

Price Discovery and Learning during the Preopening Period in the Paris Bourse

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Before the opening of the Paris Bourse, traders place orders and indicative prices are set. This offers a laboratory to study empirically the tâtonnement process through which markets discover equilibrium prices. Since preopening orders can be revised or canceled before the opening, indicative prices could be noise. We test this against the hypothesis that preopening prices reflect learning.

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Early in the preopening the noise hypothesis is not rejected. As the opening gets closer, the informational content and efficiency of prices increase and the learning hypothesis is not rejected. We also propose a GMM-based estimate of the speed of learning.

I. Introduction

One of the central issues in economics is how prices are formed, equilibrium is reached, and valuation is discovered. In the *Eléments d'économie politique pure*, Walras (1874, 1889) introduced the notion of tâtonnement, a process by which agents submit additional offers to sell (buy) when they find that the price is still high (low), which drives the price down (up) until there are no additional new orders. Walras described this process in the following words: After orders have been revised, "the system of new quantities . . . and new prices is . . . closer to equilibrium than the former one and it is only necessary to continue the tâtonnement in order to approach it closer and closer" (1889, p. 241).

An interesting market laboratory for studying the equilibrium price formation process is the preopening period in the Paris Bourse, during which, prior to the establishment of the opening price at 10:00 A.M., traders can place, modify, and cancel various types of orders and observe the resulting indicative prices and trading volume, without any trades actually taking place.¹ Because of considerable overnight valuation uncertainty, price discovery is important and difficult at the opening of the market. Because of the absence of trade executions and inventory (position) changes accompanying the transmission of orders during the preopening, we can study learning without intervening trade and inventory effects.

In fact, Walras's analysis of tâtonnement was inspired by his observation of the actual workings of the Paris Bourse. For example, he wrote in the *Eléments* that "no exchange takes place . . . without the sellers being able to lower the price and the buyers to raise it. This is the way of functioning of the stock exchanges" (1874, p. 48).²

The present paper analyzes empirically the tâtonnement process

¹ One must note, however, that the preopening period is not exactly equivalent to the Walrasian tâtonnement. First, during the preopening, actual supply and demand curves are crossed at each point in time, whereas the Walrasian tâtonnement proceeds without the posting of supply or demand functions. Second, in the Walrasian tâtonnement, agents are uncertain as to when supply will equal demand and trading will take place, whereas during the preopening the process ends at 10:00 A.M.

² Walker (1987) offers an interesting analysis of the writings of Walras on this issue.

in the preopening period in the Paris Bourse. It is, to our knowledge, the first study of field data generated during a *tâtonnement* process.³

Because there is no actual trading before the opening and because preopening orders can be canceled, they might fail to be serious and informative orders. In line with this argument, we posit the noise hypothesis, under which preopening prices and orders do not contain information about the value of the security. On the other hand, indicative prices can reflect learning about the equilibrium valuation of the security. This is the case with competitive agents, as in Kobayashi (1977), Jordan (1982), and Vives (1995). It can also arise when strategic agents try to manipulate the price, as in Medrano and Vives (1998), to the extent that the other traders rationally learn from the order flow and that, toward the end of the preopening period, there is a risk that manipulative orders cannot be canceled or revised before the opening. Also, Brusco, Manzano, and Tapia (1998) have shown that the preopening period can be used as a preplay communication device in situations in which these agents need to coordinate to exploit the gains from trade.⁴ Following these papers, we posit a learning hypothesis according to which preopening prices are conditional expectations, predicting unbiasedly the value of the security, with increasing precision. By testing the learning hypothesis against the noise hypothesis, we study to what extent the discipline imposed by immediate trading and the associated profits and losses is necessary for market prices to be informationally efficient.

Preliminary evidence against the noise hypothesis and in favor of the learning hypothesis is obtained by inspecting the order flow during the preopening period. Order placement activity is strong during the preopening after 9:30, and, in fact, the last 10 minutes before the opening are the most active of the day. Further, the majority of the orders placed during the preopening period obtain execution.

To test the alternative hypotheses more precisely and to character-

³ Amihud and Mendelson (1987, 1991) and Stoll and Whaley (1990) offer interesting analyses of the contrast between opening prices (which reflect the potentially imperfect *tâtonnement*) and closing prices (set after the market has completed learning). Our analysis complements theirs since we consider the process of price discovery, in addition to its outcome. Our analysis, based on financial market field data, also complements the experimental studies of price formation in asset markets; see, e.g., Plott and Sunder (1988) and Bronfman et al. (1996). More recently, Cao, Ghysels, and Hatheway (1998) studied preopening offers on NASDAQ.

⁴ Other papers that shed light on *tâtonnement* and equilibrium discovery in the marketplace, but to which our work is less directly related, include the analyses of adaptive learning and temporary equilibria by Bray (1982), Gouriéroux, Laffont, and Monfort (1983), Grandmont and Laroque (1989), Marcet and Sargent (1989), and Spear (1989) and the analysis of educative learning by Guesnerie and Rochet (1993).

ize the extent to which there is learning and price discovery during the preopening period, we estimate unbiasedness regressions, similar to those used in the analysis of forward exchange rates (see Hodrick 1987).⁵ We regress the return from the previous close to the closing price (our proxy for the equilibrium value of the security on which the market is learning) onto the return from the previous close to the indicative price. Because of learning and deadline effects, the economics of the preopening are altered as the opening gets closer, and the distribution of indicative returns is likely to vary at different points in the preopening (such as 9:30 and 9:55, e.g.). To take this nonstationarity into account, we estimate (across days) one unbiasedness regression for each minute between the beginning and the end of the preopening. The pattern of the parameters of these regressions provides information about the distribution of preopening prices at different points in time. In other words, the path of preopening prices each morning corresponds to one learning sample path, but we provide information on the distribution of this path at each point in time.

We estimate the unbiasedness regressions both for the index and for individual stocks. In the latter case, to avoid redundancy with the analysis of the index, we focus on market model residuals, that is, individual stock returns minus beta times the market return. For both the index and the individual stocks, we find that at the beginning of the preopening the slope of the unbiasedness regression is not significantly different from zero, and consequently, we do not reject the noise hypothesis. The estimate of this slope increases, however, as the opening gets closer, which is consistent with an increase in the informational efficiency of indicative prices. In the case of the index, toward the end of the preopening period, the slope is not significantly different from one, so that we cannot reject the learning hypothesis (under which indicative prices are martingale). In the case of the (market model residuals for) individual stocks, the slope of the unbiasedness regression is somewhat lower and, in fact, does not reach one until approximately 10:30 A.M.

We also analyze the pattern of the root mean square error (RMSE) of the unbiasedness regression. It enables one to quantify the informational content of the preopening prices. If these prices did not contain any information in addition to that contained in the previous close, then the RMSE should be equal to the variance of the close-to-close returns. This is what we find for the indicative prices quoted at the beginning of the preopening period, consistent with

⁵ Our analysis is also related to the random walk tests conducted on trading day prices as illustrated by Fama and French (1988) or Lo and MacKinlay (1988).

the noise hypothesis. After 9:30, however, the residual variance decreases as the opening gets closer, consistent with the learning hypothesis and similarly to its trading day behavior.

Although learning in the preopening period starts manifesting itself around 9:30, it sharply picks up around 9:50. At this point in time, both the order flow and the slope of the unbiasedness regression increase strongly, whereas the RMSE of the unbiasedness regression decreases strongly.⁶ This is consistent with the view that after this point in time traders have greater incentives to place truthful orders, because the risk of not being able to cancel or modify manipulative orders before the opening becomes significant. While the presence of considerable noise early during the preopening period does not come as a surprise, the extent to which the market pricing is relatively efficient toward the end of the preopening, despite the absence of immediate trade, is a more unexpected result.

