This paper is primarily an exploratory investigation into the autocorrelation structure of Swedish stock index returns. In spite of the modest mission statement, the paper provides a number of interesting results. The most important finding is the similarity between autocorrelation in individual stock returns and stock index returns.

Autocorrelation is much stronger in index returns, but autocorrelation in index returns and individual stock returns exhibit many common properties, including return dependence, volatility dependence and day-of-the-week dependence. Therefore, it is natural to conclude that common factors drive autocorrelation in both index returns and individual stock returns. The exception to the similarity is the trading volume dependence, where trading volume reduces index return autocorrelation while it increases autocorrelation in individual stock returns.

Clearly, nonsynchronous trading contributes to the measured level of index return autocorrelation. However, it cannot account for all observed return autocorrelation, particularly not in the last years of the sample

Figure 3: Autocorrelation and expected returns of daily AFGX returns conditional on the preceding day's return and trading volume



Panel *a*: The fitted values of AFGX autocorrelation plotted as a function of preceding day's trading volume and return. Panel *b*: The expected AFGX returns plotted as a function of preceding day's trading volume and return. Panels *a* and *b*: Volume and returns are normalised to have zero mean and standard deviation 1.

period. Nontrading probabilities have been significantly reduced, but index return autocorrelation remains high.

For individual stocks, it is clear that high trading volume increases autocorrelation, both when estimated cross-sectionally and when estimated using time series methods. This effect is most probably due to stronger bid-ask bounce effects for the less liquid securities, and on less active trading days. If this is true, individual stock returns are in general positively autocorrelated. Of the reviewed theoretical models, this is only consistent with profit taking in a non-competitive market.

On average, autocorrelation in individual stock returns has remained more or less constant during the sample period. However, while autocorrelation in the most liquid stocks has remained constant or increased, autocorrelation in the least liquid stocks has decreased steadily throughout the sample period. In the later parts of the sample period, autocorrelation is significantly positive for the most liquid stocks while it is significantly negative for the least liquid stocks.

One very interesting result is the asymmetry of autocorrelation. Conditional on high realised returns, index return autocorrelation is strongly positive, while, conditional on negative returns, autocorrelation is close to zero. The documented asymmetry in return autocorrelation is present in both index returns and individual stock returns. This supports the hypothesis of profit taking. Profit taking is also supported by the strong autocorrelation between Friday and Monday returns. The effect, visible in both index and individual stock returns, may be caused by particularly strong profit taking before the weekend.

The Swedish stock market transaction tax provided a direct test of the transaction cost hypothesis. Although transaction costs had only small effects on index return autocorrelation, they seem to have reduced price informativeness. This was concluded from the increased cross-autocorrelation with the market return.

For longer term returns, time-varying expected returns provide a good explanation of the data. This is mainly a passive conclusion, since it is the only theoretical model of return autocorrelation that fits the data. However, some explicit support is given by the similarity of individual stock returns and index returns.

From the collected empirical evidence, it can be concluded that autocorrelation in short-term returns is best described as a combination of profit taking and nonsynchronous trading (for index returns). This conclusion is primarily based on the observation that autocorrelation in index returns and individual stocks have similar properties in terms of return dependence, day-of-the-week dependence and volatility dependence. Further support for the profit taking hypothesis is given by the strong positive autocorrelation in the most liquid securities. Future studies, using intraday price data, will be needed to evaluate whether this is a correct interpretation of the data.

Table 6: First and second autocorrelation and cross-autocorrelation with market return