We also propose a new approach to the estimation of the speed of learning in the marketplace, based on the theoretical work of Vives (1995), using the generalized method of moments (GMM) (Hansen 1982). The estimate of the speed of learning is significantly different from zero, which leads to rejection of the noise hypothesis. While the theoretical analysis of Vives predicts that the speed of learning should be one-half, which corresponds to learning at the speed of the square root of t , our estimates are significantly above this value. This is consistent with the extensions of Vives by Germain, Meddahi, and Renault (1996) and by Medrano and Vives (1998).

What insights into tâtonnement and price discovery can be obtained from our analysis? On the one hand, the market discipline imposed by imminent trading plays a role in bringing prices close to the equilibrium value; on the other hand, it can be useful to allow for preopening tâtonnement without immediate trades, to give the market some time to adjust and discover the new equilibrium. Indeed, we find that in spite of the lack of immediate trades, investors choose to actively participate in the preopening tâtonnement and the informational efficiency of the indicative prices quoted in this process gradually increases from 9:30 to 10:00.

Our analysis of preopening prices is related to the analysis of odds in the racetrack betting market by Camerer (1998). In particular, in both markets there is a period during which bets or orders can be placed and subsequently canceled, which gives rise to the possibil-

⁶ Note that the information contained in the slope of the unbiasedness regression and the RMSE are not redundant. It would be possible, e.g., for preopening prices to be martingales, so that the slope would equal one, and for learning to be slow so that the RMSE would decrease only very slowly.

ity of market manipulation. Our result that there is a strong acceleration in the order flow during the last 10 minutes of the preopening period is similar to Camerer's result. Our focus on the informational content of preopening prices is somewhat different, however, from Camerer's emphasis on market manipulation.

Section II describes the workings of the preopening period in the Paris Bourse. The data are described in Section III. The alternative hypotheses are presented in Section IV. The econometric analysis is in Section V. Section VI relates our analysis to previous empirical studies of the informational content of prices in speculative markets. Section VII offers a brief conclusion.

II. Market Structure

The Paris Bourse is a computerized trading market.⁷ The opening price is set at 10:00 A.M. by crossing the aggregate supply and demand curves resulting from the orders present in the electronic order book at that time and selecting the price that maximizes trading volume. Trading at the opening represents approximately 10 percent of the total daily trading. Before the opening, investors can place, modify, or cancel orders. Each time an order is entered, modified, or canceled during the preopening period, the indicative market-clearing price that would result from the current book is announced electronically along with the (indicative) trading volume at that price and the four best visible offers and demands not executed at this price.

Until 1992, the preopening period lasted from 9:00 A.M. to 10:00 A.M. In 1992 the preopening period was extended to last between 8:30 and 10:00. Another institutional change that took place that year was that trading on futures on the Cotation Assistée en Continu (CAC) 40 index became possible on Globex (an electronic trading facility offered by the MATIF, which is the French futures market, and the Chicago Mercantile Exchange). Hence, while before 1992 indicative prices solely reflected the tâtonnement process, since that date it is likely that they also reflect the information contained in the actual trades carried out on Globex.⁸ In order to focus on a pure

⁷ Our earlier paper (Biais, Hillion, and Spatt 1995) includes a detailed discussion of the trading process and the market structure of the Paris Bourse.

⁸ In principle, trading in French stocks is also possible before 10 A.M. (French time) on the international Stock Exchange Automated Quotation. But, in fact, there is hardly any trading in London before the opening of the French market (see Pagano and Roell 1990). A plausible interpretation is that London market makers are reluctant to conduct trades before price discovery has been completed on the "home market."

case of learning and tâtonnement, we present results based on data from 1991.

There are a number of reasons why the role of the timing of orders during the preopening in the determination of the allocation in the opening is very limited. First, when supply equals demand at the opening price, time priority (the order in which orders are transmitted to the market) plays no role in allocation of the security to investors in the opening market. Still, as a consequence of the discreteness of the pricing grid, supply and demand need not be equal, in which case time priority could play a tie-breaking role. Until June 1995, however, priority rules at the opening in the Bourse were such that time priority could be effective only with respect to at most one additional lot of the asset for each order. Since June 1995, the role of time priority has been restored. It does not influence the results presented in the current version of the paper, however, since, as explained above, it is based on 1991 data. Second, because the opening auction is a uniform-price auction, the cost of acquiring priority by bettering one's price is much more limited than during the day. Third, the tightness of the pricing grid at the Paris Bourse reduces the role of time priority.⁹

For the "uniform-price" batch auction taking place at the opening, the limit prices (maximum prices at which buy orders can be executed or minimum prices at which sell orders can be executed) posted by small investors affect the probability that their own orders are executed but do not have much impact on the execution price. In contrast, large traders usually have an impact on the market-clearing price. Because a large number of traders are batched at the opening and because the opening is structured as a uniform-price auction, market impact and adverse selection problems are likely to be less pronounced than during the trading day, which makes trading at the opening rather attractive for investors (although, to limit their price impact, large traders are likely to split their orders between the opening and the rest of the day). Admati and Pfleiderer (1988) and Pagano (1989) analyze the attractiveness of the batching of orders.

The mechanism for forming the opening price is very different in the New York Stock Exchange (NYSE). In this market, only the specialist observes the orders submitted before the opening. He typically provides some information to floor traders about the orders in the book, but there is no formal and explicit price discovery process in which all investors can participate with equal access to market information. Stoll and Whaley (1990) note that at the point at which the specialist makes his trading decision and establishes the opening

⁹ The relation between tick size and time priority is pointed out in Harris (1994).

price, he benefits from a last-mover advantage. Madhavan and Panchapagesan (1998) complement this analysis by examining orders placed at the opening by investors and the NYSE specialist. Stoll and Whaley also argue that the lack of an explicit *tâtonnement* mechanism makes price discovery difficult and can result in exceedingly noisy opening prices.¹⁰ This provides an interpretation for the excess volatility in the opening price analyzed by Amihud and Mendelson (1987) and for the reversals between the open and the close observed by Stoll and Whaley. Stoll and Whaley also note, however, that “the ability to revise orders can lead to ‘gaming’ as traders submit fake orders that they later rescind” (p. 42, n. 6). Such gaming could reduce the informativeness of preopening prices. Our empirical analysis provides evidence that there is indeed some noise in the preopening prices, which might stem from such gaming or manipulative behavior. Yet, our empirical results (presented below) show that, in spite of such potential sources of noise, preopening prices have informational content.

III. Data

A. Data Sets

The main data set we use in this study is the TOPVAL data set that we previously used in our earlier study of the limit orders and order book within the trading day (Biais et al. 1995). It contains the history of the order book for the stocks in the CAC 40 index (composed of the largest and most actively traded French stocks) for the 19 trading days between October 29 and November 26, 1991. During this period, one stock (Arjomari Prioux) exited the index. We focus on the 39 stocks present in the index throughout the sample period.

The data set largely corresponds to the information available on brokerage screens, and all the information in this data set is available to market participants in real time through computerized information dissemination systems. During the preopening the data set reports all the indicative prices and corresponding indicative volumes along with the four best bid and offer prices and number of shares demanded or offered at each of those quotes.¹¹

¹⁰ While the relative lack of transparency before the opening in the NYSE may enhance the monopoly power of the specialist, it could be counterproductive for the NYSE to set up an explicit and transparent preopening mechanism because competing trading systems could free-ride on the information thus revealed.

¹¹ This data set does not contain information about hidden orders except to the extent that they influence the market-clearing price and indicative volume. Also, this data set does not contain information about the identity of the traders placing orders, although brokers do observe on their screens the identification codes of the brokers placing orders (but not the identity of the final customers).

The TOPVAL data set provides information about the indicative price, which is useful to study price discovery. The information it provides on the order flow is limited, however. To complement this information we also use a second data set, which records all the orders placed, modified, or canceled, for 26 days in 1993, for the 40 stocks of the French index, CAC 40. These data include detailed information about the orders, including the point in time at which orders are placed, and final execution status. This second data set suffers from two drawbacks for the present study. First, it does not contain indicative prices, and these prices cannot be recomputed from the order flow because the data do not contain the time at which orders are canceled. Second, these data pertain to 1993, a time at which Globex trading was allowed. Hence it is possible that the order flow reflects the information contained by Globex trades.

Consequently, to analyze the price discovery and *tâtonnement* process during the preopening period, we rely mainly on the TOPVAL data set. We use our second order flow data set only to complement the results based on the TOPVAL data, by means of summary statistics on the order flow.

For completeness, note that we also used a third data set, recording indicative as well as trading day values of the CAC 40 index observed every 30 seconds for 234 days in 1995. Before recognizing that there was significant trading on Globex, we designed our econometric analysis using the 1995 data. The results we obtained using this data set are presented, for example, in an earlier version of this paper (Biais et al. 1996). In order to focus on a “pure *tâtonnement* and learning case” without intervening trades, we chose to focus on 1991 indicative prices since in 1991 there was no Globex trading. Using the 1991 data, we carried out essentially the same test as with the 1995 data.¹² The results obtained with the two data sets are very similar.

B. Format of the Data

To conduct our statistical tests, we construct a time series of prices observed every minute. In fact, our data are generated in continuous

¹² In that sense the results presented in the current version of the paper can be seen as an “out-of-sample” analysis, with the 1995 observations playing the role of the initial sample and the 1991 data being the holdout sample. Differences in the empirical methods used for the analysis of the 1995 and 1991 data stem from the fact that for the latter we have only 19 trading days. To compensate for the small size of this sample, we attempt in our analysis of the 1991 data to exploit the information contained in the cross section of 40 stocks (in fact reduced to 39 because of the exclusion of Arjomari Prioux). This contrasts with our analysis of the 1995 data, which relied solely on the index.

time, with irregular time intervals between observations. We define the indicative price for minute m as the last price in our data before m . For example, the price for 9:45 (or to be more precise the price corresponding to the time interval from 9:44 to 9:45) is in fact the last price observed before 9:45. If there is no new price during minute m , we set the indicative price for this time interval to be equal to the indicative price for minute $m - 1$. Note that during the two minutes following the opening there is no trade at all in our data set (although the market is not completely inactive during these two minutes because many orders are placed but do not lead to immediate trades). Hence, because of our convention to use lagged prices when there is no price during a one-minute interval, prices for the intervals 10:00–10:01 and 10:01–10:02 are equal to the price for the last minute of the preopening. Note also that our TOPVAL data set does not directly contain the price of the opening auction (set at 10:00), but only the first transaction price of the day after the opening auction, which, as mentioned above, is typically set between 10:02 and 10:05. Finally, note that while the opening and preopening prices are set in a uniform Walrasian auction, whereby all trades are conducted at the same price, during the trading day, marketable limit orders walk up or down the book and get execution at different prices. We adopt the convention that the transaction price is the price of the last limit order hit by the trade.

C. Summary Statistics on the Preopening Order Flow

To conclude this section we present some summary statistics about the preopening order flow.

Using the TOPVAL data from 1991, we compute the average daily number of orders placed during each one-minute interval between 9:00 A.M. and 5:00 P.M. This is represented in panel *a* of figure 1. This figure shows that the last 15 minutes of the preopening are the most active period of the day in terms of order placement.

Panels *b*, *c*, and *d* of figure 1, which are based on our 1993 order flow data set, provide additional information on the order flow during the preopening period. Panel *b* depicts the final execution status of preopening orders. Along with panel *c*, it shows that the vast majority of the preopening orders are actually executed. Panel *d* shows that out of those preopening orders that end up being executed, the vast majority are filled at the opening. Panel *b* also shows that relatively few preopening orders are canceled.

This set of descriptive results on the order flow during the preopening period suggests that the preopening order flow is likely to

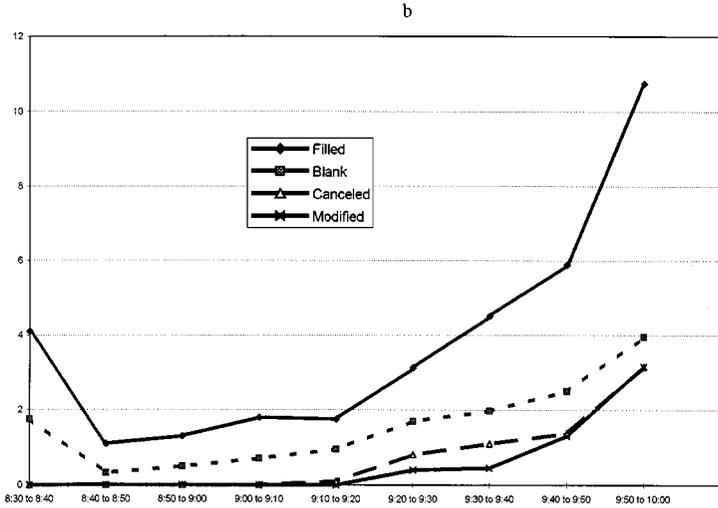
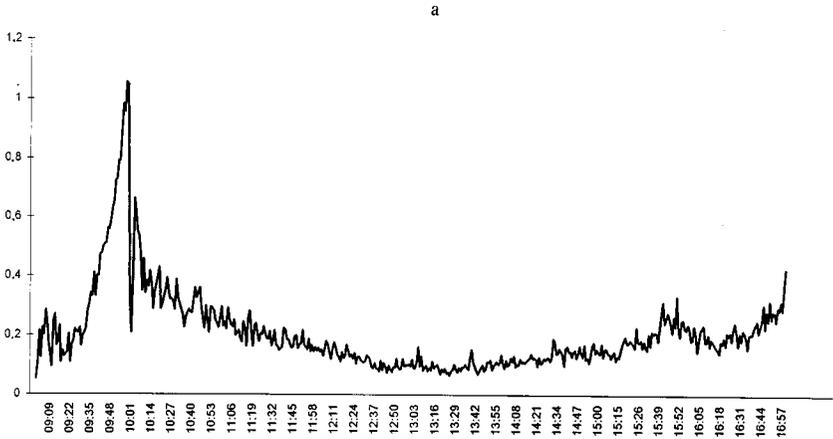


FIG. 1.—*a*, Average number of orders (per stock and day) placed during one minute, before and after the opening of the market, estimated across 39 stocks in the CAC 40 index and across 19 days in 1991. *b*, Final execution status of orders placed during each of the nine 10-minute intervals between 8:30 and 10:00. Average daily number of orders for one stock, computed for Carrefour and Schneider, based on 26 days in 1993. *c*, Fraction of preopening orders ultimately executed. Fractions are computed for each of the nine 10-minute intervals between 8:30 and 10:00, for Carrefour and Schneider, based on 26 days in 1993. On average, 56.32 percent of the preopening orders are filled. *d*, Average number of preopening orders ultimately executed per stock, for the nine 10-minute intervals between 8:30 and 10:00, for Carrefour and Schneider, based on 26 days in 1993. Orders filled at other than the opening price are executed later than the opening.