	Regression 1		Regression 2			
Name	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{\beta}_1$	$\hat{\beta}_2$	Volume†	T
Ericsson B	0.146**	0.003	−0.026	0.148**	62.4	3998
Astra A	0.168**	0.005	0.217**	0.086**	52.3	3267
Volvo B	0.147**	0.010	0.154**	0.099**	37.9	3998
Astra B	0.178**	−0.046	0.089	0.115**	25.9	2144
Electrolux B	0.178**	0.023	0.110*	0.142**	22.7	3998
Investor B	0.139**	−0.016	0.616**	−0.058°	19.4	2829
SE-banken A	0.064°	0.067	0.146°	0.095	17.1	3998
Skandia	0.153**	0.016	0.133*	0.133**	13.8	3998
Volvo BB	0.135**	0.002	−0.006	0.163**	13.4	3242
ABB B	0.228**	−0.021	0.282**	0.083**	12.8	3168
Kinnevik B	0.210**	0.024	0.178*	0.128**	11.2	1744
SHB A	0.127**	−0.025	0.184**	0.114*	11.0	3998
Stora B	0.199**	0.049	0.430**	0.088*	10.6	1834
SKF B	0.175**	0.020	0.127*	0.114**	10.3	3998
Atlas Copco B	0.174**	0.001	0.280**	0.102*	10.1	1596
ABB A	0.217**	−0.025	0.302**	0.084**	9.8	3998
Skanska B	0.159**	0.043	0.366**	0.044	9.8	3005
Avesta	−0.022	−0.028	0.266*	−0.044	9.6	1817
SCA B	0.101**	−0.034°	0.433**	−0.042	8.8	3998
MoDo B	0.152**	−0.000	0.366**	0.041*	8.1	3998
Stora A	0.205**	0.005	0.435**	0.040	7.2	3998
Atlas Copco A	0.124**	−0.013	0.242**	0.022	6.9	3998
Sandvik B	0.145**	−0.024	0.434**	−0.018	6.4	3998
Sandvik A	0.176**	−0.035	0.440**	−0.050	5.1	2509
H&M B	0.129**	−0.032	0.288**	0.009	5.1	3998
Aga B	0.118**	−0.015	0.308**	0.002	4.3	3998
Skanska BB	0.193**	0.034	0.280**	0.102**	4.3	3242
Custos A	0.060	0.012	0.764**	−0.232°	3.3	1801
Volvo A	0.116**	−0.034	0.369**	−0.013	3.1	3998
Investor A	0.061°	0.012	0.706**	−0.109**	3.1	3998
Gambro B	0.071*	−0.000	0.216**	0.035	3.1	3177
Stora AB	0.202**	0.022	0.325**	0.103**	2.8	3110
Nobel A	0.008	−0.065*	0.384**	−0.050	2.4	3548
Industrivärden A	0.127**	−0.030	0.506**	−0.035	2.1	3998
Sandvik AB	0.166**	0.011	0.354**	0.002	1.9	3108

The table continues on the next page.

Table 6 continued

	Regression 1		Regression 2			
Name	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{\beta}_1$	$\hat{\beta}_2$	Volume†	T
Volvo AB	0.104**	−0.004	0.419**	−0.036	1.9	3242
Investor AB	0.157**	0.010	0.611**	−0.043	1.8	3242
SKF A	0.010	−0.045	0.375**	−0.074°	1.5	3005
Aga A	0.022	0.007	0.377**	−0.064	1.5	3005
SE-banken C	0.012	−0.099*	0.331*	0.050	1.4	1653
Esselte B	0.048	0.040	0.379**	−0.023	1.3	3998
Industrivärden C	−0.076°	−0.011	0.465**	−0.137**	1.2	1842
Avesta B	0.028	−0.026	0.386**	−0.026	1.1	1907
Gambro BB	0.081*	−0.002	0.298**	−0.023	1.0	2421
SKF BB	0.161**	−0.003	0.390**	0.046	1.0	2096
Hufvudstaden A	0.051°	−0.032	0.432**	−0.070	0.9	3998
Custos B	0.132**	0.025	0.725**	−0.100°	0.9	3998
SCA A	0.078*	−0.055*	0.671**	−0.099**	0.8	3005
Esselte AB	0.065°	0.033	0.324**	0.029	0.6	3117
Custos AB	0.230**	0.007	0.740**	−0.109	0.6	3242
Nobel B	−0.058	−0.051°	0.547**	−0.021	0.6	3114
SKF AB	0.154**	0.007	0.554**	−0.058	0.6	3089
Kinnevik A	0.125*	0.048	0.232°	0.056	0.5	1293
Ratos A	0.065°	−0.042	0.482**	−0.072°	0.5	3998
Bergman & Bev. B	0.042	0.029	0.473**	−0.047°	0.5	3998
MoDo A	0.097*	0.038	0.697**	−0.070°	0.2	3998
Industrivärden B	0.118	0.041	0.560**	−0.118°	0.2	1195
Ericsson A	−0.054	−0.026	0.365**	−0.105**	0.2	3998
Kinnevik BB	0.209**	−0.020	0.442**	0.097**	0.1	3042
Ericsson AB	0.008	0.013	0.463**	−0.106*	0.0	3242
Industrivärden CB	0.199	−0.056	1.060°	−0.062	0.0	335
Kinnevik AB	0.135°	0.043	0.363°	−0.018	0.0	3042
Average‡	0.114**	−0.004	0.385**	0.004	7.4	3149
Standard error	(0.074)	(0.033)	(0.197)	(0.086)		

Regression models: $r_t = \beta_0 + \beta_1 r_{t-1} + \beta_2 r_{t-2} + \varepsilon_t$ and $r_t = \beta_0 + \beta_1 r_{m,t-1} + \beta_2 r_{i,t-1} + \varepsilon_t$. Regressions use least squares estimation with asymptotic GMM standard errors (not reported) that are robust to heteroskedasticity (Hansen, 1982). †Average trading volume per day in million SEK. ‡Average of the 62 individual estimates. Reported significance levels tests whether the mean is different from zero using the sample standard deviation (in parentheses). **/*/° Significantly different from zero at the 0.01/0.05/0.10 level.

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