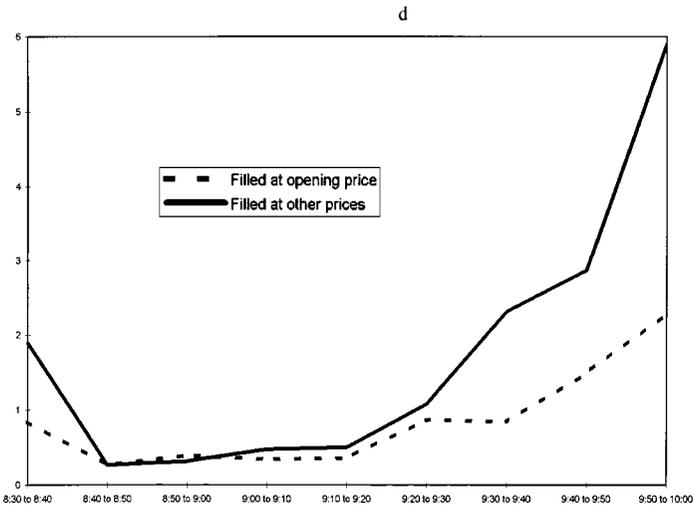
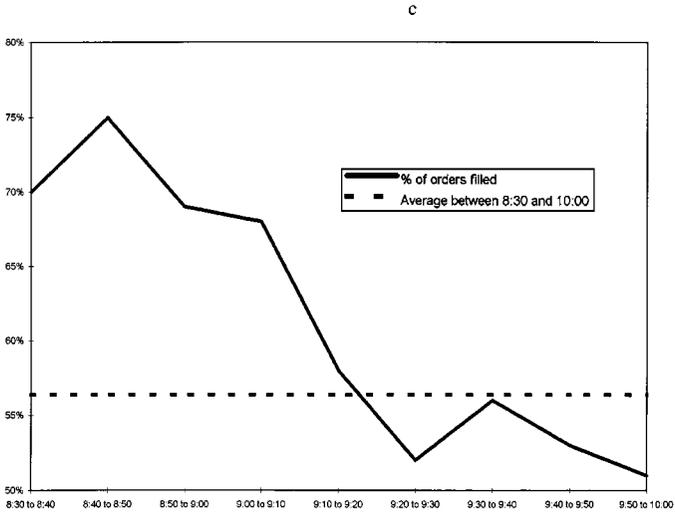


FIG. 1.—(Continued)

be directly related to the opening price and have some information content, rather than being pure noise.

IV. Alternative Hypotheses

A. The Noise Hypothesis

Orders placed during the preopening period can be freely canceled prior to 10:00 A.M. Large (potentially informed) traders may be re-

luctant to disclose their trading intentions in order to minimize price impact. This could give them incentives to wait until the very end of the preopening period to place their orders. Prior to this time, strategic traders could place “noisy,” manipulative orders, reducing the informativeness of indicative prices. Also, to the extent that orders are costly to submit, small investors could prefer to wait to place their orders at the end of the preopening to collect as much information as possible.

These arguments suggest that orders placed during the preopening could have little information content and lead to postulating the following hypothesis, hereafter referred to as the noise hypothesis:

$$H_0: P_t = E(v|I_0) + \epsilon_t, \quad (1)$$

where P_t is the indicative price at time t ; v is the equilibrium value of the asset (which we proxy by the closing price on that date); I_0 is the public information set at time 0, that is, before the start of the preopening period; and $\epsilon_t \perp v$ (where \perp denotes independence). Under this hypothesis, the indicative price at time t does not reflect any information learned or processed since the previous close.

B. The Learning Hypothesis

If the agents who set the price in the market act competitively, they drive the price to the conditional expectation of the value of the asset. This is expressed in the following “learning hypothesis”:

$$H_1: P_t = E(v|I_t), \quad (2)$$

where I_t is the public information set at time t . Equation (2) is the standard conditional expectations restriction from the trading day applied to the preopening. Of course, during the trading day the pricing is driven by the immediate trading opportunities and possibilities for immediate execution that the pricing and order flow represent, in contrast to the preopening. The learning hypothesis is consistent with several theoretical frameworks.

Equation (2) would arise when rational competitive agents react to a public information flow. It also would arise with competitive and rational agents and asymmetric information. This is the case analyzed by Vives (1995). Note that observing the price process alone would not be sufficient to empirically differentiate this model from the above-mentioned public information case because, in both cases, the main implication of the theory is that the price is a conditional expectation (see Biais et al. [1997] for a more precise analysis of this point).

In addition to (2), another empirical implication of Vives (1995)

is that the order flow should be decreasing with time. The reason is that in this model, order flow is larger when informational asymmetries are more pronounced, whereas these asymmetries decline as time passes and learning occurs. Our empirical results on the order flow, presented in the previous section, are at odds with this prediction of Vives. Indeed we find that the order flow is *increasing* rather than decreasing with time.

Vives also offers an interesting characterization of the asymptotic speed of learning in the tâtonnement mechanism:

$$\sqrt{t}(v - P_t) \rightarrow \mathcal{N}(0, \sigma^2), \quad t \rightarrow \infty, \quad (3)$$

where σ^2 is a constant that depends on the parameters of the model such as the precision of the signals and the risk aversion of the informed agents. Asymptotically, the price converges to the true value at the rate of the square root of time. This is the same rate of convergence as in the central limit theorem with identically independently distributed signals, which arises in the public information case with constant precision of the signals. One of the striking features of the Vives results is that this similarity arises, although information flows are endogenous. Germain et al. (1996) consider an extension of Vives in which new private signals are observed by the agents at each point in time. This additional information flow raises the rate of convergence to the true value from 0.5 to 1.5.

Third, the learning hypothesis and the associated information content of preopening prices can also arise, at some points during the preopening period, in the presence of strategic agents. If investors wait until the very end of the preopening period to place their orders, they run the risk that communication will break down or they will not have the time to implement fully their desired order placement strategy before the market opens. To hedge against this risk, they may have incentives to place orders somewhat before the very end of the period. This is reminiscent of the experimental and theoretical analysis of the impact of deadline effects and the risk of communication breakdown on bargaining strategies by Roth, Murnighan, and Schoumaker (1988) and Ma and Manove (1993). By using field data, we attempt to shed light on these effects in actual markets. Motivated in part by the empirical results in the present paper, Medrano and Vives (1998) extend the analysis of Vives (1995) to the case in which competitive rational agents, who can be informed or not, coexist in the marketplace with a strategic informed trader. They show that the insider attempts to manipulate the market at the beginning of the tâtonnement period, to keep the market price uninformative. On the other hand, they show that, in the presence of the above-mentioned risk of communication breakdown, to-

ward the end of the preopening period the strategic insider reduces the manipulation of the market and enters orders that he hopes to get filled and that reflect his private information. Medrano and Vives note that their theoretical results on the increase in the order flow and the informational content of preopening prices toward the end of the tâtonnement period are consistent with the empirical results of the present paper.

The analyses of Vives (1995) and Medrano and Vives (1998) emphasize asymmetric information on common values, that is, on the final value of the asset. In financial markets, however, there are also differences in private values, arising, for example, from the combination of risk aversion and differences in inventory positions or from different tax treatments. Such differences in private values generate potential gains from trade. Yet if these differences are privately known and if the agents are strategic, equilibrium can be inefficient and can fail to exploit all the gains from trade. This was shown, for example, by Chatterjee and Samuelson (1983) in the context of a stylized double auction. Against this backdrop, preplay communication by the agents, where they send messages about their eagerness to trade, can lead to more efficient allocations. For example, in the context of the Chatterjee and Samuelson bargaining game, strategic agents, eagerly desiring to sell, can find it optimal to announce this eagerness prior to the trade (see Farrell and Gibbons 1989; Fudenberg and Tirole 1991). This is similar to sunshine trading, a practice observed in financial markets, whereby liquidity-driven institutional investors preannounce their trading intentions to attract counterparties. Admati and Pfleiderer (1991) offer a theoretical analysis of this behavior. The preopening period in the Paris Bourse offers a platform for traders to express their desire to buy or sell and thus preplay communicate by placing tentative limit orders. Motivated in part by our findings, Brusco et al. (1998) show theoretically, in an extension of Kyle (1989) that includes a preopening round, that there exist perfect Bayesian equilibria in which strategic informed traders choose to participate in the preopening period to advertise their desire to share risk. As a result, in these equilibria, preopening prices are informative. In contrast to Medrano and Vives (1998), informativeness of preopening prices with strategic agents obtains in a market structure in which traders are sure that they can cancel or revise their preopening orders before the opening.

The discussion above implicitly assumes that investors are able to correctly compute conditional expectations and equilibrium prices. Performing these computations is a complex task, however. One of the purposes of the preopening period may be to offer a platform to the traders to progressively learn about the pricing, possibly by a

process of trial and error, and also by observing the evolution of the indicative prices. This might lead preopening prices to reflect noise, in addition to the conditional expectation posited in equation (2). To the extent that there is learning of the equilibrium pricing during the preopening, this noise component should decrease as the opening gets closer.

V. Econometric Analysis

The previous section refers to “the equilibrium value of the security” (v). To conduct our empirical analysis, we need a proxy for this value. We take the closing price of the security as such a proxy. Similarly, we take the previous close as a proxy for the market expectation of the value of the security before learning starts, denoted $E(v|I_0)$. Also, to control for heteroskedasticity induced by variation in the level of prices, we divide all prices (during the preopening as well as during the day) by the previous close. Hence the difference between v and $E(v|I_0)$ is measured by the close-to-close return, whereas the difference between $E(v|I_0)$ and the indicative price at time t is measured by the return from the previous close to this price.

A. Unbiasedness Regressions

To test the noise (H_0) and learning (H_1) hypotheses, we estimate unbiasedness regressions similar to those considered in the analysis of forward and spot exchange rates (see Hodrick 1987), in which we regress the close-to-close return onto the return from the previous close to the indicative price.

As analyzed in the previous section, because of learning and because as the opening gets closer the economics of the preopening are altered, the distribution of indicative prices or returns is nonstationary. For example, the distribution of the return from the previous close to the indicative price is different at the beginning and toward the end of the preopening. Also, the amount of noise in the indicative price is likely to be different at different points in time. To take this nonstationarity into account, we estimate (across days) one unbiasedness regression for each minute between the beginning of the preopening and the end of the trading day.¹³ Thus we analyze for each point in time (t) the distribution (across days) of the price.

Under H_1 the indicative price is the conditional expectation of

¹³ Time-series analysis in the presence of learning-induced nonstationarities is studied in Bossaerts (1996).

the value of the asset; hence changes in this price are entirely informative about the value of the asset. In this case, in the regression

$$v - E(v|I_0) = \alpha_t + \beta_t[P_t - E(v|I_0)] + Z_t, \quad (4)$$

the slope coefficient should be equal to one, for all t . There could exist a (plausibly small) risk premium associated with the uncertainty about the value v . If the corresponding risk aversion and amount of risk are constant across days, then this risk premium should be reflected in the intercept of the regression and would not affect our estimate of the slope or our hypotheses pertaining to it.

Under the noise hypothesis that indicative prices do not have any informational content, the difference between the indicative price and $E(v|I_0)$ does not help predict the change in the underlying value of the asset since the last close. Consequently, the slope coefficient (β_t) in regression (4) is equal to zero. Indeed under H_0 ,

$$\text{cov}[v - E(v|I_0), P_t - E(v|I_0)] = \text{cov}[v - E(v|I_0), \epsilon_t] = 0.$$

In addition to predictions on the slopes of the unbiasedness regressions, the alternative hypotheses have implications for the residual variances of these regressions. The variances measure the uncertainty remaining about the value of the security once the information contained in the preopening price has been taken into account. If there is learning in the marketplace, that is, if the informational content of the preopening price increases as the opening gets closer, then this uncertainty should decrease. In contrast, under the noise hypothesis, preopening prices provide no information; hence the residual variance of the regression should remain at the same level as the close-to-close variance.

We first present estimates of the unbiasedness regression (4) for the CAC 40 index. We construct the index, based on the individual prices of the stocks, applying the weights communicated to us by the Bourse and corresponding to the structure of the index on November 29, 1991.¹⁴ In fact, since Arjomari Prioux is excluded from the sample, we use only 39 stocks to construct this index.

Figure 2 plots the slopes of the regressions estimated for each one-minute interval between 9:30 and 12:00, as well as the bounds of the 5 percent confidence interval.¹⁵ The estimate of the slope of the unbiasedness regression increases between 9:30 and 10:00, which is consistent with the increasing informational efficiency of the pre-

¹⁴ We also carried out the analysis for the equally weighted index. The results were qualitatively very similar to those presented here.

¹⁵ We do not plot the results obtained for the 9:00–9:30 period. For this period there is a lot of noise in preopening prices, the confidence bounds are very wide, and the estimate of β_t is not significantly different from zero.

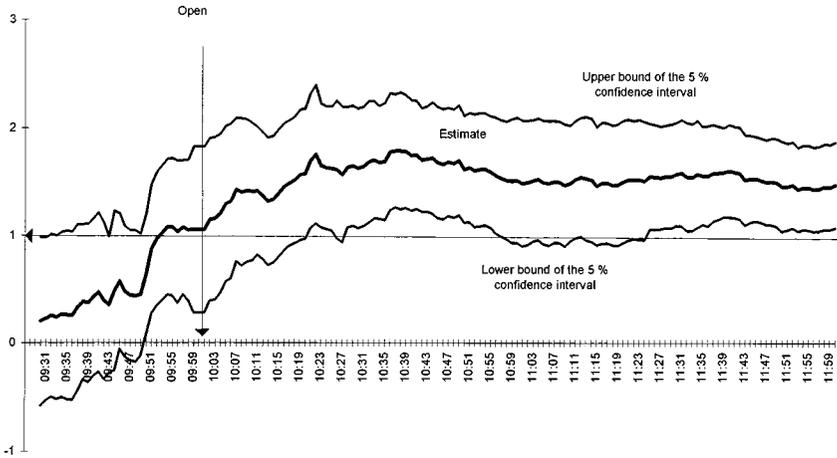


FIG. 2.—Slope of the regression across 19 days in 1991 of the close-to-close index return on the return from the previous close to the index at time t . Before 10:00 the index is indicative; after 10:00 it corresponds to actual trades.

opening prices as learning of equilibrium valuation progresses through the preopening, so that the noise component in preopening prices decreases.

The confidence interval for the slope of the regression is rather large, which reflects the relatively small size of our 19-day sample. Before 9:50, the noise hypothesis cannot be rejected, whereas it is rejected after 9:50. At approximately the same time the slope of the regression becomes near one, consistent with the learning hypothesis. Although it is likely that large traders behave in a strategic way toward the end of the preopening period, our results are consistent with the informational efficiency of the indicative prices at this point in time. This is broadly consistent with the theoretical results of Medrano and Vives (1998).

During the trading day, the slope of the unbiasedness regression is larger than one. The coefficient β_t larger than one corresponds to

$$\text{cov}[v - P_t, P_t - E(v|I_0)] > 0.$$

This can be due to staleness in the index. This staleness problem is less prevalent toward the end of the preopening because the frequency of order placement is very high (higher than during the day, as shown in fig. 1). However, in light of this discussion of staleness in the index, one should be careful in interpreting our finding that toward the end of the preopening the slope of the unbiasedness regression based on index data is very close to one. It may be that

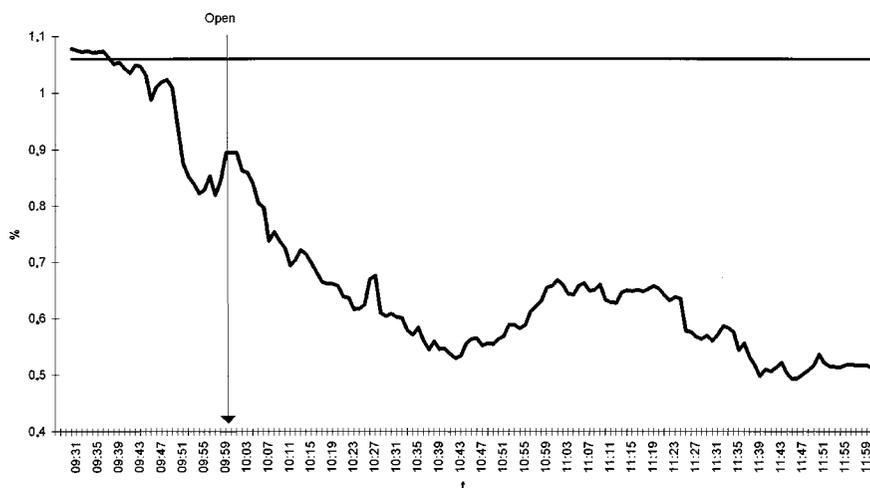


FIG. 3.—The RMSE of the regression across 19 days in 1991 of close-to-close index returns on returns from the previous close to the index at time t (compared to the close-to-close standard deviation). Before 10:00 the index is indicative; after 10:00 it corresponds to actual trades. The standard deviation of the close-to-close returns is 1.06 percent.

this reflects the countervailing effects of (i) noise in prices, which tend to drive the slope below one, and (ii) staleness, which on the contrary tends to drive the slope above one.

Figure 3 plots the RMSE of the unbiasedness regression for each minute between 9:30 and 12:00 and compares it to the standard deviation of close-to-close index returns (equal to 1.06 percent). Until 9:40 the RMSE is approximately equal to the standard deviation of close-to-close returns, consistent with the noise hypothesis. After 9:40, it starts decreasing, but this pattern is less pronounced than after 9:50. This time pattern reflects the fact that learning is not stationary in the market and that the rate at which incremental information is impounded in prices accelerates toward the end of the preopening period. This is documented further in the following subsections.

Our results are related to those of Kandel, Ofer, and Sarig (1993). They study the time pattern of the error about the inflation rate in Israel that is implicit in bond prices. They show that as trading proceeds there is learning about the inflation rate, reflected in a downward trend in the evolution of the size of the inflation expectation error. The decline in the RMSE in figure 3 is comparable to this downward trend.

Note that the time pattern of the slopes and RMSE of the unbiasedness regressions parallels that of the order flow. In particular,

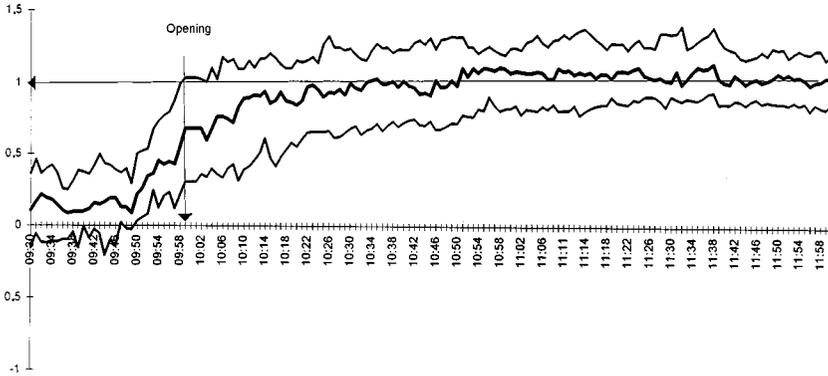


FIG. 4.—Third quartile, median, and first quartile (across 39 stocks in the CAC 40 index) of estimates of the slope of the unbiasedness regression, estimated for market model residuals across 19 days in 1991, for each minute between 9:30 and 12:00.

around 10 minutes before the opening, there is a strong increase in the order flow, as well as a pronounced increase in the slope of the unbiasedness regression and a marked decrease in the RMSE. This reflects the qualitative change in the strategies of the investors, as the risk of being unable to cancel or place an order becomes relatively greater.

To gain more insights concerning the evolution of the information content of the preopening prices, we then estimated the unbiasedness regression on individual stocks rather than on the index. To avoid using redundant information already used in the analysis of the index, we focus on the idiosyncratic component of the individual stock returns by studying market model residuals.¹⁶ More precisely, for stock i , we do not consider the close-to-close return on this stock but rather the difference between this close-to-close return and the product of the index close-to-close return and the beta of the stock. We use the betas estimated by the Bourse and reported in the Bourse annual statistics of 1991.¹⁷ Similarly, rather than the return from the previous close for stock i to the indicative price for stock i at time t , we consider the difference between this return and the product of the indicative index return and the beta of the stock.

Figure 4 plots the first and third quartiles as well as the median across the 39 stocks of the estimates of the slopes of the regression

¹⁶ We also performed the same analysis on raw individual stock returns, unadjusted for market movements, and obtained the same qualitative results.

¹⁷ We checked that these betas are rather stable over time. For example, the betas for the year 1991 are very similar to those for the year 1990.



FIG. 5.—Third quartile, median, and first quartile (across 39 stocks in the CAC 40 index) of the RMSE of the unbiasedness regression, estimated for market model residuals across 19 days in 1991, for each minute between 9:30 and 12:00.

for each minute between 9:30 and 12:00. As in the case of the index, the slope of the unbiasedness regression increases as the opening gets closer, consistent with increasing informational efficiency of indicative prices. The main difference with the results obtained for the index is that the estimate of the slope is lower. For example, at the opening the median slope is .68, whereas it was close to one in the case of the index. In fact the median slope does not reach one before 10:30. This reflects that there is more noise in market model residuals for individual stock prices than in index returns. In addition to noise, another reason why slopes are lower in the case of individual stocks is the absence of the positive serial correlation induced by staleness in the case of the index. The results presented in figure 4 suggest that at the individual stock level, price discovery is not fully achieved at 10:00 and goes on until approximately 10:30.

Figure 5 plots (for each minute between 9:30 and 12:00) the first and third quartiles as well as the median across 39 stocks of the RMSE of the unbiasedness regressions. As in the case of the index, after 9:45 the RMSE decreases as the opening gets closer, consistent with the learning reflected by the indicative prices.

B. *The Speed of Learning*

1. Moment Conditions

The asymptotic speed of learning during the preopening period can be characterized by the following equation:

$$t^\gamma(P_t - v) \rightarrow \mathcal{N}(0, \sigma^2), \quad t \rightarrow \infty, \tag{5}$$

which is consistent with Vives (1995) for $\gamma = 0.5$ or Germain et al. (1996) for $\gamma = 1.5$. Marcet and Sargent (1995) also offer an interesting analysis of the speed of convergence to rational expectations in least-squares learning models and provide conditions under which learning occurs at the rate of the square root of t .

To carry out the empirical analysis, we consider large values of t (i.e., the end of the preopening period) and approximate the asymptotic result (5) by

$$P_t - v = \frac{\epsilon}{t^\gamma} \sigma, \tag{6}$$

where ϵ is normal with $E(\epsilon|I_t) = 0$, I_t is the information set of the market at time t , and $\text{var}(\epsilon|I_t) = 1$.

In addition, to conduct the empirical analysis, we need to take into account possible errors in observing v . For example, while we proxy v by the closing price on that day, it might correspond to an earlier transaction price or to pricing on later days. To reflect this, we assume that instead of v we observe \hat{v} , where

$$\hat{v} = v + \phi, \quad \phi \perp v, \quad \phi \perp \epsilon. \tag{7}$$

Hence

$$P_t - \hat{v} = \frac{\epsilon}{t^\gamma} \sigma - \phi.$$

Taking squares, we get

$$(P_t - \hat{v})^2 = \frac{\epsilon^2}{t^{2\gamma}} \sigma^2 + \phi^2 - \frac{2\epsilon\phi\sigma}{t^\gamma}.$$

Taking expectations, we get

$$E[(P_t - \hat{v})^2|I_t] = E(\phi^2|I_t) + \frac{\sigma^2}{t^{2\gamma}} - 2E\left(\frac{\epsilon\phi\sigma}{t^\gamma} \middle| I_t\right). \tag{8}$$

Now, since ϵ and ϕ are independent and since $E(\epsilon) = 0$, this expectation simplifies to

$$E[(P_t - \hat{v})^2|I_t] - E(\phi^2|I_t) = \frac{\sigma^2}{t^{2\gamma}}. \tag{9}$$

Taking the same steps for $t - 1$, we get

$$E[(P_{t-1} - \hat{v})^2|I_{t-1}] - E(\phi^2|I_{t-1}) = \frac{\sigma^2}{(t - 1)^{2\gamma}}. \tag{10}$$

Note that $E(\phi^2|I_t) = E(\phi^2|I_{t-1})$. This is in fact a parameter of the model to be estimated, which we denote by K . Dividing (9) by (10), we get

$$\frac{E[(P_t - \hat{v})^2|I_t] - K}{E[(P_{t-1} - \hat{v})^2|I_{t-1}] - K} = \left(\frac{t-1}{t}\right)^{2\gamma}. \quad (11)$$

Taking similar steps for the comparison between P_{t-1} and P_{t-2} , one obtains after simple manipulations the following two moment conditions:

$$E\left\{ (P_t - \hat{v})^2 - \left(\frac{t-1}{t}\right)^{2\gamma} (P_{t-1} - \hat{v})^2 - K \left[1 - \left(\frac{t-1}{t}\right)^{2\gamma} \right] \middle| I_{t-2} \right\} = 0, \quad (12)$$

$$E\left\{ (P_{t-1} - \hat{v})^2 - \left(\frac{t-2}{t-1}\right)^{2\gamma} (P_{t-2} - \hat{v})^2 - K \left[1 - \left(\frac{t-2}{t-1}\right)^{2\gamma} \right] \middle| I_{t-2} \right\} = 0.$$

The parameters to be estimated are K and γ . In testing the conditions (12), we shall use instruments that are in the information set of the market at time $t-2$.

Note that from an econometric perspective, the moment condition (12) presents two advantages. First, since σ^2 is simplified away, it is robust to heteroskedasticity (i.e., changes in σ across days or stocks). Second, the moment condition is robust to temporal aggregation in the following sense: suppose that the real learning time is not t but nt , where n is an unknown constant. In this case, equation (9) should be

$$E[(P_t - \hat{v})^2|I_t] - K = \frac{\sigma^2}{(nt)^{2\gamma}}, \quad (13)$$

and equation (10) should be

$$E[(P_{t-1} - \hat{v})^2|I_{t-1}] - K = \frac{\sigma^2}{[n(t-1)]^{2\gamma}}. \quad (14)$$

However, when we take the ratio of the two equations, n simplifies away and (12) is still the right moment condition.

2. Econometric Approach

We use GMM to estimate the parameters γ and K and test condition (12). To carry out the estimation we must choose instruments. We consider the following seven instruments:

$$\begin{aligned}
 &1, \\
 &P_{t-2} - P_{t-3}, \\
 &(P_{t-2} - P_{t-3})^2, \\
 &P_{t-3} - P_{t-4}, \\
 &(P_{t-3} - P_{t-4})^2, \\
 &P_{t-4} - E(v|I_0), \\
 &[P_{t-4} - E(v|I_0)]^2.
 \end{aligned}$$

The sample used to carry out the estimation is composed of the market model residuals for the 39 stocks and the 19 days. The number of observations is $N = 39 \times 19 = 741$. Denote the sample $X_n, n \in 1, \dots, N$. Also denote $E[\phi(X_n, \gamma, K)] = 0$ the 14×1 vector of moment conditions obtained from the two moment conditions (12) and the seven instruments. The GMM estimation of the parameters γ and K stems from the following minimization program:

$$\min_{\gamma, K} \left[\frac{1}{N} \sum_{n=1}^N \phi(X_n, \gamma, K) \right]' [V]^{-1} \left[\frac{1}{N} \sum_{n=1}^N \phi(X_n, \gamma, K) \right],$$

where V is an estimator of the variance-covariance matrix of the normally distributed random variable to which $(1/N) \sum_{n=1}^N \phi(X_n, \gamma, K)$ is assumed to converge in distribution. This matrix is hereafter referred to as the weighting matrix.

Another step that needs to be taken to carry out the estimation involves determining precisely the correspondence between the theoretical variables and the empirically observed variables. As mentioned above, as in the unbiasedness regressions, we proxy the value of the asset (v) by the closing price. The choice of the times $t, t - 1, \dots, t - 4$ was driven by the following trade-off. On the one hand, since the relation we test is true only asymptotically, we want to take $t, t - 1$, and $t - 2$ close to the end of the preopening period. Hence we took t to be our last observation of the virtual index during the preopening. On the other hand, note that estimating the speed of learning is intuitively similar to estimating the slope of the decay in the variance of $v - P_t$. Now there is less numerical instability in the estimate of this slope if we consider points in time that are not too

close to one another. This is why, instead of considering one-minute intervals between t and $t - 1$ or $t - 1$ and $t - 2$, we consider five-minute intervals. Hence $t = 10:00$, $t - 1 = 9:55$, $t - 2 = 9:50$, $t - 3 = 9:45$, and $t - 4 = 9:40$.

Hansen, Heaton, and Yaron (1996) offer a comparison of two approaches to GMM estimation: the iterated method and the continuous updating method. An advantage of the latter is that it is invariant to parameter-dependent transformations of the moment conditions. The continuous updating method involves the following minimization:

$$\min_{\gamma, K} \left[\frac{1}{N} \sum_{n=1}^N \phi(X_N, \gamma, K) \right]' [V_N(\gamma, K)]^{-1} \left[\frac{1}{N} \sum_{n=1}^N \phi(X_N, \gamma, K) \right],$$

where $V_N(\gamma, K)$ is the estimate of the weighting matrix computed for the estimation of the parameters γ and K .

3. Results

Since we have only two parameters to estimate, implementation of the continuous updating method is relatively simple. We constructed a grid of possible values for γ and K , computed the χ^2 for each point of the grid, and selected the pair of parameter values for which the objective function was the smallest. The analysis was carried out for values of γ between zero and three, with increments of .05, and values of K between zero and .0005, with increments of .0001. The values of the χ^2 's obtained for the different values of γ and K are graphically represented in figure 6. The minimum is reached for $\hat{\gamma} = 1.35$ and $\hat{K} = .0001$. The minimum χ^2 is equal to 11.7, and the associated p -level is 47.1 percent.

With the iterated GMM estimation, the minimum χ^2 is found to be equal to 12.47, with an associated p -level of 43 percent, and obtains for $\hat{\gamma} = 2.7$, with a standard error of 0.86, and $\hat{K} = .00016$, with a standard error of .000025.

Note that the χ^2 's obtained in both methods are similar and are both consistent with the null hypothesis that the model is valid. The estimate of K is similar in the two methods and is significantly different from zero. While the estimate of γ differs across the two methods, it is quite high in both cases. The estimate and standard error obtained with the iterated GMM are such that both the hypothesis that there is no learning ($\gamma = 0$) and the hypothesis that the asymptotic speed of learning is the square root of t (as in Vives [1995]) are rejected. On the other hand, the hypothesis that $\gamma = 1.5$ (Germain et al. 1996) is not rejected.

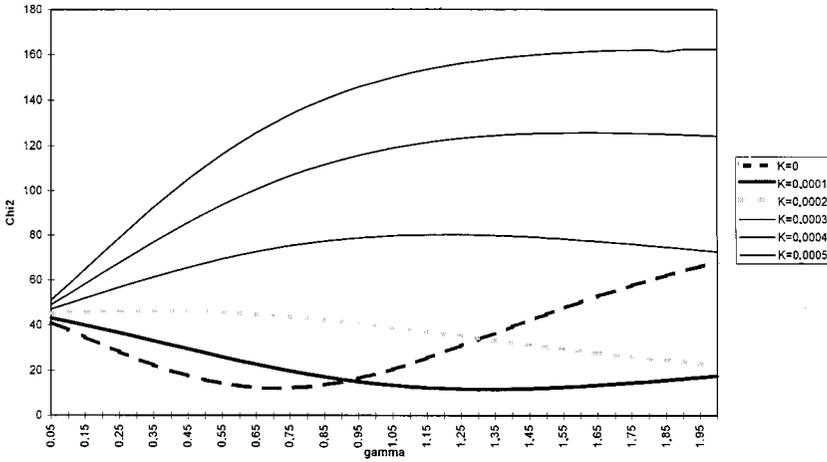


FIG. 6.—Plot of χ^2 values obtained by the continuous updating method for different values of γ and K , estimated for the period 9:50–10:00. The minimum (11.7) is reached for $\gamma = 1.35$ and $K = .0001$.

C. *Estimates of the Speed of Learning along the Learning Path*

While the theoretical foundation for equation (5) is provided by the *asymptotic* results of Vives (1995) and Germain et al. (1996), this equation can alternatively be viewed as a convenient statistical specification to provide some descriptive information on the rate at which information gets impounded in indicative prices along the learning path. In the present subsection we take this perspective and estimate equation (6) at different points during the preopening period. More precisely, we impose the moment conditions (12) to the time intervals from 9:30 to 9:40 and from 9:40 to 9:50, and we estimate γ for these two intervals, following the same steps as in subsection B.

With the continuous updating method, the estimate of γ is one for the 9:40–9:50 period and .26 for the 9:30–9:40 period; the estimate of K is .0003 for the 9:40–9:50 period and .00027 for the 9:30–9:40 period.

With iterated GMM, the estimate of γ is .59 for the 9:40–9:50 period and .473 for the 9:30–9:40 period; the estimate of K is .00022 for the 9:40–9:50 period and .00027 for the 9:30–9:40 period. The standard error of γ is .13 for the 9:40–9:50 period and .23 for the 9:30–9:40 period. In both cases γ is significantly higher than zero, in contrast with the noise hypothesis. The p -values are 6 percent for the 9:40–9:50 period and 3 percent for the 9:30–9:40 period. Hence the hypothesis that the specification is correct can be rejected at the

10 percent level for the 9:40–9:50 period and at the 5 percent level for the 9:30–9:40 period. This suggests that lack of power was not the reason why the model was not rejected for the 9:50–10:00 period.

The estimate of K is stable across methods and periods. For both methods the estimate of γ decreases as the opening gets further. This reflects nonstationarity in the preopening and an increase in the learning rate as the opening gets closer, consistent with the time pattern of the RMSE of the unbiasedness regression documented above.

VI. Relation between Our Analysis and Previous Empirical Studies of the Informational Content of Prices in Speculative Markets

Since our study examines the process by which information is impounded in prices, it is not surprising that there are some similarities between our econometric approach and those used in studies of the informational efficiency of financial markets and the random character of security prices. The specification of our unbiasedness tests is directly inspired by analyses of the efficiency of forward exchange rates. Also, our analysis bears similarities with the econometric tests for a random walk in asset prices in such studies as Fama and French (1988), Lo and MacKinlay (1988), and Richardson and Smith (1991). This is natural since the learning hypothesis is that preopening prices are martingales.

Still, the issue we analyze and the market context we study are different from those encountered in studies of market efficiency during the trading day. Since we study the price discovery process, we place emphasis on learning. Learning generates nonstationarity. This differs from the econometric setting examined in Fama and French (1988) and Richardson and Smith (1991). As mentioned above, to avoid the difficulties arising in the study of time series in the presence of learning (discussed in Bossaerts [1996]), we conduct cross-sectional analyses (for each time t , across days). This differs from the time-series approach taken in Fama and French (1988), Lo and MacKinlay (1988), and Richardson and Smith (1991).

Our analysis is also related to Camerer's (1998) recent study of racetrack betting. Before the race, bets can be placed and canceled, and the resulting odds are disseminated in real time. While both our paper and Camerer's examine whether the potential for manipulation prevents the market from reaching efficient pricing, the specific questions posed differ. To examine whether the racetrack betting market can be manipulated, Camerer placed bets, which he canceled prior to the races, and found that they did not have any

impact on the bets of the other players. Yet Camerer does not directly examine whether the bets possess information content about either the final odds or the race outcome. In contrast, we focus on whether preopening prices possess information content. While Camerer shows that the manipulative bets he placed did not disrupt the market process, we show that in spite of the potential for manipulation in the preopening, the indicative prices have informational content. Further, our results exhibit some similarities with Camerer's. In both markets, actions taken shortly before the opening or the race seem to carry more weight. In the preopening in the Bourse, prices and orders are informative during the last 10 minutes. In the racetrack betting case, Camerer finds that his interventions had a relatively greater impact on the odds when they took place and were canceled closer to post time.¹⁸ The risk that a position cannot be canceled prior to the opening or the race increases its impact or informational content. Consistent with this intuition, in both markets the order flow increases dramatically during the last 10 minutes.

VII. Conclusion

This paper studies the price discovery and tâtonnement process in the Paris Bourse during the preopening period. Very active order placement during the preopening period (in part motivated by the attractiveness of the opening call auction) shows the importance of this price discovery phase for the marketplace. For the first part of the preopening period the hypothesis that indicative prices are pure noise cannot be rejected. It is plausible that the large degree of noise in these early indicative prices reflects (at least in part) the difficulty of the task of discovering the equilibrium price. Another possible reason is strategic or manipulative behavior, made possible by the lack of immediate execution until 10:00 A.M. As the opening gets closer, the evidence is consistent with an increase in the informational content and informational efficiency of the indicative prices. We interpret this increase as reflecting price discovery and the convergence of prices toward the equilibrium market valuation. The relatively large degree of informational efficiency of the preopening indicative prices suggests that the discipline provided by the occurrence of immediate trades is not necessary for markets to reach informationally efficient outcomes.¹⁹

¹⁸ We conjecture that if Camerer's bets had run a significant risk of being executed (which would have been reflected in some of them actually not being canceled and others canceled immediately before the race), they would have had a greater impact on betting and odds.

¹⁹ Note that certain exchanges, e.g., the Brazilian Stock Exchange, impose limits on the extent to which traders can place, revise, and cancel orders during the pre-

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